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Development of an optimization methodology for pavement management systems

Doctoral Thesis in
Civil Engineering

Work developed under the supervision of
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and co-supervision of
Doctor Tien Fang Fwa

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STATEMENT OF INTEGRITY

I hereby declare having conducted my thesis with integrity. I confirm that I have not used plagiarism or any form of falsification of results in the process of the thesis elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

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“O melhor prémio de fazer algo, é tê-lo feito bem.”

“The best award you can take from doing something, is knowing you’ve done it well.”

(Pai)

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Governo da República Portuguesa



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Abstract

The expansion and quality increase of road infrastructures in developed countries during the last decades is shifting the attention towards their preservation rather than to new construction. Pavements are the most costly road asset. Therefore, their preservation management optimization is important in order to meet quality and safety demands within available budgets that are becoming increasingly limited. More recently, environmental aspects related to the pavements life-cycle have been raising concerns that must be addressed.

The present thesis describes the development of an optimization methodology that intends to be a decision support tool for road administrations. In fact, this work emerged within the scope of a highway administration related project, so it has a character of applied research.

The developed methodology is capable of suggesting pavement preservation plans at the network level for a certain time period. It considers aspects related to pavement quality, administration costs, as well as user and environmental costs. Genetic algorithms are employed to optimize problems with two or three conflicting objectives, either simultaneously or at distinct phases in order to deal with pairs of objectives at different levels.

Data selection and filtering and the development of Markov based prediction models are also included in the thesis. The methodology is flexible, so that other prediction models with better adjustment to the problem to be solved can be implemented. Similarly, preservation operations and the respective costs and effects on the pavement are also adjustable.

The use of European-level standardized performance indicators and the consideration of user costs and costs related to CO_2 emissions in a multi-objective optimization are the main differences of this methodology to existent ones.

The methodology is applied in two distinct case studies that complement each other, allowing to demonstrate the features and adaptability of the methodology. The first case study relies on historical data from an American database, while the second

one is based on data provided by a Portuguese highway administration. In the first case, preservation plans for a group of geographically separated pavement sections are defined, regarding administration costs and pavement quality at first, and user and environmental costs at last. The second case study is focused on a pavement segment that is divided in several dozens of adjacent sections. This allows the suggestion of preservation plans indicating the relative segment area that should be affected with a specific treatment in a specific year, in order to meet quality constraints while optimizing administration costs and pavement quality for the analysis period.

Key-words

Road pavement management systems; performance indicators; COST 354; prediction models; Markov chains; multi-objective optimization; genetic algorithms; two-stage optimization; sustainability; costs of CO_2e emissions.

Resumo

Título
Desenvolvimento de uma metodologia de otimização para sistemas de gestão de pavimentos.

O grande desenvolvimento verificado na expansão e na qualidade das infraestruturas rodoviárias nas últimas décadas em países desenvolvidos, faz com que cada vez seja dada mais atenção à sua preservação do que à nova construção. Os pavimentos rodoviários são o ativo mais dispendioso das estradas, pelo que é de extrema importância otimizar a gestão da sua conservação de modo a cumprir com critérios de qualidade e segurança dentro dos limites orçamentais que tendem a ser cada vez mais restritos. Mais recentemente, questões ambientais associadas ao ciclo de vida dos pavimentos rodoviários têm levantado preocupações que devem ser abordadas.

Esta tese descreve o desenvolvimento de uma metodologia de otimização que pretende constituir uma ferramenta de apoio à decisão para administrações rodoviárias. De facto, este trabalho surgiu no âmbito de um projeto associado a uma concessionária de auto-estradas, pelo que tem um carácter de investigação aplicada.

A metodologia desenvolvida é capaz de sugerir planos de conservação de pavimentos ao nível da rede para um determinado período de tempo, tendo em conta aspetos relacionados com a qualidade do pavimento, custos para as concessionárias, bem como custos para os utentes da estrada e para o ambiente. A metodologia usa algoritmos genéticos para otimizar problemas com dois ou três objetivos conflituantes, quer em simultâneo, quer em fases distintas de modo a lidar com pares de objetivos em diferentes níveis.

A tese inclui ainda uma etapa de seleção e tratamento de dados, bem como de desenvolvimento de modelos de previsão baseados em cadeias de Markov. A metodologia é flexível e pode ser alimentada com outros modelos de previsão que melhor se ajustem ao problema em causa. De igual modo, também as operações de conservação,

respetivos custos e efeitos no pavimento são ajustáveis.

O uso de indicadores de desempenho uniformizados ao nível Europeu, e a inclusão de custos para os utilizadores das estradas e de custos associados a emissões de CO_2 numa otimização multi-objectivo são as principais diferenças desta metodologia para outras já existentes na literatura.

A metodologia é aplicada a dois casos de estudo distintos que se complementam e permitem demonstrar as funcionalidades e flexibilidade da metodologia. O primeiro caso de estudo baseia-se em dados históricos de uma base de dados Americana, e o segundo em dados fornecidos por uma concessionária de auto-estradas Portuguesa. No primeiro caso, são definidos planos de conservação para um conjunto de secções de pavimento separadas geograficamente, tendo em conta custos para a administração e qualidade do pavimento, primeiramente, e custos ambientais e para o utilizador, por último. O segundo caso de estudo foca-se numa extensão de pavimento dividida em várias dezenas de secções adjacentes, permitindo assim definir planos de conservação que indicam percentagens dessa extensão que deverão receber um determinado tratamento em determinado ano, de modo a otimizar a qualidade e os custos para a concessionária, cumprindo com as restrições de qualidade para todo o período de análise.

Palavras-chave

Sistemas de gestão de pavimentos rodoviários; indicadores de desempenho; COST 354; modelos de previsão; cadeias de Markov; otimização multi-objetivo; algoritmos genéticos; otimização multi-nível; sustentabilidade; custos de emissões de CO_2e.

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List of abbreviations and symbols

AADT	Annual Average Daily Traffic
AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transport Officials
AC	Asphalt Concrete
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
ASFINAG	Autobahnen und Schnellstrassen-Finanzierungs-AG - Motorways and Highways Financing Corporation
C_A	Administration Costs
C_S	Society Costs
C_T	Total Costs
C_U	User Costs
cm	Centimetre
COST	European Cooperation in Science and Technology
COST354	COST Action 354 - The way forward for pavement performance indicators in Europe
CPI	Combined Performance Index
CPI_COM	Combined Performance Index for Comfort
CPI_SFT	Combined Performance Index for Safety
CPI_STR	Combined Performance Index for Structure
CR	Cracking Rate
CS	Condition State
DOT	Department of Transportation
EP	Estradas de Portugal - Portuguese roads administration
ESAL	Equivalent Single-Axle Load
ETS	Emission Trading System

EU	European Union
FCF	Fuel Consumption Factor
FHWA	Federal Highway Administration
FN	False Negatives
FP	False Positives
FPR	False Positive Rate (Fall-out)
FWD	Falling Weight Deflectometer
GA	Genetic Algorithm
GHG	Greenhouse Gas
GIS	Geographical Information System
GP	Goal Programming
GPI	General (Global) Performance Index
GPS	General Pavement Studies
GWP	Global Warming Potential
HDM-4	Highway Development and Management Tool
IP	Infraestruturas de Portugal - Portuguese infrastructures administration
IRI	International Roughness Index
ISTEA	Intermodal Surface Transportation Efficiency Act
km	Kilometre
km/h	Kilometres per hour
kN	Kilonewton
kPa	Kilopascal
kWh	killowatt-hour
L	Log-likelihood
LCC	Life-Cycle Costs
LFC	Longitudinal Friction Coefficient
LLH	Left Lane Half
LP	Linear Programming
LTPP	Long Term Pavement Performance

m	Metre
M&R	Maintenance and Rehabilitation
m/s	Metres per second
MCA	Multi-criteria Analysis
MCS	Monte Carlo Simulation
MIRIAM	Models for rolling resistance In Road Infrastructure Asset Management systems
mm	Millimetre
MOGA	Multi-objective Genetic Algorithm
MPD	Mean Profile Depth
mph	Miles per Hour
MSL	Maintenance Service Level
NaN	Not a Number
NCHRP	National Cooperative Highway Research Program
NLP	Non-Linear Programming
NPV	Net Present Value
NSGA-II	Nondominated Sorted Genetic Algorithm-II
NUS	National University of Singapore
PCI	Present Condition Index
PDI	Pavement Distress Index
PI	Performance Index
PI_B	Performance Index for Bearing Capacity
PI_CR	Performance Index for Cracking
PI_E	Performance Index for Longitudinal Evenness
PI_F	Performance Index for Skid Resistance
PI_R	Performance Index for Transverse Evenness
PIARC	World Road Association
PMS	Pavement Management System
PPPM	Pavement performance prediction models
PPV	Positive Predictive Value (Precision)
PSI	Present Serviceability Index
PSR	Present Serviceability Rating
QCP	Quality Control Plan

RCI	Road Condition Index
RD	Rut Depth
REC	Regression Error Characteristics
RL	Right-lane
RLH	Right Lane Half
ROC	Receiver Operating Characteristics
RRC	Rolling Resistance Coefficient
RUC	Road User Costs
SCE	Shuffled Complex Evolution
SCI_{300}	Surface Curvature Index 300
SFC	Sideways Friction Coefficient
SGC	Sistema de Gestão da Conservação - Maintenance management system
SGPav	Sistema de Gestão de Pavimentos - Pavement management system
SL	Slow-lane
SN	Structural Number
SPS	Specific Pavement Studies
SustIMS	Sustainable Infrastructure Management System
SUV	Sport Utility Vehicle
TCGA	Tchebycheff method + Genetic Algorithm
TechP	Technical Parameter
TN	True Negatives
ton	Tonne
TP	True Positives
TPM	Transition Probability Matrix
TPR	True Positive Rate (Recall)
UNFCCC	United Nations Framework Convention on Climate Change
USA	United States of America
USD	U.S. Dollars
VOC	Vehicle Operating Costs

Chapter 1

Introduction

1.1 Background

Nowadays, it is well noticed that road networks are a crucial asset for the development of every country and for the quality of life of its citizens. In the most developed countries, those networks are already well expanded, which increases the importance of its management instead of its construction. For instance, in USA, since the 1960's, highway agencies have gradually moved from a focus on expansion to one on preservation, so far that the current challenge is to manage a wide range of assets to meet public, agency and legislative expectations with limited funding (Wu et al., 2012). Similarly, in Portugal, the highway network will hardly expand more. Thus, Administrations concerns towards its management efficiency are getting more attention than new construction projects. As an example, in the last trimester of 2012, an R&D project entitled Sustainable Infrastructure Management System (SustIMS) was initiated, co-promoted by a Portuguese highway concessionaire, ASCENDI, the University of Minho and the Nova University of Lisbon. The main goal of SustIMS was to develop a computational tool to support highway operator's decisions considering all the road assets in an integrated platform (Berardinelli et al., 2014). Other countries are facing similar challenges and looking for improvements on its road asset management (Gilchrist et al., 2008).

Indeed, as a consequence of more stringent budgets, increasing demands, and stricter accountability in transportation investments and policy-setting decisions, a robust asset management is needed (Wu et al., 2012). According to the Federal Highway Administration of USA (FHWA, 1999), asset management is a systematic process of maintaining, upgrading, and operating physical assets cost-effectively, combining engineering principles with business practices and economic theory, and providing tools

to facilitate a more organised and logical approach to decision-making.

Such tools, often analytical, aim to optimize (reduce) the life-cycle costs of an infrastructure as a whole and of each of its parts individually, as well as to increase its performance. The decision making process typically occurs at strategic, network and project level (Frangopol and Liu, 2007). Among other road infrastructure assets, such as bridges, culverts, traffic signals, road furniture and road reserves, pavements comprise a major part of the total road asset value, requiring one of the higher investments in a long term perspective. This fact enhances the importance of pavement management systems focusing on network level and project level, providing outputs for the strategic management, where decisions about global funding and its distribution along time and across asset classes are made (Haas, 2011).

Pavement management was recognized as a legitimate part of highway engineering several years ago, consisting in a viable tool for the decision-makers to manage the resource allocation to pavements (Finn, 1998). Despite the development of pavement performance prediction models (PPPMs) and optimization methods together with the technology development, a lot of issues remained to be properly solved. Nowadays, the reliability and credibility of probabilistic PPPMs, the uncertainty regarding cost information over location and over time, consideration given to user costs, credibility of the preservation recommendations, and the adequacy of the performance factors and consistency of measurements keep being a matter of study to develop accurate Pavement Management Systems PMSs (Amador-Jiménez and Mrawira, 2011; Santos and Ferreira, 2012; Khattak and Alrashidi, 2013). In addition, the increasing importance given to the environmental sustainability of roads has been motivating a number of studies intending to assess the environmental impact of roads during the whole life-cycle (Flores et al., 2016). Its inclusion in the decision making of road administrations towards reducing environmental costs resulting from the construction, preservation and usage phase of pavements is another challenge that should be more consistently addressed.

1.2 Objectives

The present doctoral thesis emerged, at first, within the scope of the SustIMS project mentioned in Section 1.1, in order to contribute with scientific knowledge for the project development regarding the optimization of pavement management. The principal aim of this work was to develop an optimization methodology to support decision making regarding the planning of pavement preservation activities, considering pavement quality and administration costs. Pavement quality is related to several pavement dis-

tresses that must not exceed certain threshold values on its deterioration. Costs for the administration are mainly related to the direct costs of M&R. In addition, increasing attention has been given to user costs and environmental impacts due to the use and preservation activities of pavements. Therefore, these aspects are also to be included in the developed methodology in some extent.

Besides the development of the optimization methodology itself, PPPMs are addressed in this work because they are an essential input to optimize the decision-making for a long-term period. Consequently, this thesis also includes work related to the standardization of pavement performance indicators (PIs), since they are crucial to standardize information retrieved from pavement databases and to assess pavement condition.

This work intends, then, to integrate several objectives, constraints and related aspects in the same optimization methodology, which is later expected to be suitable to be applied in a road management platform. The methodology must be able to define optimal M&R plans for a single pavement section, as well as for a network of several sections. The quantification of pavement quality through performance indicators defined at the European level and the consideration of user and environmental costs as a third conflicting objective in a multi-objective optimization methodology are expected to be the major contributions of this thesis to the frontier of knowledge. The quantification of environmental costs rely on the fact that a direct cost affected to the emissions of CO_2 is actually becoming a widely implemented mechanism towards reducing worldwide emissions.

Finally, the methodology should be easily adaptable to various contexts, allowing the definition of different pavement performance prediction models, M&R costs and effects and other inputs that are likely to change among road administrations or countries.

1.3 Thesis outline

In the present chapter, entitled as "Introduction", a background context that justifies the development of this thesis, its main objectives as well as the thesis outline are briefly presented. Besides this chapter, there are six more chapters in this thesis.

The literature review is presented in Chapter 2, which covers four main aspects. At first, an overview of some pavement management systems (PMSs) used around the world is presented in order to understand and expose the main features and objectives of a PMS. Then, a review of prediction models suitable for road pavements is made.

In Section 2.3, several decision support methods that have been used for pavement management purposes are introduced, from a mathematical perspective as well as from the practical application features. Finally, a review on the quantification procedures of user and environmental costs is presented in Section 2.4 with particular focus on the influence of rolling resistance in those costs.

Chapter 3 is related to the selection of a database and pavement performance indicators that were necessary to develop the prediction models and the optimization methodology. The process of retrieving, filtering and preparing raw data to be transformed in performance indicators is explained in this chapter.

The development of pavement performance prediction models to be used in this thesis is explained in Chapter 4. They are based on Markov chains, so a theoretical presentation of the Markovian approach is also included. Reference to Monte Carlo simulation and the definition of the preservation model is also presented in Chapter 4.

Chapter 5 is the longest of the thesis and the one that presents the development of the optimization methodology, explaining in more detail the optimization variables and objectives. A theoretical presentation of multi-objective optimization and of genetic algorithms is made in this chapter. Some practical examples are performed in order to test different approaches to consider constraints and conflicting objectives. Finally, in Section 5.6, an hypothetical case-study is used in order to test the functionality of the methodology when a third conflicting objective is included, either considering just one pavement section as well as a group of sections. A two-stage approach that allows the consideration of different pairs of objectives at different optimization levels is presented within the same case study. Finally, a probabilistic and uncertainty analysis is also performed.

The optimization methodology was applied to two practical and real-based case studies, in order to assess its applicability. This is presented in Chapter 6, at first for a case study with data from the Long Term Pavement Performance (LTPP) database, and then for a case study with real data of a Portuguese highway administration. The two cases differ in the type and amount of available data and on the optimization approach used for each one, thus complementing each other in the assessment of the developed methodology.

Finally, the conclusions of this thesis are presented in Chapter 7, regarding the successful achievements and the difficulties faced during the development of this thesis. Aspects that were not successfully addressed and other suggestions for future works are also indicated in this chapter.

The bibliography and appendices list are located at last.

Chapter 2

Literature review

2.1 Pavement Management Systems

Pavement Management Systems (PMSs) are a part of a road infrastructure management system, where strategic decisions are typically made. Under the strategic level, at network level management, the main goal is to develop for the whole network a maintenance and rehabilitation (M&R) program, including a budget plan and a work plan over the analysis period, ensuring that the right pavement sections receive the right treatments at the proper time (Wang et al., 2003; Abo-Hashema and Sharaf, 2009a). At project level, decisions are made about concrete projects and are concerned with detailed life-cycle economic consequences (Broten, 1996; Tsunokawa and Ul-Islam, 2007).

Technically, a PMS must comprise a complete and efficient database in order to facilitate the development or adoption of pavement performance prediction models (PPPMs) and to define the most important decision criteria according to the pavement condition. It is also important to evaluate the results obtained in previous experiences in order to improve the construction or rehabilitation techniques. From the administrative side, a PMS allows defining the general condition of the road network, planning of preservation actions, determining the consequences of different financing levels in the pavement condition and it constitutes an objective platform to support political decisions (Branco et al., 2005; Oliveira et al., 2011). A PMS should be capable of predicting the future conditions of the network, depending on the available budget, and to define the best preservation strategy to obtain the highest cost-effectiveness rates for the community according to the available resources. The prediction of pavement performance has always inherent uncertainties which influence the effectiveness of the whole PMS, denoting the importance of including optimization models that

takes uncertainty into account with the performance prediction (Soleymani and Shivakoti, 2006). By analysing and understanding the uncertainty sensitivity, the decisions become more robust.

Many of the PMSs found in the literature were first developed in USA, namely due to the Intermodal Surface Transportation Efficiency Act (ISTEA) approved in 1991 that mandated the development of PMSs for each State Department of Transportation (DOT) (Wiegmann and Yelchuru, 2012). The FHWA (1999) reported that most of the states had already implemented some kind of system for pavement management. Many other countries around the world have been implementing PMS as well, either based on the ones developed by DOTs of USA or developed by their road administrations in order to face particular challenges from each country (Javed, 2011; Zimmerman et al., 2013).

Recently, the Transportation Research Board (TRB) released a report entitled as "A Synthesis of Highway Practice" (Zimmerman, 2017) with the main goal of reporting on current knowledge and practice among several road administrations of USA and Canada regarding the use of PMSs. A significant number of road administrations reported to be using a PMS that was developed in house or specifically customized in place.

Generally, different PMSs differ from each other regarding several aspects, such as the collected data, the way of collecting and organizing it in a database and the geographic referencing system used. There are also differences regarding the levels of analysis (strategic, network and project) and the way to connect them towards obtaining a final decision. An important part that can get many variances is related to the evaluation and prediction of pavement performance, since there are many distresses and forms of combining their measurements into performance indicators in order to appraise pavement condition, as well as there are several types of prediction models, as further presented in Section 2.2. Finally, the approach to make management decisions differ on the number and type of objectives to attain, the type of imposed constraints and the methodologies and/or algorithms used to support the decision making, as explained later in Section 2.3. In the following paragraphs, some PMSs are briefly described in order to indicate relative differences among them and point out possible issues found during the literature review. It is not intended to present an extensive review of PMSs, but a light overview of its existence and evolution in different geographies.

One of the most well-known PMS is the Highway Development and Management Tool (HDM-4), which development was promoted by the World Road Association (PIARC) in cooperation with several other institutions. This tool has been used in several agencies from more than one hundred countries (Tsunokawa and Ul-Islam, 2007).

The second version of HDM-4 improved some features of the first one and constitutes a powerful system for programming road works, estimating funding requirements, allocating budget, predicting road network performance, appraising projects and studying policies impacts. The technical analysis within the HDM-4 is undertaken using four sets of models: (1) Road Deterioration - that predicts pavement deterioration for bituminous, concrete and unsealed roads based on traffic loading, environmental weathering and drainage conditions, (2) Works Effects - to simulate the effects of road works on pavement condition and to determine the corresponding costs, (3) Road User Effects - to determine costs of vehicle operation, travel time and road accidents to the economy and (4) Social and Environment Effects - that determines the effects of vehicle emissions, energy consumption and traffic noise (Kerali et al., 2009). HDM-4 applications cover strategy, programme and project analysis. The overall structure of HDM-4 is illustrated in Figure 2.1.

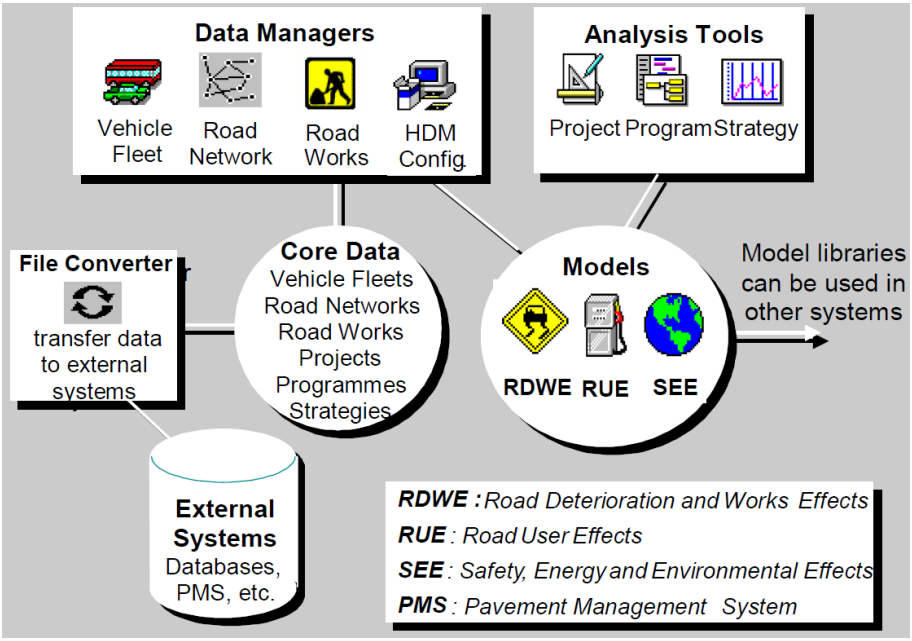


Figure 2.1: HDM-4 system architecture (Kerali et al., 2009)

The main goal of the strategy analysis is either to determine the required funds to meet specific network performance standards or to determine network performance for given funding levels. HDM-4 provide three different objective functions to be individually optimized at the strategy level: (1) maximize benefits measured by the Net Present Value (NPV); (2) maximize improvement in network condition measured by longitudinal roughness only (IRI); (3) minimize agency costs.

The programme analysis deals with the prioritization of a defined long list of candidate road projects, specified for discrete road sections, into a one-year or multi-year

work programme, under budget constraints. The selection criteria depends on thresholds for maintenance and rehabilitation or on development standards defined by the agency. For multi-year programming, HDM-4 employs the *incremental NPV / cost* ratio as the ranking index for prioritization purposes in order to maximize the economic benefits for each additional unit of expenditure (Kerali et al., 2009). According to Javed (2011), this benefit/cost analysis is not preferred, because not all the benefits can be conventionally and rationally converted into monetary value, which tempted the incorporation of a relative Analytic Hierarchy Process (AHP), requiring large number of pairwise comparisons for larger number of alternatives. The prioritization of the candidate projects at this level does not consider multi-objectives, which is a drawback of this methodology.

The project analysis assesses the physical, functional and economic feasibility of specified project alternatives by comparison against a base case. In HDM-4, this level of analysis is the only one with a multi-criteria analysis (MCA), considering several issues such as (1) the structural performance of pavements, (2) life-cycle predictions of road deterioration, road works effects and costs, (3) road user costs and benefits, (4) economic comparisons of projects alternatives, (5) preservation of the road network's asset value. Through the MCA, each possible alternative is evaluated in terms of the defined objectives, according to the assignment of preferences for each criteria (Kerali et al., 2009).

While in project analysis, the definition of scenarios are based on the requirements to conduct sensitivity analysis, in programme and strategy analysis, scenarios are based on different budget levels to be optimized. The different levels of analysis are not dynamically linked, so it is hard to evaluate the consequences that a decision taken at one level has in other level (Javed, 2011). Indeed, the main difference between strategic, program and project analysis is in the details at which data are defined, thus the funding requirement at strategy level involves more uncertainty and is not the true representation of what pavement network requires. Some experts have been defending the need to integrate project level and network level pavement management (Zimmerman and Peshkin, 2004; Ong et al., 2010). Being just a tool for economic assessment of road investment projects, HDM-4 utilizes existing data to perform an analysis, so a calibration of pavement deterioration models is imperative to fit the local conditions and some of the parameters included in the model may not be appropriate for some highway administrations (Javed, 2011).

In Portugal, the first consistent pavement preservation management system (SGC) was developed between 1990 and 1995 with the purpose of supporting the Portuguese road network administration, known as *Junta Autónoma de Estradas* at the time,

regarding its preservation strategies (Pereira and Miranda, 1999). Later, between 2003 and 2007, a new PMS, named SGPav was developed for the former *Estradas de Portugal (EP)*, presently *Infraestruturas de Portugal (IP)*. Ever since, several improvements have been made in order to optimize the management process. The SGPav framework is illustrated in Figure 2.2.

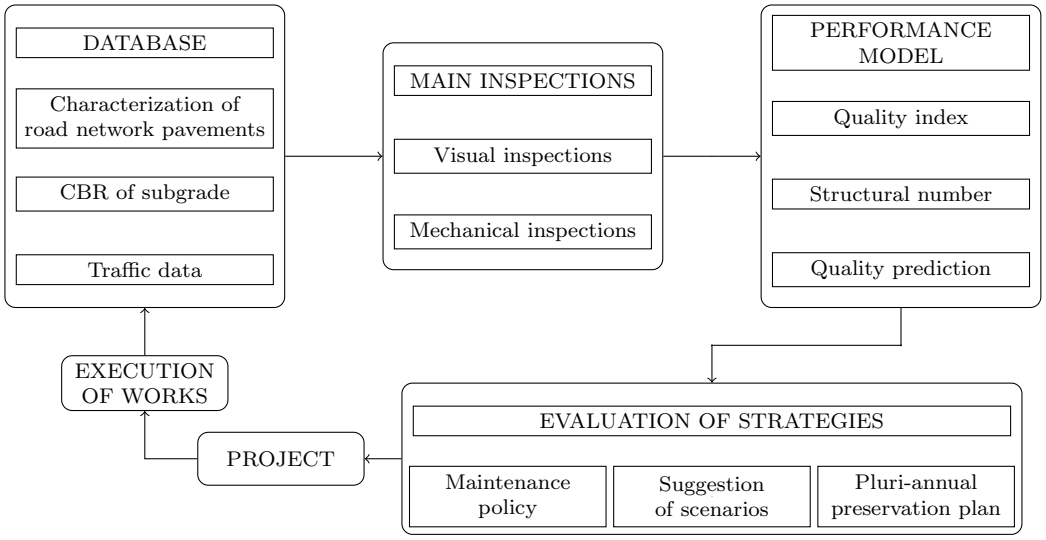


Figure 2.2: SGPav framework (adapted from Horta et al. (2013)).

It contains a database with information about the traffic, pavements surface and foundation characteristics, a list of historical visual and mechanic inspections and their results, a PPPM to estimate the future conditions regarding a quality index and a structural number, and a strategic evaluation field to define the management strategies by comparing different possible scenarios based on the preservation policy. A geographic information system (GIS) is used as an interface to represent the road condition. Pavement data can be aggregated by (1) road section, (2) 1000 m segments, (3) 100 m segments or (4) 10 m segments. The management strategy is led by the identification of needs and priorities, so each possible operation is evaluated according to two criteria: (1) the technical urgency of operation and (2) the relation between the required investment with the traffic demand (Horta et al., 2013). The prioritization of operations according to the ranking of its urgency does not necessarily lead to an optimal strategy for the performance and life-cycle costs of a network on the long-term.

Ferreira (2006) presented SIGPAV, a PMS developed in Portugal that consists in a database where all the road information is stored, a quality assessment system and a decision support system, as schematically illustrated in Figure 2.3. It is connected with a GIS to facilitate the information interpretation. The quality assessment system allows the calculation of several individual parameters and a global quality index: the Present

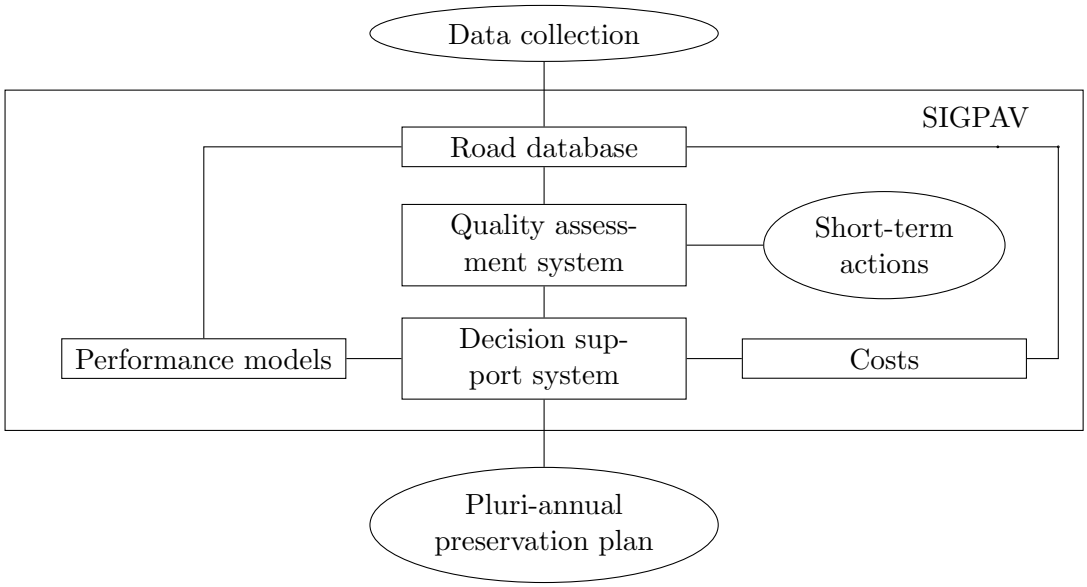


Figure 2.3: SIGPAV framework (adapted from Ferreira (2006))

Serviceability Index (PSI). The decision support system helps to define a pluri-annual preservation program for all the network.

First, an extensive and well defined list of thresholds for pavement quality is predefined and used to activate the corresponding M&R actions. The cost of these actions partially depends on the distresses condition. The criteria to activate specific M&R actions is used to define an initial preservation programme for pavements, which is based on a corrective approach. To define a more economic programme, it is necessary to test several preservation alternatives that can optimize costs at the medium and long term. For this purpose, rehabilitation actions are evaluated (or classified) according to his efficiency period, defined as the time interval between its application and the moment when the PSI reaches its terminal value. Similarly, for each corrective intervention, there are several preservation actions to be used, which differ on their range of effects, so that some are more preventive than others (Ferreira, 2006).

The final programme is then obtained through the usage of deterministic PPPMs and a single-objective optimization methodology. The aim is to minimize costs, when constrained by performance parameters, or to maximize benefits, when constrained by annual budgets. Costs can include user costs and residual value of pavements at the end of the planning period (Ferreira, 2006). As many variables that influence pavement condition evolution are stochastic, deterministic models might be too much rigid to predict future pavement conditions. The single-objective approach limits the number of alternatives that a decision maker might have if more objectives are considered simultaneously.

Chan et al. (1994), at National University of Singapore (NUS), developed a single-objective model called PAVENET which was the first optimization model in PMS working with genetic algorithms (GA) to solve PMS programming problems (Javed, 2011), capable to formulate multi-annual preservation plans. Fwa et al. (2000) improved PAVENET by incorporating the capability to solve multi-objective problems, using a rank based priority model in the form of priority weights assigned to individual preservation activities.

In Austria, in 2001, the motorway company *Autobahnen- und Schnellstrassen-Finanzierungs-AG (ASFINAG)* started with the practical application of a computer-assisted PMS. Since then, a development of an algorithm and a software module for the generation of segments characterized by homogeneous pavement conditions using Bayesian statistics were developed, as well as PPPMs (semi-probabilistic deterioration functions) for various pavement condition attributes using "Bayesian updating-process". The Austrian PMS also includes a section-based calibration method for pavement models, a pavement structural number specifically for Austria and a module for the integration of user costs into the optimization process (Weninger-Vycudil et al., 2004).

In USA, several DOTs developed their own PMS. For instance, the original Arizona PMS includes a network level pavement management procedure that was implemented in the States of Alaska and Kansas and in countries such as Holland, Finland, Hungary and Australia (Golabi and Pereira, 2003). It was structured as a single objective cost minimization linear programming model, expected to minimize agency discounted costs of pavement M&R actions over a horizon planning time, while keeping the network within given quality standards in terms of proportion of roads. Markov chains were adopted to predict pavement deterioration. Since the pavement management involves multiple and conflicting objectives, the fact of being a single objective model requires the decision maker to know beforehand the ranges of variation of each constrained objective in order to establish coherent goals (Javed, 2011). A new PMS has been developed, in which various relevant data have been integrated into one centralized database to support the system's functions. The main advantage of the new system is that it provides a great deal of flexibility in allowing individual pavement sections under different conditions to be treated differently in performance prediction analysis and project prioritization. Consequently, it is required to set up many parameters for the analysis, which demands a great deal of engineering experience and judgement (Li et al., 2006).

The new Arizona PMS defined a global quality index named Pavement Distress Index (PDI) that depends on levels of cracking, rutting, flushing and patching for a

pavement section. This indicator is used to classify each pavement section into three conditions: acceptable, triggered and failure. Nevertheless, the original Pavement Serviceability Rating (PSR) is still used. User-defined decision trees and economic analysis are used to determine feasible M&R strategies and its respective costs and benefits (i.e. effectiveness). In this PMS, effectiveness depends on the relative importance of the section (weighting), its area, and the *Area-Under-The-Curve* which is the area under the representative performance curve if a M&R is applied and above the do-nothing curve or the minimum defined performance level. A network optimization analysis is then performed to determine optimal programs of M&R for the network, providing a given budget and/or performance constraints, as schematically represented in Figure 2.4. The optimization can be executed in a cost-minimization or effectiveness-maximization mode (ADOT, 2006). It is, then, a single-objective optimization that cannot provide a decision maker with a set of solutions differing in conflicting objectives for pavement management. The selection of feasible alternatives through user-defined decision trees is another drawback of the programming methodology, since some M&R strategies might be excluded from the optimization process in advance, leading to sub-optimal solutions.

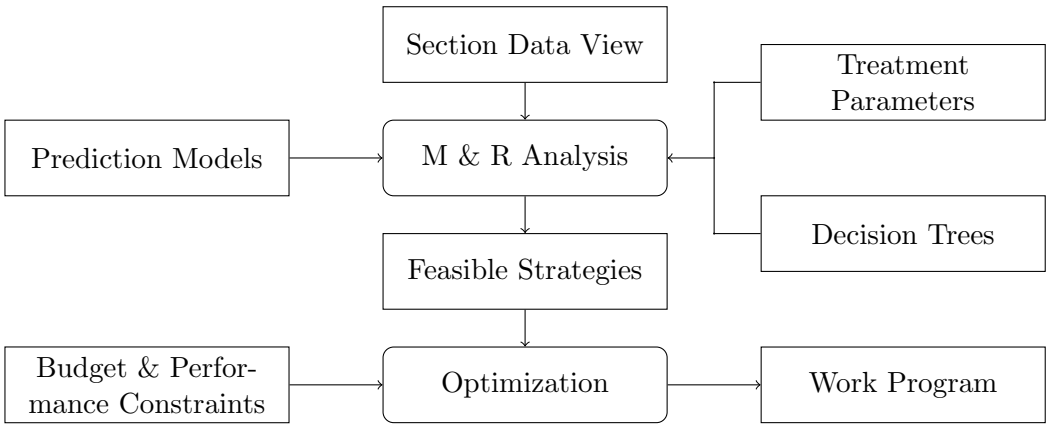


Figure 2.4: M&R analysis and optimization framework of the Arizona PMS (adapted from ADOT (2006)).

California Department of Transportation (Caltrans) has been using a resource allocation system based on pavement distress to perform its M&R needs analysis for its highways, using a rating system to identify the severity and extent of the pavement distresses, which are, later, correlated with feasible repair strategies with support of a series of decision trees (Branco et al., 2005). Trigger values are established for all severity/extent combinations of each distress type in order to identify the appropriate timing at which various M&R strategies should be selected. Then, the dominant M&R strategy is selected considering that it could best address all the distresses identified

for that project. This original system lacks of PPPMs, prioritization or optimization programming and, thus, the system is unable to perform multi-annual repair needs analysis (Javed, 2011). Recently, Caltrans have been using a pavement condition priority matrix in order to prioritize pavement needs. The matrix uses the combination of IRI, structural distresses and Maintenance Service Level MSL to examine the pavement. MSL describes the function of the route within the network and volume of traffic it serves. Each pavement section is then assigned with a priority number, which correspond to a specific range of alternative treatments (Caltrans, 2013). In the last few years, Caltrans developed a new tool, PaveM, that includes pavement distresses prediction models and enables the implementation of a proactive approach for prioritizing, preserving, rehabilitating and maintaining the existent highway pavements (Caltrans, 2016). Furthermore, efforts have been made in order to consider pavement effects on vehicle emissions of greenhouse gases (Caltrans, 2014).

2.2 Pavement deterioration prediction

2.2.1 Introduction

The prediction of pavement deterioration is an important part of a PMS, essential to enhance the programming of pavement management for a long range period. PMSs purpose is to predict pavement condition in the future, by forecasting the evolution of one or more parameters or indicators that represent the pavement condition. The reliability of such models is essential for the definition of efficient M&R strategies along the years by a management entity, as they constitute a fundamental input to support decision making. In fact, the prediction accuracy is important to reduce to a minimum the distance between preservation solutions established at network level and those that are effectively applied after studies at project level.

Regarding its formulation, there are probabilistic and deterministic models. A probabilistic model can be a probability function that predicts future condition with a certain level of probability or can be defined by transition probability matrices with probabilities of transition between condition states (CSs). A deterministic model is represented by a mathematical function, derived from observed or measured pavement deterioration using mechanistic, empirical or mechanistic-empirical methods. The methods can be considered mechanistic if they rely on physical and chemical research on material behaviour attempting to quantify cause-effect relationships; empirical if they are based on readily-observed data in the field, attempting to directly predict the future condition, ignoring the cause-effect study; or mechanistic-empirical for a

combination of the previous (Abaza, 2004; Ferreira et al., 2010; AASHTO, 2011).

Both formulations are typically represented by a mathematical approach and the predictions are based on current state, deterioration factors and effects resulting from M&R actions (Ferreira et al., 2010).

Besides their type and formulation, prediction models also vary according to the classification system used to quantify the pavement quality. Predictions can be made for single parameters that can be directly observed, for performance indicators that result from the observed parameters or even for other aspects such as, for instance, the number of loads that can be supported before failure (COST 324, 1997). Gupta et al. (2014) categorized prediction models for pavements in three groups:

- Surface characteristics based models, which mainly included information on roughness, rut depth and surface defects, being generated as a result of traffic factors and pavement age;
- Models based on environmental factors that influence pavement deterioration;
- Pavement performance rating models, which define and predict the evolution of pavement performance indexes that usually varies within a specific range and represent an overview of the pavement quality.

Variables that are potentially taken into account in the models are related, for instance, with pavement characteristics, inspections surveys, M&R activities, traffic and weather conditions. Past and present data, as well as future perspectives regarding these variables are usually important to build PPPMs. They are stochastic variables, thus, deterministic models provide an average estimate to a future which is not necessarily achieved. When prediction has to be made based on limited or non-existing information and/or there is the need to clearly reveal the uncertainty of the predicted performance, probabilistic models are important. Nowadays, several practitioners consider using both probabilistic and deterministic models (Austroads, 2012). Austroads adapted their deterministic model into a probabilistic one in order to estimate the range of possible outcomes. They adopted Monte Carlo simulation to test all combinations of the input parameters used for prediction according to the pattern of their occurrence, described by probability distribution functions (Austroads, 2013).

Finally, pavement performance prediction models (PPPMs) can be applied at a network-level to predict the future condition of roads, constituting the basis for assessing the short-term and long-term M&R needs of the road network, or at a project-level to carry out economic evaluation of alternative pavement design strategies (COST 324, 1997).

According to Zimmerman (2017), most of USA road administrations have developed their own agency-specific models, and the most commonly considered variables are: pavement type; pavement functional condition; highways system; treatment history; traffic data. In the next Subsection (2.2.2), some methods used for (PPPMs) are presented.

2.2.2 Methods used for pavement performance prediction

Regression models are widely used in predicting pavement performance by correlating known variables with an output indicator of performance. One of the first models was developed by the American Association of State Highway and Transportation Officials (AASHTO), defining and predicting the present serviceability index (PSI) based on the AASHO road test (AASHTO, 1962), which was later used by others to develop other models with adaptations to local conditions or improvements along the years (Abaza, 2004; Pan et al., 2011). Ioannides and Tallapragada (2012) presented a review on the application of regression models in some departments of transportation (DOTs) around USA. In Europe, COST 324 (1997) reported at the time other indexes and its prediction functions, such as the Residual Life for superficial layer (Denmark), the Structural Deterioration Index (Spain) and the Predicted Deterioration Index (Finland), among others (COST 324, 1997).

Luo (2011) presented an auto-regression model that takes advantage among other regression models because it is able to capture the impacts of other factors on pavement performance that are not considered or fully understood. In fact, the development of accurate empirical regression models require a reasonable amount of consistent data and the consideration of several factors that might explain the performance evolution. Professionals experience and mechanistic principles help to enhance the accuracy of empirical regression models (mechanistic-empirical). For instance, HDM-4 PPPM follows a structural empirical approach based in mechanistic principles together with empirical methods supported by regression models (Odoki and Kerali, 2013).

Longitudinal models consist in a different regression approach. Since the measurements to different pavement sections are independent among each other, longitudinal data are generated in time, which can be analysed combining Multivariate Analysis and Time Series Analysis. These models have the particularity of distinguish cross-sectional effects from longitudinal effects, so they are applicable to predict the deterioration law of pavements (Lorino et al., 2012; Sousa, 2013; Santos et al., 2014a). Similar to longitudinal models, Yu et al. (2007) proposed the use of a linear mixed effects model that differs from the others because the mean response is modelled as a combination of

population characteristics, assumed to be common to all individuals, with the subject-specific effects that are unique to a particular individual. "The former are referred to as *fixed effects*, while the latter are referred to as *random effects*".

Regression methods are relatively simple to implement and to understand and have the capability of considering several factors simultaneously. The major problem of empirical (or mechanistic-empirical) regression methods is that the response variables usually depend on several explanatory variables, thus requiring a significant amount of data regarding all those variables. Furthermore, mechanistic reasons alone can hardly include stochastic factors that affect pavement deterioration.

Markov chains in its different types are widely used as a probabilistic model to predict pavement performance (Butt et al., 1987; Li et al., 1996; Yang et al., 2005; Hassan et al., 2015). The fundamental aspect of the Markov process consists in the definition of the transition probability matrix (TPM) that rules the probabilities of a performance indicator to change its CS for a specific or range of pavement sections. In homogeneous (or stationary) Markov process, the TPM is constant for the whole analysed period, while in the non-homogeneous (or non-stationary) process, the probabilities are likely to change from time to time to meet changing conditions such as traffic load, environmental conditions, sub-grade strength or M&R operations (Hong and Wang, 2003; Abaza, 2006). Therefore, for practical applications in pavement management, non-homogeneous models are commonly used (Panthi, 2009). Previous research has argued, however, that whereas homogeneous Markov processes do not fit real conditions, non-homogeneous Markov processes lack the support of real data (Butt et al., 1987; Li et al., 1996) *apud* (Nii and Mills, 2010). TPMs are usually constructed based on statistical analysis of historical data, or, if no reasonable historic exists, pavement expert knowledge is sought to determine a reasonably accurate matrix (Yang et al., 2005; Ortiz-garcía et al., 2006).

A typical Markov chain is characterized by the so called Markov property, which supports that the next state depends only on the current state, ignoring the previous states of the system. In other words, a typical Markov chain is memoryless. There are, however, Markov chains of higher-order that take into account previous states to predict the future one (Rose, 1999; Ching and Ng, 2006). The main advantage of the higher-order Markov chains consists in improving the accuracy of predictions for problems with historical dependency. However, the number of transition probabilities increases exponentially with respect to the first order of the model, which discourages the use of higher-order Markov models directly (Ching et al., 2013). Equation 2.1 represents a constant probability of transition among discrete condition states for a

period of time Δt:

$$\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_i \end{bmatrix}^T_{t+\Delta_t} = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_i \end{bmatrix}^T_{t} \times \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1j} \\ 0 & p_{22} & \cdots & p_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & p_{ij} \end{bmatrix}_{\Delta_t} \tag{2.1}$$

where $S_{t+\Delta_t}$ and S_t are the state probability vectors at times $t+\Delta_t$ and t, respectively. These vectors are defined as the probability of a given element (a pavement section, for instance) being in each performance state, C_i. P is the transition matrix, where P_{ij} defines the probability of the transition between state i to j from instant t to $t+\Delta_t$.

Markov models are explained in more detail in Section 4.2.

Artificial neural networks ANNs are a machine learning based technique that has been used in different applications of pavement engineering (Ceylan et al., 2014), namely for predicting deterioration (Yang et al., 2003; Terzi, 2007; Ziari et al., 2015; Sollazzo et al., 2017). An ANN is essentially a computational model that simulates the functional aspects of interconnected networks (Irfan et al., 2011). By simulating the computational execution of the functionality of nerve cells, neural networks aims to reproduce an artificial brain (Rosenblatt, 1962) *apud* (Loia et al., 2000). An ANN model is composed by a large number of nodes connected by links associated with weights. Each node is associated with a state variable and an activation threshold. ANNs must be trained with significant amount of data in order to "learn" the consequences that the input data produce on the output. They behave like a "black-box", as the results disregard the casual relationships between input and output (Sollazzo et al., 2017). A simplified scheme of a ANN is illustrated in Figure 2.5.

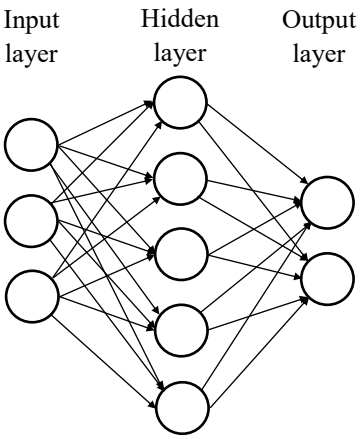


Figure 2.5: Simplified scheme of an artificial neural network (adapted from Tutorialspoint (2017)).

In fact, ANNs, fuzzy systems and hybrid soft-computing systems are becoming more popular because they can handle the many uncertainties involved in the prediction process (Ferreira et al., 2010; Pan et al., 2011; Wang and Li, 2011). Neurofuzzy systems are an example of an hybrid technique by mixing ANN with fuzzy systems (Bianchini and Bandini, 2010). Amin (2015) discussed a back-propagation ANN method where the estimated output is compared with the desired output to estimate the errors. These are then transferred backward from the output layer to intermediate levels, so that the connection weights are updated in order to cause the network to converge toward a state allowing all the training patterns to be encoded.

Several variants of prediction models using some of the concepts mentioned above have been found in the literature. Neves et al. (2012) presented an evolutionary system for asphalt pavement modelling that is based on an extension to logic programming, considering traffic, environment and pavement thickness as the factors to explain pavement deterioration. Ziari et al. (2015) used grouped method data handling (GMDH) models in partial description configurations of 1^{st}, 2^{nd}, 3^{rd} and 4^{th} polynomials, using nine independent variables related to pavement structure, age, traffic and environment to predict pavement condition. Mariani et al. (2012) used a truncated levy flight distribution to describe the decrease of pavement serviceability level offered by the structure of flexible pavements, caused by traffic and environmental conditions. Shen et al. (2016) introduced a statistical based framework that uses a binary logistic regression method together with a partial least squares regression method to predict top-down cracking. Meegoda and Gao (2014) presented a linear regression model coupled with a reliability analysis based on the Weibull model to estimate the remaining service life of asphalt pavements, based on the evolution of the international roughness index.

The Bayesian inference can be used in both deterministic and probabilistic models (Ferreira et al., 2010), since its main goal is to update the models with new available data so the expressions are adjusted in order to make them more accurate. In addition, Bayesian models are usually developed from observed data combined with expert experience using Bayesian regression techniques, which are useful to deal with small quantities of poor quality observed data and to incorporate uncertainty (Amador-Jiménez and Mrawira, 2011; Austroads, 2012; Han et al., 2014).

Some of the aforementioned models, as well as many others, were developed with data from the Long Term Pavement Performance (LTPP) database from the Federal Highway Administration FHWA. As more data are becoming available through pavement inspections, some models have been updated in order to become more reliable. Kobayashi and Kaito (2017) pointed out that "technical knowledge related with the analysis of existing data is more important than hardware technologies for obtaining

new data." In fact, in this era of big-data, data-analysis techniques are becoming more and more important in order to derive meaningful and reliable conclusions.

2.3 Decision support methods for pavement preservation management

2.3.1 Introduction

Pavement preservation management at the network-level can be divided in two sub-levels: programming level and project selection level. At the programming level, decisions regarding the budgets and general resource allocations are made over an entire network. The project-selection level then identifies which projects should be carried out in each year of the programming period (Wang et al., 2003; Denysiuk et al., 2017). Similarly, a macroscopic approach can be distinguished from a microscopic approach, as this considers significantly more variables in the analysis. In the former approach, the analysis consists in associating proportions of pavement that should be treated with certain maintenance or rehabilitation activities, while the latter approach associates maintenance or rehabilitation activities with each pavement segment (Javed, 2011).

Furthermore, top-down approach and bottom-up approach can be distinguished as two categories of addressing maintenance and rehabilitation planning at the network-level management. The former is efficient in incorporating system-level budget constraints, as it provides a simultaneous analysis of an entire system. The inability to specify optimal activities for each individual facility is its main disadvantage. The latter approach is better at providing facility-specific decisions, avoiding the loss of identity of each facility during the optimization process (Lee and Madanat, 2015; Denysiuk et al., 2017). A framework proposed by Javed and Fwa (2016) fits on the bottom-up approach, as it first establishes needs and funds requirements for individual districts given multiple objectives, and then the system-wide fund appropriation strategy is selected. Similarly, the approaches proposed by Denysiuk et al. (2017) and Moreira et al. (2017a) divide the optimization in two stages that can consider distinct pairs of objectives at different levels of analysis.

Additionally, decision making support can be made by prioritization and/or optimization (Yew, 2004; Cafiso et al., 2002), as these approaches can be used separately or together as complementary.

Prioritization involves ranking competing pavement sections requiring maintenance using subjective judgement, so the projects with highest priority are executed until the

finances are expended (Javed, 2011). The "worst first" approach is a common practice that select the road sections in worst conditions to be treated, which is logical from the point of view that those sections are the ones with highest user costs, but might be a failure to account for the level of change in benefit for the funds expended. Deterioration rates of pavement sections and incremental effectiveness of repair treatments are not considered in the "worst first" approach (Javed, 2011). However, a survey presented in 2008 by Saadatmand (2008) stated that among all the USA agencies, 9 out of 41 administrations were still using the "worst first" approach in their project prioritization. Another type of ranking using a single condition indicator is the "reverse prioritization," which has been used by some agencies to avoid the "worst first" drawbacks. "Reverse prioritization" assign the highest priority to pavements that are at the point in their life cycle where repair is most cost-effective (Broten, 1996). Because of the multi-objective character of pavement management, this strategy of maximising effectiveness may not be optimal in terms of safety and condition (Javed, 2011).

Optimization involves evaluation of all possible repair strategies and selection of the optimal strategy to meet predefined objectives, maximising or minimizing one or more objective functions while satisfying equality or inequality constraints (Javed, 2011). For this reason, optimization is more suitable than prioritization in the long term planning. For optimization of more than one objective function simultaneously, usually there is not a unique optimal solution. Hence, there is a group of non-dominated solutions that belong to the Pareto front (Deb, 2008a). Figure 2.6 illustrates an example of what could be a Pareto front, and a more detailed explanation about multi-objective concepts can be seen in Subsection 5.3.1. Several optimization methods, algorithms and their related concepts are presented in the following subsections.

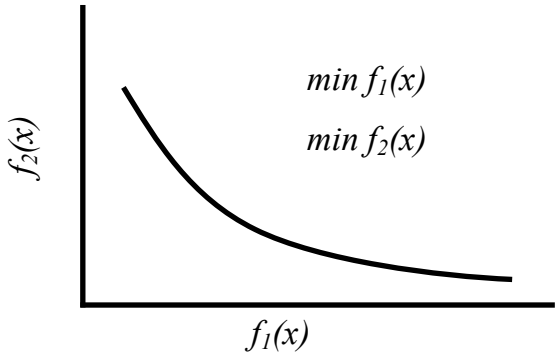


Figure 2.6: Example of a Pareto front.

2.3.2 Mathematical formulation types

PMSs, as a tool to support decision making, often uses mathematical techniques to create, evaluate and compare different scenarios for pavement preservation programs, thus providing useful information to help decision makers choosing the best solutions. Since the main problem of a decision maker is to attend to one or more objectives, while respecting certain constraints, optimization techniques are well suited to find potential preferred solutions. Indeed, several optimization techniques have been developed and adopted for pavement preservation programming. Those are typically classified by its formulation type: linear, non-linear, geometric, integer, dynamic or stochastic programming. Another type of techniques that have been gaining increasing interest are based in evolutionary algorithms. The programming techniques are often combined between them and may include evolutionary algorithms as well, constituting useful optimization models. It is important to note that there is no single method available that solves all optimization problems efficiently; hence there are several optimization methods to solve different types of problems (Rao, 1996; Deb, 2011).

In linear programming (LP) (Akyildiz, 2008; Gao et al., 2010; de la Garza et al., 2010, 2011), objective functions and constraints are formulated as linear equations, which makes this programming method a relatively simple one. Indeed, Nunoo and Mrawira (2004) stated that LP was the most common method used in PMSs. In non-linear programming (NLP) (Wu and Flintsch, 2009), functions and constraints are formulated as non-linear equations, so they can represent better real problems than with LP equations. Both the LP and NLP lack of capacity to handle large number of decision variables, suffer from combinatorial explosion problems and do not maintain the identity of individual sections (Nunoo and Mrawira, 2004).

Integer programming (Ng et al., 2011; Meneses and Ferreira, 2012) represent the particular cases, either with LP (Wang et al., 2003) or NLP (Mahoney et al., 1978; Colucci-Rios and Sinha, 1985; Bako et al., 1995) *apud* (Irfan et al., 2011), when the decision variables may be represented by discrete values. For instance, there are mixed-integer nonlinear programming models (Jawad, 2006; Irfan et al., 2011) and binary (also referred as zero/one) programming models. The zero/one integer value of a decision variable implies rejection or selection of a candidate project (Li et al., 2010).

For problems in which the decisions are to be made sequentially (also known as multi-stage decision problems), dynamic programming (Feighan et al., 1987; Abaza and Murad, 2006; Yoo and Garcia-Diaz, 2008; Albitres et al., 2012) can be a useful technique, because it decomposes a multi-stage decision problem as a sequence of single-stage decision problems (Rao, 1996). Considered to be the most accurate of the

optimization techniques that renders optimal solutions and capable of handling a larger number of M&R alternatives in less computational time (Nunoo and Mrawira, 2004; Javed, 2011), de la Garza et al. (2011) pointed the lack of flexibility and scalability as major weaknesses. Furthermore, the identity of pavement sections is not maintained, too many stages are needed for large problems and a new formulation is required every time a new objective or constraint is added (Nunoo and Mrawira, 2004; Javed, 2011). For Rao (1996), dynamic programming is very suitable for the solution of a wide range of complex problems in several areas of decision making; its major drawback is known as the curse of dimensionality, i.e., the exponential increase of computational cost and difficulty of problems as the number of variables (dimensions) increase (Bellman, 1957) *apud* (Kuo and Sloan, 2005).

2.3.3 Scalarization methods for multi-objective optimization problems

A typical approach for multi-objective optimization problems is to gather several objective functions into only one equation and/or to transform some objectives into constraints. These kind of approaches, such as the weighting sum method, the weighted metric method, the goal programming and the ϵ-constraint method are known as scalarization methods. They are briefly described in the following paragraphs.

Weighting sum method combines various objective functions (f_k) into a single-objective function by assigning positive weights (w_k) to each of the objective functions, as indicated in Equation 2.2, and parametrically varying the weights to generate the Pareto optimal set (Wu et al., 2012).

$$\begin{aligned} \text{Minimize:} \quad & \sum_{k=i}^{N} w_k f_k(x) \\ \text{With:} \quad & \sum_{k=1}^{N} w_k = 1 \end{aligned} \tag{2.2}$$

It is a simple approach and probably the most widely used (Deb, 2008b; Wu and Flintsch, 2009), characterized by an easy-to-understand approach sufficient for Pareto optimality, simple to implement and compatible with many different algorithms to incorporate preferences *a priori* as well as *a posteriori* process. This method might have some problems in finding the true optimal solution (or set of solutions), because *a priori* selection of weights do not necessarily guarantees the acceptance of the final solution, different weight sets may generate the same Pareto optimal set and in case of

non-convexity it may not be able to obtain the Pareto optimal set (Wu et al., 2012).

Similar to the weighting sum method, some agencies adopt priority weights to choose and allocate more importance to certain aspects of highway preservation. For instance, priorities can be given regarding the pavement distress (type and extent), as indicated in Equation 2.3, pavement condition, road class (importance of road) and traffic volume (importance of user costs).

$$\begin{aligned} \text{Minimize:} \quad & \sum_{k=1}^{N} w_k C_k(x) \\ \text{With:} \quad & \sum_{k=1}^{N} w_k = 1 \end{aligned} \tag{2.3}$$

where w_k is the priority weight assigned to distress k and C_k is the cost for repairing distress k. The most common approach is to incorporate priority weights in the decision variables of the objective function. The other way is to use constraint functions with weighted parameters (Farhan and Fwa, 2012).

The weighted metric method transforms the multi-objective problem into a single function that corresponds to a weighted distance from a reference point, as mathematically formulated in Equation 2.4:

$$\begin{aligned} \text{Minimize:} \quad & \left(\sum_{k=1}^{N} w_k |f_k(x) - z_k^\star|^p \right)^{1/p} \\ \text{With:} \quad & \sum_{k=1}^{N} w_k = 1 \end{aligned} \tag{2.4}$$

where $z_k^\star$ is the reference (ideal) point for function f_k and the parameter p reflects the importance of the maximal deviation from the ideal point, thus influencing the obtained solutions. This method is also sometimes called compromise programming. The intention is to identify solutions that are closest to the ideal one by some measures of distance. It can be used for continuous or discrete settings, the procedure is easily understandable and the solution results in a reduction of the Pareto optimal set. Depending on the searching strategy, non-convex Pareto frontiers might be impossible to solve with this method. However, using the min-max method, or its augmented version known as the Tchebycheff method, the search strategy ensures that non-convex Pareto frontiers can also be looked up (Marler and Arora, 2004). Nevertheless, the choice of the reference point must be carefully made in order to not exclude potential optimal solutions from the search space. The Tchebycheff method is explained with more detail

in Subsection 5.3.2.

Goal programming (GP) is also a "distance based method" that aims to minimize the weighted sum of deviations of all objective functions from their respective goals (reference point), as formulated by Equation 2.5:

$$\begin{aligned} &\text{Minimize:} && \lambda \\ &\text{Subject to:} && f_k(x) - w_k\lambda \leq F_k \\ &\text{With:} && \sum_{k=1}^{N} w_k = 1 \end{aligned} \tag{2.5}$$

where λ is an unknown parameter and F is the reference point. For preemptive GP, the deviations from a certain goal for an objective function receive so much weight that the model will first meet that goal (if it is feasible) before considering the other goals, while for non-preemptive GP, all objectives are roughly of comparable importance. Conceptually easy to understand and simple to implement (Wu et al., 2012), GP is adequate to address problems encompassing conflicting objectives with different degrees of importance (Ravirala et al., 1997).

In general, the definition of weights and reference points are crucial to the success of the referred methods, because different choices can lead to different solutions, possibly non-optimal. Furthermore, the assigning of weights can mislead the real preferences of the decision maker, so this task constitutes a difficult step of scalarization methods.

When using the ϵ-constraint method, all the objective functions, except one, are transformed into constraint functions. It is to say that the decision maker choose objective values as constraints for all but one function that is the only one to be minimized. The variety of constraint limits allow the method to discover several Pareto solutions. If a solution is unique for different combination of constraints limits, it is an optimal Pareto solution. The main difficulty of this method is the choice of constraint limits, because it can lead to optimization problems with no admissible solution space (Frangopol and Liu, 2007). Figure 2.7 illustrates a two-objective minimization problem where the second objective is constrained and the first one is minimized.

When a multi-objective problem is reduced to a single-objective one, several optimization problems are required to be solved, since only one Pareto solution is generated at each run of the solver with specified weights. Thus, complex problems are likely to demand long time to generate a good Pareto frontier.

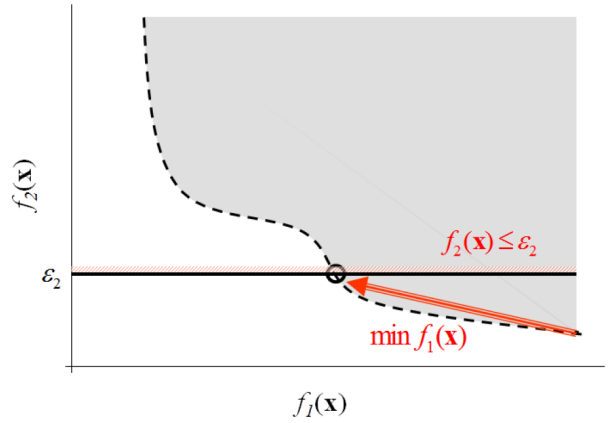


Figure 2.7: *epsilon*-constraint method for two objectives (retrieved from Costa (2007))

2.3.4 Heuristic algorithms

Heuristic algorithms are useful to provide solutions for optimization problems in reasonable time frames when compared with exact-algorithms. The true optimal solution might not be always found, but these algorithms are likely to provide near-optimal solutions. They are specially advantageous for optimization problems defined by several non-linear and non-continuous functions and have been gaining popularity with the advance of computational capacities, artificial intelligence and data mining techniques. Tabu search (Gopalakrishnan et al., 2001), simulated annealing (Torres-Machí et al., 2014) and genetic algorithms (GAs) are some examples of algorithms that have been used for scheduling problems.

Genetic algorithms are more popular regarding their applications into PMSs (Fwa et al., 2000; Chan et al., 2001, 2003; Cheu et al., 2004; Bai et al., 2012; Salini et al., 2015). A GA is an optimization technique based on the mechanics of natural selection and evolution that uses operators inspired by natural genetic variation and natural selection (Mitchell, 1996). At any step of a search (or generation), GA progresses towards the optimal solution from a population of points, instead of a single point commonly found in conventional optimization techniques. The GA does not use much knowledge about the optimization problem and does not deal directly with problem parameters. Instead, the parameters may be coded as heuristics in GA operations (Cheu et al., 2004).

The main strengths of GAs that can be highlighted are: the efficiency in producing good solutions for difficult combinatorial optimization problems and the potential capability to converge on the Pareto optimal set as a whole (Wu et al., 2012), the reduced probability of the solution converge to local minima, the exemption to express the objective function, constraints, or any other problem parameters in mathematical form

and its high adaptability to different types of problems (Cheu et al., 2004). Due to the GA degree of flexibility and scalability, each pavement type can be treated differently in terms of deterioration and repair types (de la Garza et al., 2011).

Goldberg (1989) pointed out four main differences from GA to other optimization and search processes, such as: (1) GAs work with a coding of the parameter set, not the parameters themselves; (2) GAs search from a population of points, not a single point; (3) GAs use pay-off (objective function) information, not derivative or other auxiliary knowledge and, finally, (4) GAs use probabilistic transition rules, not deterministic rules.

The Nondominated sorting genetic algorithm-II (NSGA-II) (Deb et al., 2002) is the state of the art regarding the implementation of GAs. It measures the performance of solutions based on the concept of dominance, using binary codification of solutions, deterministic selection, and traditional crossover and mutation. The preservation of diversity is made by crowding in the objectives' space. Comparing to the original NSGA, the NSGA-II is better because it is an elitist algorithm, the mechanism for graduation of fronts is more efficient and there is no need to have parameters for diversity control. However, the mechanism to preserve diversity is computationally heavy. A more detailed explanation about GAs and the NSGA-II is presented in Section 5.4, as this was the elected algorithm to use in the developed optimization methodology presented in this thesis.

Although they are more frequently used for pavement deterioration models, artificial neural networks, after being trained, are capable of solving combinatorial problems with a large number of decision variables in a reduced computational complexity and are, thus, suitable to support decision making (Fwa and Chan, 1993; Taha and Hanna, 1995; Papadrakakis and Lagaros, 2002). However, the model can be slow during the training phase and it is difficult to interpret what the network is learning. In fact, the individual relations between the input variables and the output variables lacks of engineering judgement, so the model tends to produce results without providing any physical relationship useful for practical decision making (Javed, 2011).

A more specific algorithm was developed by Nunoo and Mrawira (2004), called shuffled complex evolution (SCE) algorithm, that combines the strengths of the simplex procedure with the concept of controlled random search, competitive evolution and complex shuffling. The main advantages include "(1) a search capability that can achieve rapid global convergence in the presence of multiple regions of solution, (2) robustness of the search against local traps on 'pits' and 'bumps' on the objective function surface, (3) robustness against differing parameter sensitivity or parameter interdependence, and (4) capability to model a problem with high parameter dimensionality (i.e.,

a large number of decision factors)" (Nunoo and Mrawira, 2004). According to the authors, one of the most important comparative advantages against other methods is that SCE algorithm maintains the individual identity of pavement sections. Furthermore, they claim that by directly assigning M&R treatments to road sections, it is ensured that a true local and global optimum investment is achieved. The minimization of cost-effectiveness as a single-objective may not always be always the best approach due to the multi-objective character of pavement management. Furthermore, the higher costs usually necessary to repair pavement sections in worst conditions or to apply M&R operations with better performance at the long-term might decrease the cost/benefit ratio and, consequently, be neglected as a good solution to be considered by the decision-maker.

Regarding the combination between programming techniques and evolutionary algorithms, in his doctoral thesis, Javed (2011) presented an approach that aims to complement prioritization needs with optimization benefits. The methodology was based in dynamic programming and genetic algorithms to incorporate priority preferences into pavement preservation programming in two stages of post-processing of the optimal programming process (Farhan and Fwa, 2012). Loia et al. (2000) used genetic algorithms, neural networks and fuzzy sets to design a decision support for pavement management and Yoo and Garcia-Diaz (2008) presented an approach which is a hybrid dynamic programming and branch-and-bound procedure. The hybrid optimization method presented by Yepes et al. (2016) first uses a greedy randomized adaptive search procedure to define an initial population of feasible solutions, which is later subjected to a local search based on thresholds looking for better solutions.

2.3.5 Other decision making support methods

Pavement performance evaluation and pavement management decisions are far from being an "exact science", thus, pavement assessment are often made by qualitative measurements. Analytical hierarchy process (AHP) (Cafiso et al., 2002; Lima et al., 2008; Moazami et al., 2011b) is a method to put in a quantitative form those qualitative assessments and is more suitable for prioritization models (Ustinovichius et al., 2007). AHP is based on the principle that in decision making, experience and knowledge is at least as valuable as the data used to support the decisions (Wu, 2008), hence, it is designed for subjective evaluation, providing a vector of weights expressing the relative importance of a set of alternatives based on multiple criteria (Wu et al., 2012). Figure 2.8 illustrates a scheme of a AHP. Cafiso et al. (2002) evidences the capability of producing a multi-criteria ranking index for every preservation alternative as a mea-

sure of utility, the suitability for implementation in an iterative process of a life cycle analysis and the ease of determining the relative importance of each criteria, allowing the decision maker to focus on each small part of the problem. The idea of pairwise comparisons inherent to AHP at the stage when all the alternatives are considered ensure that the most favourable one is not eliminated (Kinoshita, 2005). The uncertainty about the range of judgements used to express preferences, the sensitivity to measurement errors made by decision makers and the length of the process when a vast number of alternatives need to be considered are the major weaknesses of AHP (Wu et al., 2012).

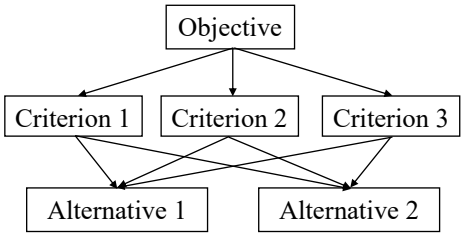


Figure 2.8: Simplified scheme of an analytical hierarchy process

Fuzzy set theory (Chen et al., 2004; Sandra et al., 2007; Moazami et al., 2011a) is another method based on initial qualitative assessments that later takes a quantitative form aiming to represent the uncertainty involved in any situation and manipulate imprecise knowledge data (Loia et al., 2000; Ustinovichius et al., 2007). Basically, a fuzzy system converts human knowledge to mathematical formula by using linguistic variables, fuzzy rules and mapping system (fuzzy engine). Fuzzy approach has to be utilized only when uncertainty is predominant, so such approach does not need to be used for parameters with fair degree of accuracy, but to the ones which are predominantly uncertain (Sandra et al., 2007). As drawbacks, Ustinovichius et al. (2007) refers the sensitivity to measurement errors made by decision makers and Javed (2011) defends that fuzzy assessments made on individual alternatives may not provide any information about the relative importance of alternatives.

A way to correlate pavement distresses to preservation strategies is by using a decision-tree method, which is based on the knowledge acquired from a pavement management engineer, requiring specialized knowledge, skill and expertise in the field (Wei and Tighe, 2004; Abo-Hashema and Sharaf, 2009b). Theoretically, a decision-tree and decision rules induced by algorithm should have a consistent decision making with those made by engineers, hence, once the decision-tree is defined, the decision for road-network treatment strategies is consistent, avoiding human factors for decision-

making treatment. An example of a decision tree for selecting pavement preservation strategies is illustrated in Figure 2.9 (Wu, 2008). As disadvantages, decision tree induction method is not smart enough because the decision rules induced by algorithms for pavement treatment are not completely correct, which evidences the need of post-process for verifying the decision made. The high number of leaves and nodes may result in redundant individual decision rules and the organization of individual rules into a logically ordered decision rules is time-consuming and sometimes incorrect (Zhou and Wang, 2012).

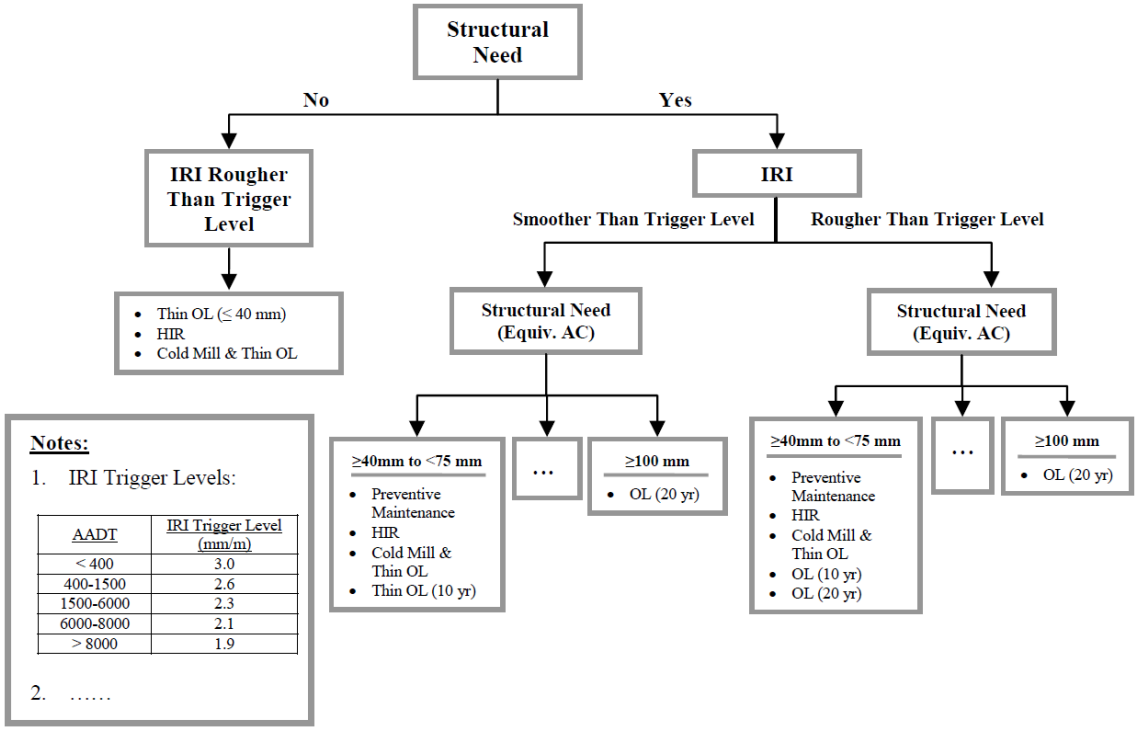


Figure 2.9: Decision tree for selecting pavement preservation strategies (Wu, 2008)

2.3.6 Uncertainty assessment

Finally, it is important to note that most of the decision making tools, independently of its mathematical procedure, have a stochastic character, since some or all the optimization problems' parameters are described by stochastic, random or probabilistic variables rather than by deterministic quantities (Rao, 1996). A typical stochastic parameter is the predicted pavement performance. Furthermore, uncertainty is also associated with measurement inaccuracies, lack of information, inefficiencies in manufacturing or human errors. To analyse its associated uncertainty, Monte Carlo Simulation (MCS) can be an useful tool (Soleymani and Shivakoti, 2006; Noshadravan et al., 2013). "In brief, MCS randomly samples values for the uncertain parameters according to their

pre-constructed probability distributions and records the responses from the model for the sampled values" (Jawad, 2006). For instance, Soleymani and Shivakoti (2006) ran several MCSs to randomly generate transition probabilities from the fitted distribution in order to evaluate the effects on the objective function and constraints. A sufficiently large number of simulations were able to evaluate the impact that the uncertainty in the transition probabilities of a Markov prediction model had on several optimization solutions obtained with GAs.

The inherent uncertainty on the decision making process leads to the development of risk-based optimization approaches. Wu et al. (2015) proposed a performance-based pavement preventive maintenance optimization methodology in which discount rates, traffic growth and M&R costs are probabilistically analysed in order to probe risks of different scenarios.

In the Colorado Department of Transportation (DOT) asset management plan, risks are divided into agency (e.g.: politics; available revenue), programmatic (e.g.: delivery risks; construction cost variations) and project risks (e.g.: cost; schedule; quality of projects). The Georgia DOT developed a risk matrix that considers annual average daily traffic, percentage of truck traffic and the population of the county (Saha and Ksaibati, 2015).

The uncertainty analysis is important because it provides the decision-maker a range of scenarios that might happen as a consequence of certain decisions.

2.4 Cost consideration in pavement preservation management

2.4.1 Introduction

The design and preservation of pavements must take all the costs associated with its life-cycle into consideration. Pavement life-cycle costs (LCC) refer to its total economic worth considering "initial costs and discounted future cost, such as maintenance, user, reconstruction, rehabilitation, restoring and resurfacing costs, over the life" of the pavement. The analysis of LCC intends to enhance decision making towards better investment options. The analysis period should be long enough to reflect long-term cost differences among distinct design and preservation strategies (Walls and Smith, 1998).

Traditionally, the parcels accounted for pavement LCC were related to administration costs and user costs. Nowadays, the consideration of environmental impacts in

LCC analyses is becoming more popular as environmental concerns around the world arise.

Administration costs typically include initial preliminary engineering, contract administration, construction supervision and construction costs as well as future costs related with the pavement preservation activities. These include inspection campaigns to assess pavement performance, routine and preventive maintenance, resurfacing and rehabilitation costs (Walls and Smith, 1998). Additionally, administrations might have other expenditures if pavement quality requirements are not met and/or if road accidents are proved to be caused by road failures.

User costs are costs incurred by the road users during its life cycle, after the opening to traffic. This period is known as the use phase of the road. Environmental impacts occur during the construction of a new road, but also during the use phase due to preservation related activities and to the normal use of the road for transportation purposes, namely because of emissions of pollutant gases. Both the user costs and the environmental impacts during the use phase of a road are a significant parcel of the LCC (Bennett and Greenwood, 2003; Araújo et al., 2014). These parcels highly depend on the pavement quality and, thus, on the planning of preservation activities.

In fact, among all transport costs, road user costs (RUC) comprise the largest parcel (Bennett and Greenwood, 2003). They are typically a sum of vehicle operating costs (VOC), accident costs and the value of time (Santos et al., 2011b,a). The parcel of VOC has been studied for several decades and has been continuously changing due to the evolution of car technology and roads(Bennett and Greenwood, 2003). Nowadays, there are several RUC models for road management, although its effective consideration by road administrations does not happen so often. Nevertheless, road administrations are moving towards a service-based approach, so that customer-driven priorities such as safety, reliability of travel and comfort are becoming the key aspects to define road preservation (Zimmerman, 2017).

The HDM-4 is a reference model in quantifying RUC, and includes the environmental impact in addition to the three parcels mentioned in the previous paragraph. This model is adaptable to local conditions and is, therefore, a base for the development of RUC models in different countries. Portugal is one of the countries, where Santos et al. (2011a) proposed a model (PTRUC) that might also include the toll cost of highways. In PTRUC, VOC depend on fuel consumption, tires and maintenance costs and on the depreciation of vehicles; accident costs depend on costs per accident and casualty costs; the value of time depends on the time cost for travel purpose and the occupancy rate of vehicles.

According to the HDM-4 model for user costs, illustrated in Figure 2.10, pavement

characteristics as friction, texture and roughness are the relevant ones to affect user costs. They all are related to the free speed which ultimately affects travel time. Texture and roughness directly influence the necessary power required to move the vehicle so that fuel and tyre consumption is affected. Roughness alone is given responsibility for the vehicle and its parts deterioration. The mentioned aspects are signalized with grey colour in Figure 2.10.

In addition, the maintenance and rehabilitation activities to preserve pavement quality are likely to cause delays or to force users to choose an alternative route to their normal trip, increasing the travel time. This issue is more commonly addressed at the project level management (Morgado, 2012).

Besides affecting the speed adopted by drivers, the skid resistance, characterised by the friction value, is directly related to the road safety as the lack of it is a cause of car accidents. Road management authorities have been defining thresholds for friction values, although an accurate relationship between skid resistance measurements and accidents rate has been difficult to establish (Fernandes and Neves, 2014). Nevertheless, de León Izeppi et al. (2016) related friction data with crash records to conduct a network-level analysis that intended to improve the prediction of crash rates and use that information to compare two different friction repair treatments. A quantitative relationship between skid resistance and crash rates was also established by Wu et al. (2014).

The parcel for VOC is the one that has been studied more by researchers and given more attention by practitioners for pavement preservation management at the network level (Santos et al., 2011a). Chatti and Zaabar (2012) reviewed various existing VOC models, concluding about the importance of pavement roughness in many components of VOC, namely to the fuel consumption, which is shown to be the primary cost component (Barnes and Langworthy, 2004) *apud* (Chatti and Zaabar, 2012). Indeed, the drastic increases in automotive fuel prices in the decade of 1970 in USA motivated a project about the highway effects on vehicle performance, highlighting the importance of geometric parameters, such as vertical grade and horizontal alignment, but also pointing out the importance of pavement roughness as a "feature" that can affect fuel economy up to 4 or 5 percent (Klaubert, 2001; Karcher and Downey, 2017). In fact, rolling resistance is recognised to be a main cause of energy consumption on the interaction between pavement and tyres for an in motion vehicle, as it is exposed in Section 2.4.3.

Overall, the road transportation is responsible for a high percentage of the total energy consumption of the transport sector, and, consequently, for a considerable amount of pollutant gases emissions. For instance, in 2012, the European transport sector ac-

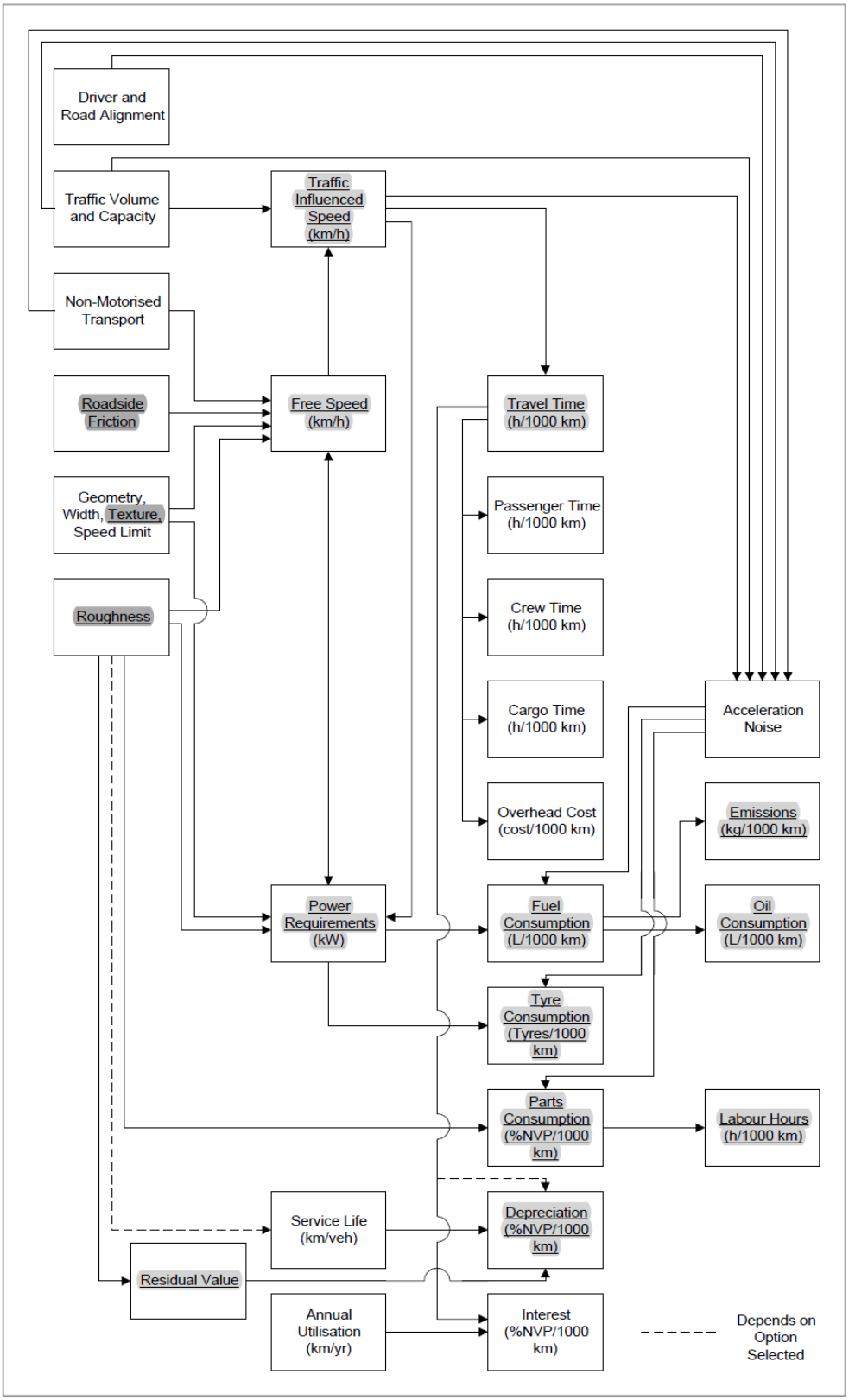


Figure 2.10: HDM-4 road user effects and their interactions (adapted from (Bennett and Greenwood, 2003))

counted for 25.4% of all CO_2 equivalent emissions in Europe, with road transport generating 71.8% of this total (European Commision), which shows the importance of reducing this parcel towards the goal established by the EU to reduce in 60% the greenhouse gases emissions from 1990 levels by 2050 (Santos et al., 2014b). In USA, approximately 71% of the petroleum used in 2011 was utilized for the transportation sector (Willis et al., 2015).

All activities related to repairing or re-constructing road pavements have an environmental impact due to the consumption of energy and natural resources as well as the release of pollutant gases into the atmosphere. However, considering the life-cycle period of a road pavement, the energy consumption by the everyday traffic represents a much more significant impact than other activities (Tohme et al., 2016). Depending on its volume, the traffic is responsible for about 95% to 98% of the total energy used, while the construction and maintenance activities represent about 2% to 5% only (EAPA/Eurobitume, 2004). In addition, and in line with those numbers, Araújo et al. (2014) work concludes that the reduction of energy consumption during the use phase is several times higher than the total energy spent at the construction phase, evidencing that its impacts can be quickly dissipated by providing smoother surface course with lower rolling resistance, causing great reduction in the impact during the use phase. Similar conclusions can be extrapolated for preservation phases as well. These findings are, however, dependent on the amount of traffic, as the use phase becomes less significant for lower traffic volumes (Cirilovic et al., 2017).

In fact, a growing number of studies have been recently published with regard to the influence of pavement preservation management in the environmental impact of the use phase of pavements. The increase of public awareness and government regulatory measures towards environmental sustainability motivate stakeholders to identify different alternatives in which environmental aspects are accounted for (Goh and Yang, 2014; Babashamsi et al., 2016; Inyim et al., 2016; Lee and Madanat, 2017). For instance, the European COST Action 354 tried to develop environmental related indicators, assuming they will play a decisive role in the decision procedures of road administration authorities, private concessionaires, and finally policy makers. The environmental indicators could not be well defined due to the lack of data but some recommendations about possible approaches were given (Litzka et al., 2008). Another European project, the LCE4ROADS FP7 project - *Life Cycle Engineering approach to develop a novel EU-harmonized sustainability certification system for cost-effective, safer and greener road infrastructures* - intends to develop a new sustainability certification system for roads in which the consideration of the use-phase is important (Flores et al., 2016). Environmental concern was well stated as a strategic goal of the U.S. DOT during

Obama's Administration (US DOT, 2014).

Reger et al. (2014) used a case study for a road network of California to show the existence of a range of potentially optimal preservation solutions in which the decrease of GHG emissions is not possible without increasing agency costs. A similar conclusion was obtained in the study of Bryce et al. (2014) using data of the Virginia DOT, where a clear trade-off between the most cost-effective solutions and those where the energy consumption was minimized. Lee et al. (2016) proposed a solution to define pavement reconstruction and resurfacing policies that minimizes agency and user costs by defining a GHG emissions constraint. Alternatively, Wang et al. (2014) defined roughness values for triggering treatments in order to minimize GHG emissions considering both treatment and use phase emissions.

Recent years have been marked with a notorious growing attention towards electric vehicles and related technology has been developing at reasonable pace. There are, in fact, some ambitious political goals for drastically change the motorization of cars in few decades, as noticed by the German intention to stop selling petrol-fuelled cars by 2030 (Khan, 2016). Nevertheless, the reduction of energy spent in the road transportation sector will still be a priority, as this change of combustion is likely to take several decades to occur throughout the whole world and because new impacts and challenges will certainly arise with regard to the power supply of so many electric vehicles. As for the closest decades to come, a position paper from the road industry in Europe claims that an upgrade of one third of the European network by 2030 could reduce the emissions of CO2 in 14 million tonnes per year, which is equivalent to replace 3 million petrol-fuelled cars with "zero-emissions" cars (Karcher and Downey, 2017).

2.4.2 Pricing carbon emissions

The environmental impact from several industries and other economic sectors through the emission of pollutant gases is well recognized worldwide for decades. Techniques to quantify those emissions and to reduce them have been developing. Similarly, decision making is also capable of considering pollutant emissions as a variable and/or objective, as it is seen in some PMS and related research (Bennett and Greenwood, 2003; Araújo et al., 2014; Wang et al., 2014; Chen et al., 2016). Zhang et al. (2010a) developed a model to determine an optimal preservation strategy looking for minimizing the total life-cycle energy consumption, greenhouse gas (GHG) emissions and costs. Araújo (2016) in his thesis investigated the environmental impacts during a pavement life-cycle through GHGs emissions from the construction until the use phase of a road.

Only few pavement preservation management related works have been attributing

a cost to GHG emissions at a network and strategic level, which is important in order to push road administrations for an effective consideration of environmental impacts. As the carbon pricing and carbon market have been gradually implemented in several countries and industries (Capoor and Ambrosi, 2008), the attribution of those costs can become less subjective, thus more useful. Cirilovic et al. (2017) studied the influence of different unit costs of CO_2 emissions on the pavement preservation planning at the network level, concluding that the unit cost of CO_2 emissions change the "optimal" solution.

The theoretical goal of pricing carbon is to capture the external costs of "carbon emissions - costs that the public pays for in other ways, such as damage to crops and health care costs from heat waves and droughts or to property from flooding and sea level rise - and tie them to their sources through a price on carbon. (...) A carbon price gives an economic signal and polluters decide for themselves whether to discontinue their polluting activity, reduce emissions, or continue polluting and pay for it" (World Bank, 2017). Carbon pricing can be made through an emission trading system (ETS) or through carbon taxes. The first option allow industries with low emissions to sell their extra allowances to larger emitters, while the second option directly sets a price by defining a tax rate on GHG emissions or on carbon content of fossil fuels (World Bank, 2017).

In May 2016, few months after the 21st Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC), in Paris, 162 intended nationally determined contributions, representing 190 Parties, had been submitted to the UNFCCC. More than 90 included proposals for ETSs, carbon taxes and other initiatives. In 2016, about 40 jurisdictions and over 20 cities, states, and regions, responsible for almost 25% of global GHG emissions, were putting a price in carbon as illustrated in Figure 2.11 (World Bank Group and ECOFYS, 2016). More than 1000 companies are currently using an internal price on carbon, which the United Nations Global Compact called for a minimum of US\$100/tCO_2e by 2020 in order to be consistent with the goals established on the Paris Agreement (World Bank Group and ECOFYS, 2016). In fact, carbon prices vary in a wide range from less than US\$1/tCO_2e to US\$137/tCO_2e as it can be observed in Figure 2.12 (World Bank Group and ECOFYS, 2016), although some studies claim that the price should be even higher than the maximum one in order to effectively represent the environmental cost of GHG emissions (Moore and Diaz, 2015).

Although the term "carbon" is often used, prices are actually established for carbon equivalent (CO_2e), which differs from CO_2 because it considers other gases with global warming potential (GWP), a metric used to compare the impact of several GHG. The

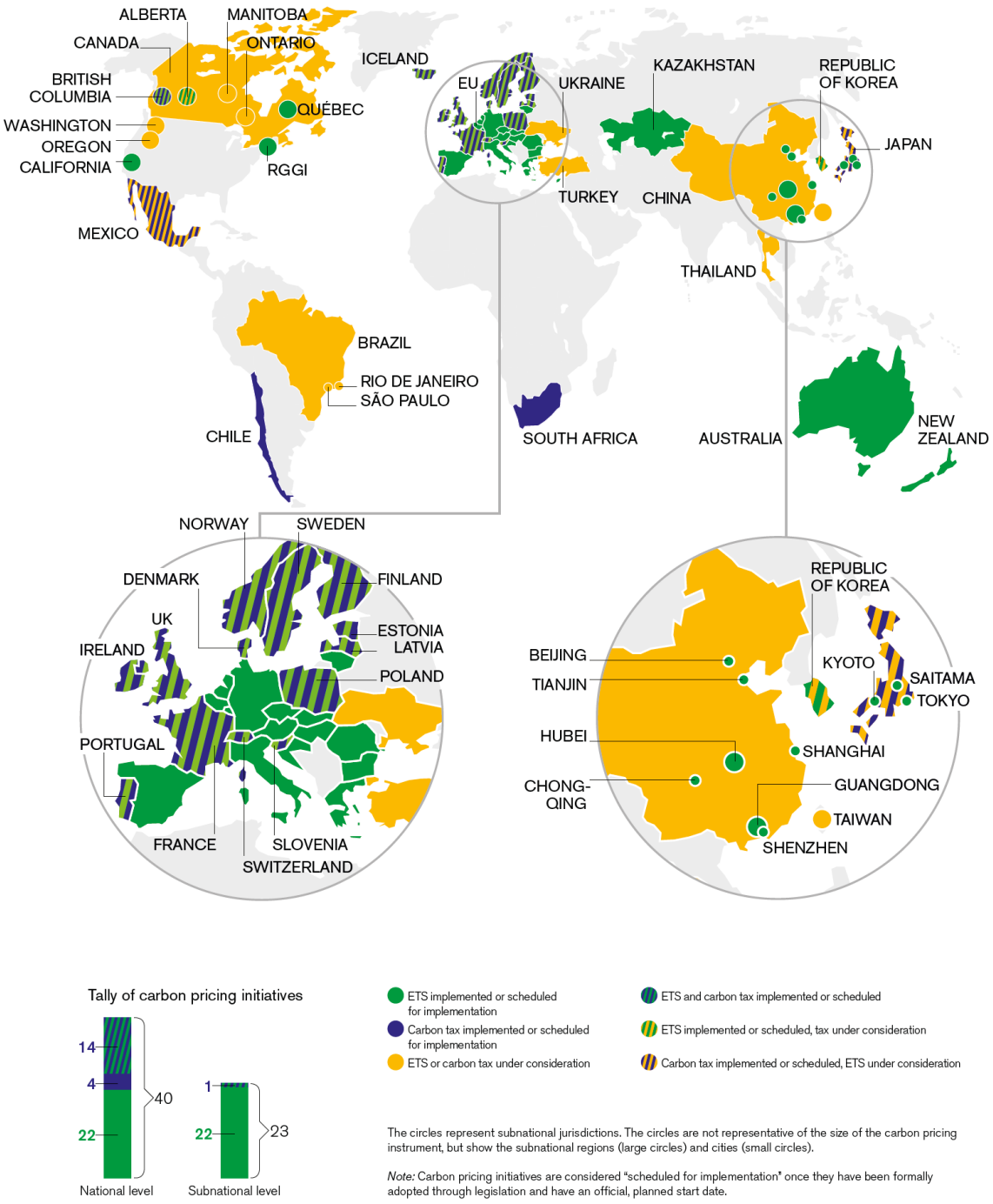


Figure 2.11: Map of carbon pricing initiatives (World Bank Group and ECOFYS, 2016)

multiplication of the amount of a GHG with its GWP results in the amount of GHG in terms of CO_2e.

In the combustion of petrol and diesel vehicle engines, the emissions of CH_4 and N_2O are much lower than of CO_2, but their impact is important as they have 25 and 298 higher GWP, respectively, resulting in Equation 2.6 (EPA, 2014).

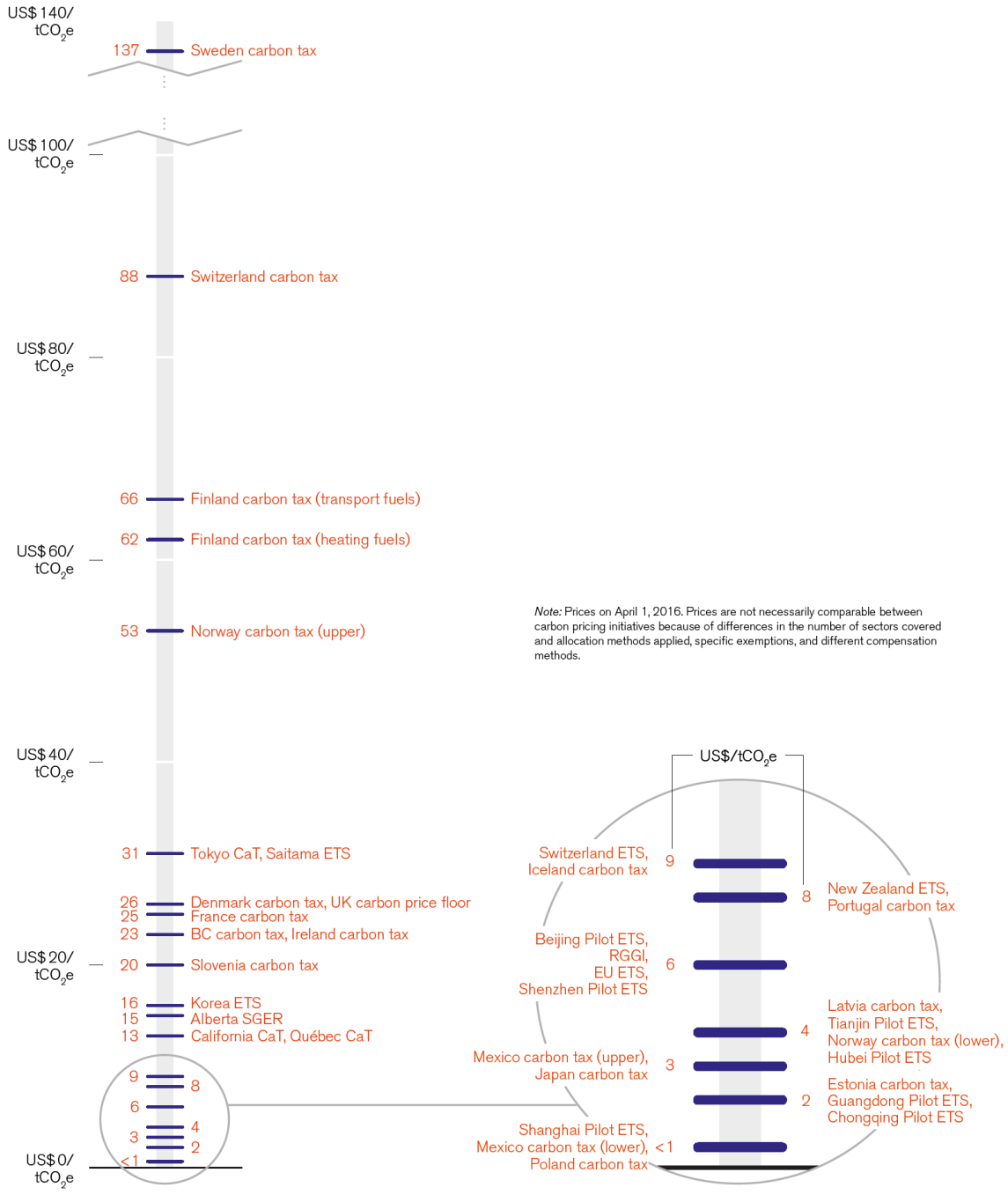


Figure 2.12: Prices in existing carbon initiatives (World Bank Group and ECOFYS, 2016)

$$GWP = CO_2 + 25\ CH_4 + 298\ N_2O \tag{2.6}$$

While emissions of CO_2 can be well estimated per litre of petrol and diesel, emissions of CH_4 and N_2O are more difficult to estimate, because they depend on the design of the engine and emission control system, rather than only fuel consumption. CO_2 emissions

fall in between 95% to 99% of the total GHG emissions of a passenger vehicle, after accounting for the GWP of all GHGs (EPA, 2014). In a report of the Intergovernmental Panel on Climate Change (Waldron et al. (2006)), 97% of CO_2e is admitted to be from CO_2 emissions. The combustion of a litre of petrol and diesel releases 2,3477 and 2,6893 Kg of CO_2. These values are considered in the present thesis for the work presented in Chapter 5.

Summing up, World Bank Group and ECOFYS (2016) states that carbon pricing is becoming a widely used tool for corporate strategic investments, helping companies to shift to lower-carbon business models. This enhances the importance for road administrations to consider carbon costs in their pavement preservation management planning as they can soon become real costs to account in the business balance. Ultimately, consideration of carbon costs leads to a better position in the corporations social responsibility.

2.4.3 Rolling resistance and fuel consumption

Fossil fuels are still the main source of energy used by vehicles to overcome the resistance to movement, which is due to several resistance forces, such as: rolling, air, inertial, gradient and side forces resistance; losses from transmission, suspension and auxiliary equipment; engine friction. From all these forces, the pavement surface and structure have direct influence on the rolling resistance and on the suspension losses. The first is broadly associated with the forces opposing the rolling of the tyres, whereas the second is related to frictional forces in the shock absorbers. However, as the latest forces are caused by the tyre movement during rolling on an uneven road, they are often included in the rolling resistance forces (Sandberg et al., 2011; van Haaster et al., 2013). This is also considered to define the term rolling resistance used in this thesis.

Sandberg et al. (2011) stated that, roughly, the return factor of rolling resistance is 20% for cars and 30% for trucks when riding on highways, meaning that a reduction of 10% of rolling resistance decreases the fuel consumption in 2%. van Haaster et al. (2013) adopted a return factor of 25% for his study about potential energy savings by reducing rolling resistance in Dutch road pavements. These estimates are coherent with Beuving et al. (2004) *apud* (Willis et al., 2015) that indicates rolling resistance accounts only for 20% of the vehicle's energy consumption when travelling at 70 mph (113 km/h). Although many rolling resistance factors are vehicle dependent, its reduction due to changes in pavements characteristics are also considerable and help to reduce the absolute fuel consumption and pollutant emissions in a long term. Bendtsen (2004) summarised that road surfaces can be responsible for nearly

doubling the rolling resistance which can change the fuel consumption of around 10%. It is, then, important to understand which pavement characteristics are relevant for the rolling resistance to take them into account when analysing several M&R strategies.

It is recognized that surface texture, roughness and stiffness are relevant aspects for the rolling resistance at different levels. Texture and roughness create vibrations that are absorbed by the shock absorbers and tires of the vehicle, causing a loss of energy. The pavement deflection might contribute to some energy consumption due to the constant formation of a "wave" travelling in the pavement at front of the contact patch (Tohme et al., 2016; Sandberg et al., 2011). Litzka et al. (2008) suggests longitudinal evenness as an indirect indicator for air pollution and vibrations, texture as an indirect indicator for noise emission and surface defects as an indirect indicator for vibrations. Willis et al. (2015) gather together an extensive literature review, since 1974 to 2013, concluding the following:

- Texture - Megatexture affects the rolling resistance in a negative way. In many cases, a reduction of texture could reduce rolling resistance by 5 to 10 percent, or even more according to some studies. No correlation was found between speed and texture in pavement-vehicle interaction;
- Roughness - All studies about the effect of unevenness on pavement-vehicle interaction showed that smother pavements reduced rolling resistance. Some studies suggested a relation between the travelling speed and the effect of smoothness;
- Stiffness - Although many studies suggest that overall, concrete pavements are more fuel efficient than asphalt pavements (presumably because of higher stiffness), the results from studies relating pavement vehicle interaction with pavement stiffness and type have been inconsistent.

The influence of different texture wavelengths in several aspects of the vehicle-pavement interaction is defined in ISO 13473-2 (ISO, 2002), as illustrated in Figure 2.13, where it can be seen that rolling resistance depends on the unevenness, mega-texture and on the higher wavelength of macro-texture. Note that a darker shade on the bars means an unfavourable effect. Several studies have been made in order to quantify the influence of these parameters on rolling resistance and, consequently, on fuel consumption, which is of more interest for this thesis.

Sandberg et al. (2011), within the scope of MIRIAM (Models for rolling resistance In Road Infrastructure Asset Management systems) project, suggested that every millimeter increase in the Mean Profile Depth (MPD) raises the Rolling Resistance Coefficient (RRC) by in 0.0017 to 0.0020. In the same report, the author highlights the results of

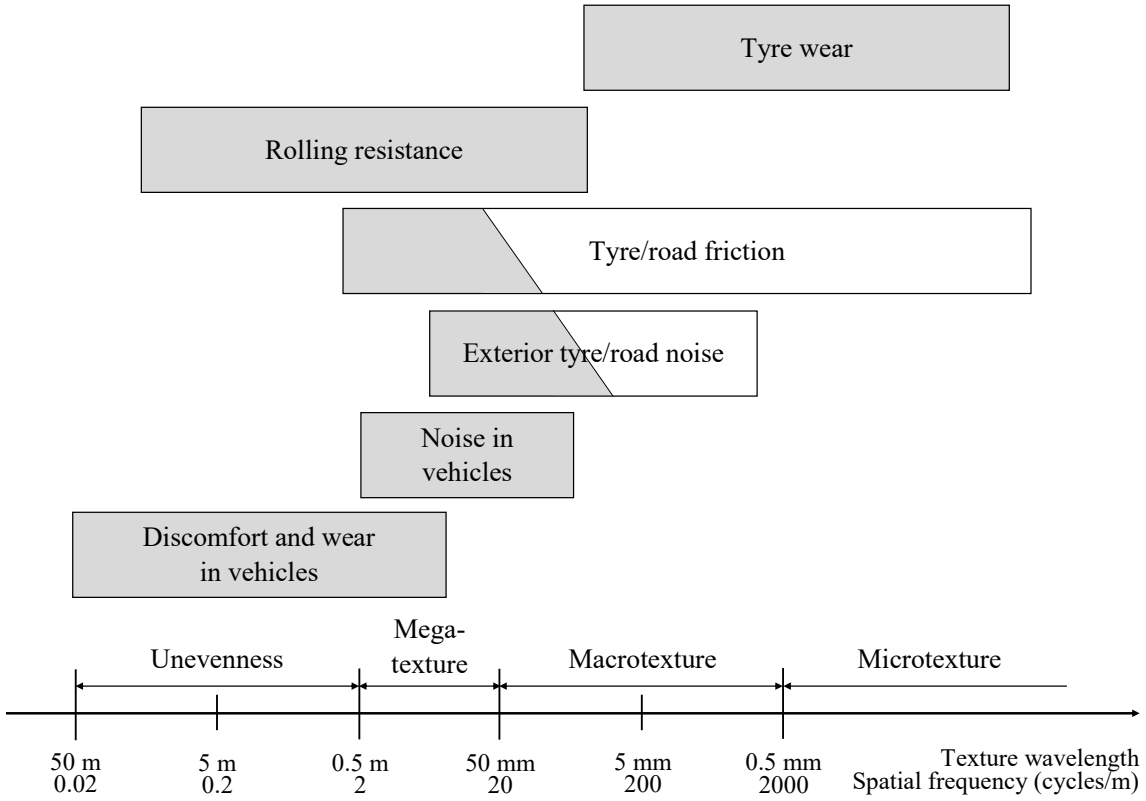


Figure 2.13: Ranges in terms of texture wavelength and spatial frequency of texture and unevenness and their most significant, anticipated effects (adapted from ISO (2002))

tests made in Poland, around the year 2000, by presenting its regression equation:

$$RRC = 0.01065 + 0.002012 * MPD + 0.0000064 * MPD * (V - 20) \tag{2.7}$$

where MPD is in mm and V, the velocity, is in m/s. Assuming that the speed parcel is nearly equal to zero, the factor of MPD is coherent with the interval range indicated by (Sandberg et al., 2011). They also suggest that mega-texture is, indeed, the most important texture range for rolling resistance, although the macro-texture range is also of some importance. Regarding unevenness, wavelengths range between 0.5 m and 5.0 m have great influence on rolling resistance, but longer wavelengths may be neglected. Despite recognizing its importance, the authors did not indicate specific relations between unevenness measurements and rolling resistance. In a more recent study about the influence of road surface and tyre tread pattern in rolling resistance, Hoever and Kropp (2015) achieved a good relation between RRC and MPD, indicating that every millimeter increase in MPD raises the RRC by approximately $0.16 * 10^{-}2$.

Other part of MIRIAM project measured the RRC of test tyres rolling on surfaces

with MPD ranging from 0.08 mm to 2.77 mm, observing an increasing by 21% to 55% of RRC from the smoothest to the roughest surfaces, corresponding to 7% to 18% in fuel consumption differences (Sandberg et al., 2011).

In 1998, the FHWA studied the influence of roughness on fuel consumption in the WesTrack, an accelerated pavement test facility in Nevada. Fuel consumption was measured in two trucks before and after the rehabilitation of the track pavement. Fuel economy was found to improve in 4.5% as a direct result of the improvement of roughness in 10% after rehabilitation, since all other variables were fixed (Robbins and Tran, 2015). Sime et al. (2000) suggested that the improvement could have been higher if it was possible to eliminate all uncontrollable environmental effects such as wind speed and temperature. The validity of these results was disbelieved by Bennett and Greenwood (2003) because the roughness was not quantified and the change of wind speed could in fact be the origin of such difference on fuel consumption. Nevertheless, based on the WesTrack project, Zhang et al. (2010b) used a linear equation (2.8) to represent the influence of IRI on the fuel consumption through a Fuel Consumption Factor (FCF):

$$FCF = 0.0397 * IRI + 0.9524 \tag{2.8}$$

where FCF must be greater than 1.0. A FCF is a dimensionless value used to multiply by the ideal fuel consumption that occurs on a perfectly smooth pavement.

The Missouri Department of Transportation performed an analysis to the pavement smoothness and fuel efficiency by using four trucks on a 22 mile loop. Each truck was driven more than 50 hours and more than 2000 miles on the test loop before and after resurfacing the pavement. Amos (2006) reported that the diesel trucks used in that study showed an increase of nearly 2.5% in fuel efficiency due to the decrease of roughness. This study was used by Yu and Lu (2012) to develop relations of FCF with IRI for passenger cars and for trucks, indicated by equations (2.9) and (2.10) respectively:

$$FCF = 7.377 * 10^{-}3 * IRI + 0.993 \tag{2.9}$$

$$FCF = 2.163 * 10^{-}2 * IRI + 0.953 \tag{2.10}$$

where IRI is measured in (m/km). The same equations were used by (Chen et al., 2016) for his study about environmental burdens of regular and long-term pavement designs. However, the equation related to passenger cars lacks of data support, since the Missouri test used only one SUV and did not carry such carefully analysis and control as it was done with the four trucks.

HDM-4 (Bennett and Greenwood, 2003), in its complex approach to determine user

and environmental costs, includes a rolling resistance parcel based on the following equation (Biggs, 1988):

$$Fr = CR2(b11 * Nw + CR1(b12 * M + b13 * V^2)) \tag{2.11}$$

where

Fr	rolling resistance (N)
$CR1$	rolling resistance tyre factor
$CR2$	rolling resistance surface factor
$b11, b12, b13$	rolling resistance parameters
Nw	number of wheels
V	velocity (m/s)

By its turn, CR2 is calculated according to equation 2.12

$$CR2 = Kcr2[a0 + a1 * Tdsp + a2 * IRI + a3 * DEF] \tag{2.12}$$

where

$Kcr2$	calibration factor
$a0$ to $a3$	coefficients
$Tdsp$	texture depth from the sand patch method (mm)
IRI	international roughness index (m/km)
DEF	Benkelman Beam rebound (mm)

Equation 2.12 indicates that texture, unevenness and bearing capacity are influencing factors, being the latest applied just for trucks.

As mentioned, rolling resistance is just one of several parcels used by HDM-4 to determine the fuel consumption to include in the overall vehicle operating costs. A report of the National Cooperative Highway Research Program (NCHRP) (Chatti and Zaabar, 2012), aiming to estimate the effects of pavement condition on vehicle operating costs, used data from instrumentation on board vehicles driven on roads of known conditions in order to validate and calibrate the HDM-4 fuel consumption model. Regarding the pavement surface characteristics, roughness (IRI), grade (%), texture depth (mm) and pavement type were the collected factors for each road section. IRI and texture were considered the covariate variables, being fuel consumption the dependent variable. The performed tests led to conclude that only the IRI was statistically significant for all vehicle classes whereas the texture was only statistically significant for articulated trucks rolling at low speed. Therefore, more focus was given to predict the effect of roughness on fuel consumption. Generally, the effect of roughness was found to be also less

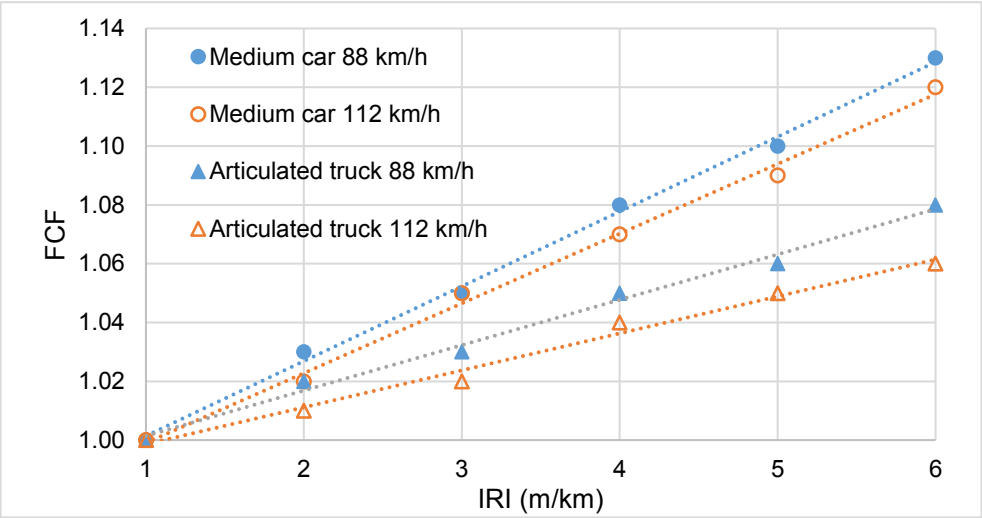


Figure 2.14: Fuel consumption factors as a function of IRI (deduced from (Chatti and Zaabar, 2012))

influential as the speed was increasing. For the scope of this thesis, only high speeds matter, so that the FCF (or adjustment factors) determined by Chatti and Zaabar (2012) for 88 km/h and 112 km/h are presented in Table 2.1.

Table 2.1: Effects of roughness on fuel consumption (adapted from Chatti and Zaabar (2012))

Speed	Vehicle Class	Base (mL/km)	Adjustment factors from the base value				
			IRI				
		1	2	3	4	5	6
88 km/h (55 mph)	Medium car	83.38	1.03	1.05	1.08	1.10	1.13
	Van	96.98	1.01	1.02	1.03	1.04	1.05
	SUV	101.29	1.02	1.04	1.07	1.09	1.11
	Light truck	180.18	1.01	1.02	1.03	1.04	1.05
	Articulated truck	447.31	1.02	1.03	1.05	1.06	1.08
112 km/h (70 mph)	Medium car	107.85	1.02	1.05	1.07	1.09	1.12
	Van	128.96	1.01	1.02	1.03	1.03	1.04
	SUV	140.49	1.02	1.04	1.06	1.08	1.10
	Light truck	251.41	1.01	1.02	1.02	1.03	1.04
	Articulated truck	656.11	1.01	1.02	1.04	1.05	1.06

From Table 2.1, FCF functions can be deducted by adapting trend-lines, as shown in Figure 2.14. The coefficient of determination (R^2) is very high (near 1.0) for all the cases, resulting in the following equations:

- Medium car at 88 km/h: $FCF = 0.0254 * IRI + 0.976$
- Medium car at 112 km/h: $FCF = 0.0237 * IRI + 0.9753$
- Articulated truck at 88 km/h: $FCF = 0.0154 * IRI + 0.986$
- Articulated truck at 112 km/h: $FCF = 0.0126 * IRI + 0.986$

It is observed that the influence of roughness becomes less significant as the speed increases. That is explained partially because of the increasing significance of the air drag as the speed increases. This fact is more noticeable for trucks which are less aero dynamical vehicles. Furthermore, for the same speed, the relative changing of fuel consumption for trucks is smaller than for medium cars.

Chapter 3

Database

3.1 Introduction

Databases are a nuclear part of PMSs, since they contain fundamental data to support decision making. Their complexity may range from simple spreadsheets to relational databases or agency-wide databases (Zimmerman, 2017). Typically, they include past and present information about road location, geometry, drainage, pavement structure, climatic conditions, traffic, pavement condition, M&R operations and their costs (Branco et al., 2005). Some of that information is essential to build pavement performance prediction models PPPM to predict the evolution of pavement distresses or performance indicators.

In the present work, Markov chains are adopted as the PPPM. Its development requires the existence of historical data about pavement distresses and/or performance condition, urging the need for a database with the most comprehensive and coherent information as possible. The LTPP database is adopted for this effect. The reasons to use the LTPP database and its features and organization are presented in Section 3.2.

Furthermore, to build Markov models based on discrete pavement condition states (CSs), the several pavement distresses of interest to analyse its performance ought to be converted into the same numerical scale, either individually or combined. Such conversion results in the so called performance indicators PIs. Different ways of determining them can be found in actual PMSs and in the literature. The methodology presented by the COST Action 354 (hereinafter referred as COST354) is used in this work, as further explained in Sections 3.3 and 3.4 (Litzka et al., 2008).

3.2 Long Term Pavement Performance database

3.2.1 Scope

From the literature review, it was observed that the LTPP database from the Federal Highway Administration FHWA was used for several studies where pavement condition data were needed. The LTPP is likely to be the largest pavement performance research program ever undertaken (TRB, 2001) and its data are freely accessed from the website www.infopave.com. LTPP studies began in 1987 as a comprehensive program to satisfy a wide range of pavement information needs. It seeks to develop models that explain how pavements perform and how that is influenced by design features, traffic, environment, construction quality and preservation practices.

"The overall objective of the LTPP program is to assess long-term performance of pavements under various loading and environmental conditions over a period of 20 years" (Elkins et al., 2009). More specifically, and with regard to the scope of the present thesis, it is intended to use LTPP to develop improved design methodologies and strategies for the rehabilitation of existing pavements and to determine the effects of loading, environment, material properties, construction quality and maintenance levels on pavement distress and performance (Elkins et al., 2009).

The LTPP program is a study of in-service pavement sections subjected to real-life traffic conditions. Those sections are classified as General Pavement Studies (GPS), consisting on nearly 800 in-service sections throughout the United States and Canada, and Specific Pavement Studies (SPS) which are intensive studies of specific variables that influence pavement behaviour. Indeed, at the start of the LTPP program, GPS sections were already in-service while SPS are sites where multiple test sections of differing experimental treatment factors were constructed (Elkins et al., 2009). There are 18 types of GPS experiments, from which only 7 regard completely flexible pavements, while there are 10 types of SPS experiments in order to asses the influence of structural factors, maintenance, rehabilitation and environmental effects on both flexible and rigid pavements. A study about the asphalt aggregate mixture specifications is also included as SPS experiments.

Although SPS program consists in a more controlled set of experimental design and construction features, its main objective is to provide a more detailed and complete database to refine the results obtained from the GPS studies. For the present thesis, only GPS sections were considered, since they are a much larger amount of sections, with longer history and comprise a wider range of features and external factors, thus allowing the development of general prediction models which "automatically" take into

account several influential factors. A GPS section consists of a lane with 152 m length and a maintenance control zone, extending another 152 m before and 76 m beyond the limits of the monitoring section, as shown in Figure 3.1 (Elkins et al., 2009). Each section is uniquely identified by a *state code* and a *shrp_id*.

All data used for this work were last downloaded on 18th March of 2015.

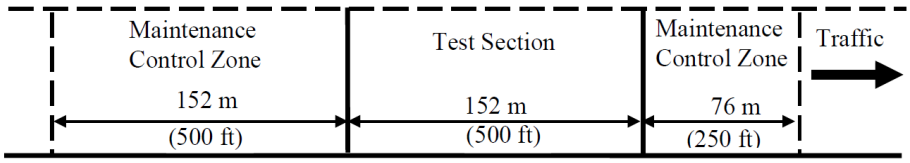


Figure 3.1: Layout of a generic GPS section (Elkins et al., 2009)

3.2.2 Data of interest

The database is divided into modules containing similar sets of data. Data from different modules and tables can be related through the use of queries. For the present work, useful data to be collected are in the following modules (Elkins et al., 2009):

- **Administration**: It contains tables describing the structure of the database, each field of each table from other modules, codes used in all the database, among other important information that helps to navigate and understand all other data;
- **Inventory**: This module contains information about the location of the section and its age, pavement type, layer thickness and type, material properties, composition, previous construction improvements and other background information;
- **Monitoring**: This is the largest module in the database. It contains pavement performance monitoring data such as deflection, surface distresses, friction, longitudinal profile and rutting;
- **Maintenance**: Information about maintenance-type treatments that were applied to a test section and its application dates are in this module;
- **Rehabilitation**: This module contains information on rehabilitation treatments, indicating when and which types of treatments were applied to each section;
- **Traffic**: It contains traffic load, classification and volume data.

A more detailed information about the most relevant data of each module is presented below (Elkins et al., 2009).

Inventory

From this module it is possible to select the pavement types of interest for this work, which are the flexible pavements only:

- Asphalt concrete (AC) with granular base;
- AC with bituminous treated base;
- AC overlay on AC pavement.

An important table of this module is the *INV_LAYER*, from where the thickness and material type of each layer of each section can be retrieved.

Pavement monitoring

Within this module, there are several separate databases and tables to store results of all inspections made to assess pavement quality. Deflection measurements are made using the Falling Weight Deflectometer (FWD). Because of the large volume of deflection testing performed by the LTPP program, data are spread across multiple tables. In fact, the second largest table of the whole LTPP database is the *MON_DEFL_DROP_DATA*, which contains information about peak deflection and applied load measurements for every drop conducted at each test point on a section. Four drop heights are tested on each test point, with four repeated drops, targeting the loads of 27 kN, 40 kN, 53 kN and 71 kN. For most of the pavement sections, drops are made every 8 m or 15 m, approximately, at the mid lane and at the outer wheel path.

Tables for distresses that are manually of photographically observed provide a measure of pavement surface condition, including the amount and severity of cracking, potholes and patching, among others. Regarding flexible pavements, a reasonable amount of information about cracking is available, while there is lack of data for other surface distresses. Cracking is, therefore, the only considered surface distress for the present work. Different types of cracking are measured: alligator, block, edge, longitudinal and transversal; all classified into low, moderate or high severity.

Regarding the longitudinal profile, relevant data are stored on the table *MON_PROFILE_MASTER*, namely about the measurement device, measurement date and computed parameters such as the International Roughness Index (IRI). For each monitoring date there are at least five repeated measurements.

Friction related data are all stored in one table only, the *MON_FRICTION* table, which contains the results of friction tests on pavement sections where the

State/Provincial highway agency was willing to provide the data. Due to the litigious nature of this data, submission is voluntary, thus the amount of available data are relatively low when compared to other pavement performance data. Relevant data on this table are the friction number at the beginning and the end of test sections. The LTPP program tried to established general guidelines to be followed by DOTs of all the states, recommending the usage of the ASTM E-274 as the preferred method for obtaining data. This standard method measures the friction force on a locked test wheel as it is dragged over a wetted pavement surface under constant load and speed while its major plane is parallel to its direction of motion and perpendicular to the pavement (Titus-Glover and Tayabji, 1999; ASTM E274-06, 2006). Information on test section rutting is based on the interpretation of transverse profile measurements. These are obtained using photographic and manual techniques. To obtain rutting information, the transverse profile shapes are then interpreted and stored in two tables: *MON_T_PROF_INDEX_POINT* and *MON_T_PROF_INDEX_SECTION*. The first table stores the computed values for each measurement location, while the second comprises the summary statistics for all measurements on a pavement section. The latter is the one used for this work and contains rutting values for the right and left wheel paths, for each lane.

Maintenance and rehabilitation

Information about M&R operations belong to one database named as *Maint_Rehab*. Its tables *MNT_IMP* and *MNT_RHB* contain information about the improvement date and type, which is fundamental to define the moment from which a pavement test section potentially changes its deterioration pattern. A sequence of inspections (monitoring data) for the same test section used to build the Markov models is interrupted whenever an influential M&R operation is applied to that section. Rehabilitation operations consist in major interventions that interfere with the evolution of all pavement distresses, while maintenance operations are lighter interventions that might just interfere with some distresses. These are detailed in Section 3.5.

Traffic

The provision of traffic monitoring data was assigned to participating highway agencies. Data demanded by the LTPP program was based on a balance between pavement research program needs, constraints of existing traffic monitoring technology and limited highway agency resources. There is a wide range of accuracy on traffic data estimates due to the diversity of collection efforts by the several agencies. However, the "raw"

traffic data submitted to the LTPP program are subjected to a quality control and assurance process involving review by the submitting agency. Only then, data are used to produce the annual estimates. In fact, all traffic volume, classification and load data consists on annual estimates based either on agency supplied estimates or computed from reported raw traffic data. All information given in traffic related tables are specific to each test section lane.

Traffic volume according to vehicle classification is available, as well as the corresponding number of equivalent single-axle loads ESAL. Indeed, for the present work, the tables of interest are: *TRF_HIST_EST_ESAL* and *TRF_MON_EST_ESAL*. The first contains estimates of 80 kN ESALs at each section for each year since construction date or 1965, whichever is later, until its inclusion in the LTPP program or 1990, whereas the second contains identical data for periods after 1990 or open to traffic date, whichever is later. Note that the ESAL refers to trucks traffic only, and is estimated by LTPP according to five methods:

1. ESAL/Truck;
2. ESAL/Truck by vehicle class;
3. ESAL/axle - single, tandem, tridem axles;
4. Other or Unknown;
5. General Project Estimate. Not section specific.

3.3 COST354 approach

Efficient design, construction and preservation of road pavements require the specification of performance criteria, from the perspectives of both road users and road operators. Regarding pavement management and life-cycle analysis, the exact definition of goals to be achieved or performance criteria to be satisfied is of high importance and can be quantified by special indices characterizing the pavement quality. Such indices are typically composed of several information about the pavement and are a measure of the effects perceived by the road users as well as a measure reflecting the structural condition of a road pavement. In addition, indices are useful to develop pavement performance prediction models (Litzka et al., 2008).

Several indices are used around the world to classify pavement condition. Some of the most commonly used are the Pavement Serviceability Index (PSI) from AASHTO, the Pavement Condition Index (PCI), the Road Condition Index (RCI) and the Present

Serviceability Rating (PSR). Different countries and agencies might adopt different indices according to their needs and available information. In Europe, these are hardly comparable because different factors, rating systems and measuring procedures are used. The COST Action 354 - *The way forward for pavement performance indicators in Europe* - intended to uniform the pavement performance indicators and indices used in the European context. Given the wide variety of potential users of the COST354 approach, its procedure was developed in such a way so it could be applied in different realities, depending on the type of measurements available and the analysis approach already in place. In total, twenty three European countries and the FHWA from USA participated in the Action (Litzka et al., 2008).

COST354 defines performance indicator as a term that indicates the condition of a pavement in the form of a technical parameter (TechP) (dimensional) or an index (dimensionless). A TechP is a physical characteristic of the road pavement condition, derived from measurements or other forms of investigation. A performance index (PI) is a dimensionless number that is determined from TechP through the use of a transfer function. The PI developed by COST354 vary from 0 to 5. Single performance indices (also abbreviated as PI in this document) represent a single TechP and can be combined in order to obtain combined performance indices CPIs that represent the functional and structural performance of a pavement. CPIs can be further combined in order to obtain a general (global) performance index (GPI). Figure 3.2 illustrate the aforementioned relations (Litzka et al., 2008).

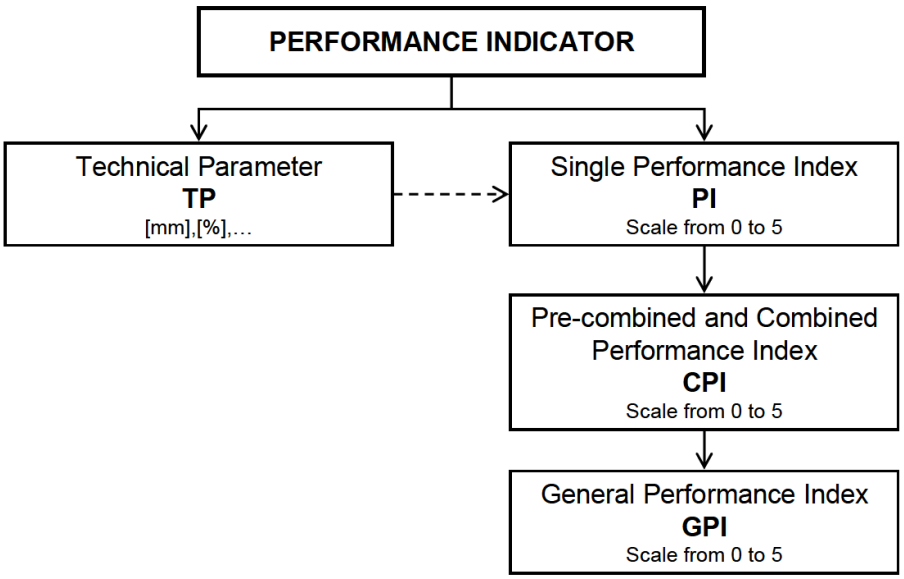


Figure 3.2: Overview of the development of performance indicators (Litzka et al., 2008)

COST354 defined PIs for the following performance indicators:

- Bearing capacity;
- Cracking;
- Longitudinal evenness;
- Friction;
- Transverse evenness;
- Macro-texture;
- Surface defects.

Additionally, there was an attempt to develop PIs for noise and air pollution, which failed due to insufficient data.

Three CPIs, derived from PIs were developed to represent important aspects of pavement performance, relevant to road users and operators:

- Comfort index;
- Safety index;
- Structural index.

COST354 also identified the importance of defining an environmental index. However, it would be strongly related to PIs for noise and air pollution which were not developed, thus, the environmental index was not defined as well.

Finally, a GPI was defined based on the combination of the three CPIs. All PIs are defined for different pavement types and road categories.

The COST action comprised the following main steps:

- Collection of existing basic information, creating an inventory of performance indicators used around Europe, for different road categories and pavement types, and including target values, limits, transfer functions, classification systems and methods for measurement and data collection;
- Selection and assessment of single performance indicators and definition of target values and limits based on statistical and empirical studies, as well as analytical evaluations. This allowed the development of transfer functions;

- Comparison of existing combination procedures and development of a procedure with unified weighting factors to determine CPIs. A similar task was performed to define the determination of a GPI.

3.4 Performance indicators

3.4.1 Individual performance indices

The selection of performance indicators for this work, based on the COST354, depended on the technical parameters for which there is sufficient available data. Therefore, five indicators were considered: Bearing Capacity, Cracking, Longitudinal Evenness, Friction and Transverse Evenness.

Bearing Capacity: PI_B

Bearing capacity is related to the structural performance of the pavement. COST354 adopt the abbreviation PI_B to refer to the bearing capacity index. The proposed TechPs for its calculation are the Residual life/ Design life or the Surface Curvature Index 300 (SCI_{300}). For this thesis, the SCI_{300} is adopted because it can be calculated from the deflection measurements with the FWD (ASTM D4694-09, 2003), as indicated in equation 3.1 (La Torre et al., 2007).

$$SCI_{300} = d_0 - d_{300} \tag{3.1}$$

where

d_0 Deflection at the load application point (µm);

d_{300} Deflection at 300 mm away from the load application point (µm).

From the three proposed transfer functions by COST354, the number 3 (equation 3.2) is adopted since the pavement sections to be studied are flexible structures mainly from motorways, which can be assumed as having strong bases.

$$PI_B = Max(0; Min(5; (SCI_{300}/253))) \tag{3.2}$$

This transformation results in the relation between SCI_{300} and PI_B as shown in Table 3.1.

Table 3.1: Range of transfer function for PI_B

	Very Good		→		Very Poor
Bearing Capacity, PI_B	[0; 1[	[1; 2[	[2; 3[	[3; 4[	[4; 5]
SCI_{300} (µm)	[0; 253[	[253; 506[	[506; 759[	[759; 1012[	[1012; 1265]

Cracking: PI_CR

Indices for cracking are usually composed from different input variables, so that it is defined as a pre-combined performance indicator by COST354. Nevertheless, the resulting pre-combined indicator can be used similarly to other single performance indicators. The transfer function proposed by COST354 for motorways is indicated in equation 3.3:

$$PI_CR = Max(0; Min(5; 0.16 * CR)) \tag{3.3}$$

The TechP for cracking, named as Cracking Rate (CR), is defined as a weighted sum of different types and dimensions of cracking, as suggested by equations 3.4, 3.5 and 3.6 Litzka et al. (2008):

$$TP_{cr} = Min(100; TPcr, A + TPcr, L + TPcr, E) \tag{3.4}$$

$$TP_{cr,A} = Min\left(100; \frac{1}{A_{ref}} * \sum_{m}\left[W_m * \sum_{i}(S_{cr,a,i} * A_i)\right] * 100\right) \tag{3.5}$$

$$TP_{cr,L} = Min\left(100; \frac{1}{A_{ref}} * \sum_{n}\left[W_n * I_{width,l} * \sum_{j}(S_{cr,l,j} * L_j)\right] * 100\right) \tag{3.6}$$

where

$TP_{cr,A}$	cracking rate area [%]
$TP_{cr,L}$	cracking rate length [%]
$TP_{cr,E}$	cracking rate element [%]
A_{ref}	reference-area
W_m	weight of cracked areas
$S_{cr,a,i}$	severity of crack type i
A_i	cracked area of crack type i
W_n	weight of cracked length
$I_{width,l}$	standard influence width of linear cracking (0.5 m)
$S_{cr,l,j}$	severity of crack type j
L_j	cracking length of crack type j

$TP_{cr,E}$ is not considered for this work since it refers to cracking elements (e.g. concrete slabs) which are not applicable for flexible pavements. $TP_{cr,A}$ and $TP_{cr,L}$ assumed the mean weights suggested by COST354 after a linear transformation in order to make the highest weight equal to 1.0 (Table 3.2). $S_{cr,l,j}$ can assume the values 1, 2 or 3 according to the severity level (Weninger-Vycudil et al., 2008).

Table 3.2: Weights for Cracking Technical Parameter

Cracking type	Weights W [0-1]
Alligator cracking	1.0
Longitudinal cracking	0.8
Transverse cracking	0.8
Block cracking	0.9

In Table 3.3, the correspondence between the cracking rate range with the PI_E values is presented.

Table 3.3: Range of transfer function for PI_CR

	Very Good		→	Very Poor	
Cracking, PI_CR	$[0;1[$	$[1;2[$	$[2;3[$	$[3;4[$	$[4;5]$
CR (%)	$[0;6.3[$	$[6.3;12.5[$	$[12.5;18.8[$	$[18.8;100.0[$	$[25.0;31.3]$

Longitudinal evenness: PI_E

COST354 proposes the International Roughness Index (IRI), measured in m/km as the TechP to determine the performance index PI_E. The proposed transfer function number 2 was selected since its range is less restrictive, more suitable for the historical IRI values from LTPP and applicable to motorways (equation 3.7):

$$PI_E = Max(0; Min(5; 0.816 * IRI)) \tag{3.7}$$

This transformation results in the relationship between IRI and PI_E as shown in Table 3.4.

Table 3.4: Range of transfer function for PI_E

	Very Good		→		Very Poor
Longitudinal Evenness, PI_E	[0; 1[	[1; 2[	[2; 3[	[3; 4[	[4; 5]
IRI (mm/m)	[0; 1.2[	[1.2; 2.5[	[2.5; 3.7[	[3.7; 4.9[	[4.9; 6.1]

Friction: PI_F

Skid Resistance is the PI used to evaluate the frictional properties of the pavement surface. COST354 propose two TechPs: (1) the Sideways Force Coefficient (SFC) (60 km/h) and (2) the Longitudinal Friction Coefficient (LFC) (50 km/h).

Although friction data available on LTPP are derived from several DOTs that might differ on the methods of performing inspections, the LTPP study tried to established general guidelines and recommendations to be followed by DOTs of all states. The LTPP data collection guidelines for friction recommend using the ASTM E-274 as the preferred method for obtaining data. This standard method measures the friction force on a locked test wheel as it is dragged over a wetted pavement surface under constant load and speed while its major plane is parallel to its direction of motion and perpendicular to the pavement (Titus-Glover and Tayabji, 1999; ASTM E274-06, 2006). However the majority of tests registered in LTPP were made at 65 km/h, the fact of having the major plane of the blocked wheel parallel to the movement direction justified the use of LFC as the TechP to calculate PI_F. Therefore, the adopted transfer function is:

$$PI_F = Max(0; Min(5; (-13.875 * LFC + 9.338))) \tag{3.8}$$

This transformation results in the relation between LFC and PI_F as shown in Table 3.5.

Table 3.5: Range of transfer function for PI_F

	Very Good		→		Very Poor
Skid resistance, PI_F	[0; 1[	[1; 2[	[2; 3[	[3; 4[	[4; 5]
LFC	[0.67; 0.60[	[0.60; 0.53[	[0.53; 0.46[	[0.46; 0.38[	[0.38; 0.31]

Transverse Evenness: PI_R

To evaluate transverse evenness, COST354 proposes the use of Rut Depth (RD), measured in mm, as the TechP. The transfer function number 2 is chosen because it is the most suitable for motorways (equation 3.9).

$$PI_R = Max(0; Min(5; (-0.0015 * RD^2 + 0.2291 * RD))) \tag{3.9}$$

This transformation results in the relationship between RD and PI_R as shown in Table 3.6.

Table 3.6: Range of transfer function for PI_R

	Very Good		→		Very Poor
Transverse Evenness, PI_R	$[0;1[$	$[1;2[$	$[2;3[$	$[3;4[$	$[4;5]$
RD (mm)	$[0;4.5[$	$[4.5;9.3[$	$[9.3;14.5[$	$[14.5;20.1[$	$[20.1;26.4]$

3.4.2 Combined performance indices

To combine individual PIs, COST354 adopts the advanced maximum criteria, so that the maximum weighted PI, represented with letter I in further equations, gets more importance than the others. From the two proposed alternatives, alternative 1 was chosen to obtain the values for the CPIs, because it is strongly influenced by the maximum weighted PI, but considers all the other weighted PIs as an average value with less importance, as indicated in Equation 3.10. In opposition, alternative 2 does not consider all the weighted PIs.

$$CPI_i = min\left[5; I_1 + \frac{p}{100} * \overline{(I_2, I_3, \ldots, I_n)}\right] \tag{3.10}$$

where

$$I_1 \geq I_2 \geq I_3 \geq \ldots \geq I_n \tag{3.11}$$

and

$$I_1 = W_1 * PI_1; I_2 = W_2 * PI_2; \ldots; I_n = W_n * PI_n. \tag{3.12}$$

A value between 10 and 20 units for p is recommended by COST354. In order to increase the influence of other weighted single performance indices, a value of 20 units was assumed for p. Comfort, Safety and Structural combined indicators are obtained

using the mean values of the proposed weights with appropriate linear transformations to ensure that the highest weight is always equal to 1 (Table 3.7). The calculation of the GPI follows similar procedure as the CPIs, but its inputs are the CPI instead of PIs. In this case, the weights defined by COST354 for motorways are adopted, as indicated in Table 3.8.

Table 3.7: Weights for input parameters for the CPIs

Performance Index	Comfort Index	Safety Index	Structural Index
PI_B	—	—	1.0
PI_CR	0.5	—	0.9
PI_E	1.0	—	0.6
PI_F	—	1.0	—
PI_R	0.7	1.0	0.5

Table 3.8: Weights for input parameters for the Global Performance Indicator

Road Safety	Riding Comfort	Pavement Structure
1.00	0.70	0.65

COST354 makes distinction between the level of PIs combination as a minimum, standard and optimum level, depending on the number of considered PIs. In this work, all the available PIs with respect to a certain CPI are combined. As a consequence, only the structural indicator determination procedure is equal to the optimum level defined by COST354, while Comfort and Safety indices fall somewhere between the standard and optimum level of PIs.

3.5 Data understanding and preparation

3.5.1 Obtaining technical parameters

In this section, the calculation of the TechP for each indicator, inspection date and test section is explained. In fact, the LTPP data as provided requires some compilation steps in order to have only one value for the TechPs to be used by the transfer functions of COST354 to determine PIs for each test section. The application of COST354 with American data from the LTPP was first tested during preliminary works for

this thesis, resulting in reasonably coherent classifications of pavement performance. Indeed, American standards are different from European ones and some inspections procedures are distinct. Nevertheless, the COST354 methodology was followed to accomplish the objectives of this work.

Bearing Capacity

For the majority of pavement sections, LTPP has FWD results for each 8 or 16 m. In each position there are sixteen drops, grouped by four different heights (approximately 27 kN, 40 kN, 53 kN and 71 kN), either for the mid lane (code F1) and for the outer wheel path (code F3). Nine sensors measure the peak deflection, distributed from 305 mm behind the load plate to 1524 mm in front of it (Schmalzer, 2006). Data of interest for this work refers to the peak deflection measured under the load plate (sensor D1) and at 305 mm in front of it (sensor D3) in order to calculate the SCI_{300} at the outer wheel path. For illustration purposes, a sample of these data is presented in Table 3.9.

At some tested locations, there are repeated tests for the same drop height. From these results, an average of the measured deflection is considered as the unique result. Then, an interpolation is made in order to obtain deflection values for a desired impact load at the sensor D1 and D3. Typically, a load of 65 kN is used in Portugal to assess the structural condition of the pavement (Oliveira et al., 2008). However, the COST354 transfer function for PI_B was defined for an impact load of 50 kN, thus it is the adopted value for this work (Litzka et al., 2008; Fog et al., 1998). The SCI_{300} is then obtained through equation 3.1. The percentile 85 of all SCI_{300} values of a test section is then determined and used as the TechP that quantifies the bearing capacity of the section (Shell, 1978). Table 3.10 exemplifies this procedure for one test date at one section.

In conclusion, the PI_B characterizing the pavement condition regarding bearing capacity of that section is 0.88 (Equation 3.13), which is a very good condition according to Table 3.1:

$$PI_B = Max(0; Min(5; (223/253))) = 0.88 \tag{3.13}$$

Cracking

The TechP for cracking considers alligator, block, longitudinal and transversal cracking. The cracked area or length is multiplied by 1, 2 or 3 according to its severity level, in order to obtain the $S_{cr,a,i} * A_i$ and $S_{cr,l,j} * L_j$ as indicated in equations 3.5 and 3.6. A width of 0.5 m is considered to determine the area of influence of longitudinal and

Table 3.9: Sample of collected data of deflection

State code	Shrp ID*	Test date	Location	Drop no.	Drop stress (kPa)	Drop load (kN)	Peak deflection D1	Peak deflection D3
1	1001	11/10/1989	0	4	406	28.7	248	109
1	1001	11/10/1989	0	8	573	40.5	313	149
1	1001	11/10/1989	0	12	753	53.2	392	193
1	1001	11/10/1989	0	16	1059	74.9	480	246
1	1001	11/10/1989	7.9	4	419	29.6	274	116
1	1001	11/10/1989	7.9	8	576	40.7	351	160
1	1001	11/10/1989	7.9	12	739	52.2	436	205
1	1001	11/10/1989	7.9	16	1037	73.3	537	261
1	1001	11/10/1989	15.2	4	413	29.2	266	106
1	1001	11/10/1989	15.2	8	569	40.2	324	147
1	1001	11/10/1989	15.2	12	742	52.4	416	189
1	1001	11/10/1989	15.2	16	1034	73.1	501	242
1	1001	11/10/1989	22.9	4	406	28.7	268	109
1	1001	11/10/1989	22.9	8	565	39.9	337	152
1	1001	11/10/1989	22.9	12	740	52.3	421	199
1	1001	11/10/1989	22.9	16	1042	73.7	513	253
1	1001	11/10/1989	30.5	4	410	29.0	270	120
1	1001	11/10/1989	30.5	8	565	39.9	351	171
1	1001	11/10/1989	30.5	12	742	52.4	430	221
1	1001	11/10/1989	30.5	16	1040	73.5	543	284

* Four-character identifier that is unique for each section when combined with the state code.

transverse cracking (Litzka et al., 2008). The reference area (A_{ref}) corresponds to the total length of the test section times the survey width given for every measurement by the LTPP database. Finally, the TechP for each section is the sum of TP_{cr}, A with TP_{cr}, L. An example of TP_{cr} calculation is shown in Table 3.11 for a section of 547.2 m^2 with alligator and transverse cracking only. The PI_CR is, then, equal to 3.06 (refer to equation 3.14), indicating a section in very bad condition in terms of cracking.

$$PI_CR = Max(0; Min(5; 0.16 * 19.10)) = 3.06 \tag{3.14}$$

Longitudinal evenness

In LTPP studies, IRI is measured for the right and left wheel path by several runs, normally between 5 and 7, for each section. LTPP database provides its values and the average from both wheels. The final value to be used as the TechP for each section

Table 3.10: Sample of calculated SCI_{300} for a drop load of 50 kN

State	Shrp ID	Test date	Location	Deflection D1	Deflection D3	SCI_{300}
1	1001	11/10/1989	0	372	182	190
1	1001	11/10/1989	7.9	420	196	223
1	1001	11/10/1989	15.2	398	181	217
1	1001	11/10/1989	22.9	405	190	215
1	1001	11/10/1989	30.5	415	211	203
1	1001	11/10/1989	38.1	420	198	223
1	1001	11/10/1989	45.7	464	201	263
1	1001	11/10/1989	53.3	396	202	193
1	1001	11/10/1989	61.0	355	167	188
1	1001	11/10/1989	68.6	326	146	180
1	1001	11/10/1989	76.2	336	155	181
1	1001	11/10/1989	84.1	367	178	189
1	1001	11/10/1989	91.4	365	180	186
1	1001	11/10/1989	99.1	378	181	198
1	1001	11/10/1989	106.7	360	185	176
1	1001	11/10/1989	114.3	430	216	214
1	1001	11/10/1989	121.9	378	183	195
1	1001	11/10/1989	129.5	362	166	196
1	1001	11/10/1989	137.5	420	210	210
1	1001	11/10/1989	144.8	455	239	215
1	1001	11/10/1989	152.4	523	274	249
					Percentile 85	223

is the average of all the runs, as illustrated in Table 3.12. For instance, the PI_E of that section on the 17/02/1994 is 0.81 (Equation 3.15), which indicates a very good condition regarding the longitudinal evenness.

$$PI_E = Max(0; Min(5; 0.816 * 0.9882)) = 0.81 \tag{3.15}$$

Friction

Friction coefficient is provided on LTPP for the beginning and the end of each pavement section. An average of those values was assumed as the representative TechP of the section. For sections where more than one measurement at the same date was available, all values were considered to calculate the average, as seen in Table 3.13. For instance, the PI_F of section 4_1003 on the 11/06/1992 is 1.91 (Equation 3.16), which indicates

Table 3.11: Example of TP_{cr} calculation for one inspection date at one section

Severity	Alligator (m^2)	$S_{cr,a,i} * A_i$	Transverse (m)	$S_{cr,l,j} * A_i * 0.5$	TP_{cr}
1	71.70	71.70	20.25	20.25	
2	4.90	9.80	4.25	8.50	
3	0	0	0	0	
Total		81.50		28.75	19.10

a good condition regarding the skid resistance of the pavement.

$$PI_F = Max(0; Min(5; (-13.875 * (53.5/100) + 9.338))) = 1.91 \tag{3.16}$$

Rutting

Information about rutting on LTPP database is usually available for 11 test points per section. Furthermore, an average of measurements for all the points is provided for both left lane half (LLH) and right lane half (RLH). The average of those two values are used as the TechP fo calculate the PI_R, as exemplified in Table 3.14. In this case, the PI_R on the 26/07/2004 is equal to 1.53 (Equation 3.17), represent a good condition of the section regarding the transversal evenness.

$$PI_R = Max(0; Min(5; (-0.0015 * 7^2 + 0.2291 * 7))) = 1.53 \tag{3.17}$$

3.5.2 Preparing input data for Markov

The Markov models to be used require the input of valid sequences of PIs in chronological order. Additionally, due to the discrete character of Markov chains used in this work, all PIs must be converted into integer numbers that represent distinct condition states (CS). Therefore, the continuous range of 0 to 5 as defined in COST354 is transformed in a range of 1 to 5 of integers only, being 1 is the best CS that a PI can get, while a CS of 5 represents the worst possible condition. The PIs derived from TechPs as exemplified in Section 3.5.1, which can result in decimal numbers, ought to be converted into its respective integer according to Table 3.15. A valid sequence is defined as a group of inspections for a pavement section, regarding a specific PI, organized in a chronological order with no influential maintenance and rehabilitation (M&R) operations in between. Indeed, the inspections before and after an influential M&R operation mark the end and beginning of a valid sequence of inspections, respec-

Table 3.12: Example of calculation of the TechP for longitudinal evenness for three inspection dates at one section

State	Shrp ID	Profile Date	IRI	Run no.	IRI average
1	1021	06/06/1990	0.967	1	
1	1021	06/06/1990	0.962	2	
1	1021	06/06/1990	0.971	3	
1	1021	06/06/1990	0.924	4	
1	1021	06/06/1990	0.971	5	
1	1021	06/06/1990	0.963	6	
1	1021	06/06/1990	0.976	7	0.9620
1	1021	03/04/1992	0.932	1	
1	1021	03/04/1992	0.927	2	
1	1021	03/04/1992	0.962	3	
1	1021	03/04/1992	0.955	4	
1	1021	03/04/1992	0.966	5	0.9484
1	1021	17/02/1994	0.977	1	
1	1021	17/02/1994	0.977	2	
1	1021	17/02/1994	0.997	3	
1	1021	17/02/1994	0.995	4	
1	1021	17/02/1994	0.995	5	0.9882

tively. An influential M&R operation is defined as an activity that actually improves the quality of a section regarding the targeted PI, thus causing a reduction of its value. Table 3.16 lists the M&R operations recorded in LTPP that are theoretically expected to influence one or more TechPs.

For each section and PI, the respective influential M&R operations are chronologically included. Those that revealed to not influence the deterioration behaviour of a certain TechP were not considered, thus, did not mark an interruption of a sequence of inspections. Similarly, M&R operations that improve the pavement quality regarding a specific TechP were considered, even though that M&R was not expected to be influential.

In some pavement sections, a quality improvement between consecutive inspections without any record of a M&R operation was noticed. This is unlikely to happen since the pavement deterioration is a natural and continuous process, so that every time an inspection resulted in a PI value lower than the one obtained on the previous inspection, that record was given the same PI value as the previous one. In fact, it might be occasionally reasonable to verify a quality improvement for a TechP, such as a friction gain as a result of the bituminous wearing of new surface layers. Nevertheless,

Table 3.13: Example of calculation of the TechP for friction for two sections at several dates

State	Shrp ID	Test date	Friction at the beginning (%)	Friction at the end (%)	Average (%)	Section average (%)
4	1003	11/06/1992	53	59	56.0	53.5
4	1003	11/06/1992	53	49	51.0	
4	1003	30/06/1993	49	48	48.5	48.5
4	1006	11/06/1992	45	50	47.5	50.0
4	1006	11/06/1992	52	53	52.5	

Table 3.14: Example of calculation of the TechP for transversal evenness for one section at several dates

State	Shrp ID	Survey date	LLH mean depth	RLH mean depth	Average
31	6700	04/11/1999	3	6	4.5
31	6700	07/10/2001	7	10	8.5
31	6700	20/11/2002	5	8	6.5
31	6700	22/07/2003	3	7	5
31	6700	26/07/2004	5	9	7

these very rare cases are ignored in order to use the Markov models as presented in Chapter 4.

Some valid sequences for the PI_E are presented in Table 3.17. It shows two sequences for section 4_6060 with 5 and 4 records and another two for section 18_1028 with 7 and 5 records.

The number of valid sequences of inspections for each performance index and its respective records, excluding M&R, are indicated in Table 3.18. The transition from a record to the next one within the same sequence can either indicate that the pavement does not change its CS or denote a deterioration to a higher CS. The performance

Table 3.15: Limits of performance indices for condition states

	Very Good → Very Poor				
Performance index	$[0;1[$	$[1;2[$	$[2;3[$	$[3;4[$	$[4;5]$
Condition state	1	2	3	4	5

Table 3.16: Influential M&R operations

M&R code	Description	Bearing Capacity	Cracking	IRI	Friction	Rut
1	Crack Sealing	X	X			
12	Grinding Surface				X	
13	Grooving Surface				X	
19	AC Overlay	X	X	X	X	X
25	Patch Pot Holes: Hand Spread, Compacted With Truck	X	X			
28	Surface Treatment, Single Layer	X	X	X	X	X
29	Surface Treatment, Double Layer	X	X	X	X	X
30	Surface Treatment, Three or More Layers	X	X	X	X	X
31	Aggregate Seal Coat		X	X	X	X
32	Sand Seal Coat		X	X	X	X
33	Slurry Seal Coat		X	X	X	X
34	Fog Seal Coat		X	X	X	X
43	Hot-Mix Recycled AC	X	X	X	X	X
44	Cold-Mix Recycled AC	X	X	X	X	X
45	Heater Sacrification, Surface-Recycled AC	X	X	X	X	X
51	Mill Off AC and Overlay With AC	X	X	X	X	X
55	Mill Existing Pavement and Overlay With Hot-Mix AC	X	X	X	X	X
56	Mill Existing Pavement and Overlay With Cold-Mix AC	X	X	X	X	X

indicator for longitudinal evenness is the one with more amount of records, in opposition with the one for friction. For a better characterization of the database, the observed transitions of CS and time between inspections are presented in Table 3.19 and Figure 3.3, respectively.

The number of transitions from CS 5 to 5 are not indicated because that is the worst CS a pavement section can get and so it remains in that CS until a M&R operation is performed. It is, therefore, a useless value for the Markov models. The majority of transitions for all PIs do not denote a change of CS. PI_B and PI_E are the indicators with less records of being in CSs 4 and 5, suggesting a slow deterioration. On the other hand, PI_CR and PI_F have a relatively large amount of records in the higher CSs and

Table 3.17: Valid sequences of inspections

State	Shrp ID	Date	IRI	PI_E	M&R
4	6060	18/03/1990	0.721	1	
4	6060	12/01/1992	0.670	1	
4	6060	26/02/1993	0.730	1	
4	6060	04/02/1997	0.711	1	
4	6060	17/12/1997	0.845	1	
4	6060	01/10/1998			51
4	6060	10/12/1998	0.502	1	
4	6060	11/11/1999	0.506	1	
4	6060	10/12/2004	0.691	1	
4	6060	16/08/2006	0.869	1	
18	1028	02/12/1989	1.113	1	
18	1028	26/07/1990	1.335	2	
18	1028	15/12/1990	1.306	2	
18	1028	19/12/1991	1.238	2	
18	1028	05/10/1992	1.389	2	
18	1028	15/01/1994	1.357	2	
18	1028	15/03/1995	1.539	2	
18	1028	23/06/1995			55
18	1028	15/01/1999	0.784	1	
18	1028	21/11/2004	0.840	1	
18	1028	25/06/2008	0.846	1	
18	1028	20/07/2010	0.936	1	
18	1028	12/10/2011	1.026	1	

Table 3.18: Number of valid sequences and records

	PI_B	PI_CR	PI_E	PI_F	PI_R
No. sequences	670	652	663	472	695
No. records	3090	2411	4160	1691	3794

several transitions of more than one CS are observed, suggesting a faster deterioration. It is noticed from the histograms (Figure 3.3) that most of the inspections occur with less than 2 years intervals.

3.5.3 Additional data

Typically, Markov based prediction models represent a deterioration process along the time. Indeed, *Time* is often used as the parameter for Markov models, i.e., the inde-

Table 3.19: Summary of the number of transitions from state i to state j considering all records

From/To		CS_1	CS_2	CS_3	CS_4	CS_5
PI_B	C_1	1821	67	2	0	0
	C_2	0	406	15	3	0
	C_3	0	0	86	1	1
	C_4	0	0	0	14	2
PI_CR	C_1	835	145	25	9	37
	C_2	0	142	55	25	24
	C_3	0	0	70	34	33
	C_4	0	0	0	41	48
PI_E	C_1	1560	166	0	0	0
	C_2	0	1451	81	1	0
	C_3	0	0	202	16	0
	C_4	0	0	0	13	2
PI_F	C_1	61	18	6	5	2
	C_2	0	107	37	13	3
	C_3	0	0	226	41	6
	C_4	0	0	0	314	35
PI_R	C_1	791	164	3	0	0
	C_2	0	1510	98	0	0
	C_3	0	0	378	29	0
	C_4	0	0	0	102	7

pendent variable from which intensity matrices are deduced (Sánchez-Silva and Klutke, 2016). It is, however, well known that pavements deterioration are caused by other factors such as the traffic volume and its interaction with the pavement structure. By using *Time* as the only Markov parameter causing deterioration, it is expected to find sections with different structure and/or traffic volumes having the same deterioration behaviour. Therefore, it is useful to capture the influence of those parameters in order to enhance the reliability of Markov models to be developed. From the available data on LTPP database, information about traffic and pavement structure was retrieved.

Traffic data of interest consist in the yearly equivalent single axle load (ESAL) relative to heavy vehicles passed in each section. Having such data for all the years allow the determination of the accumulated ESAL between inspection dates. However, some of the years with inspection records have no information about traffic, so an estimation of the number of ESAL is necessary for those years. To do so, a traffic

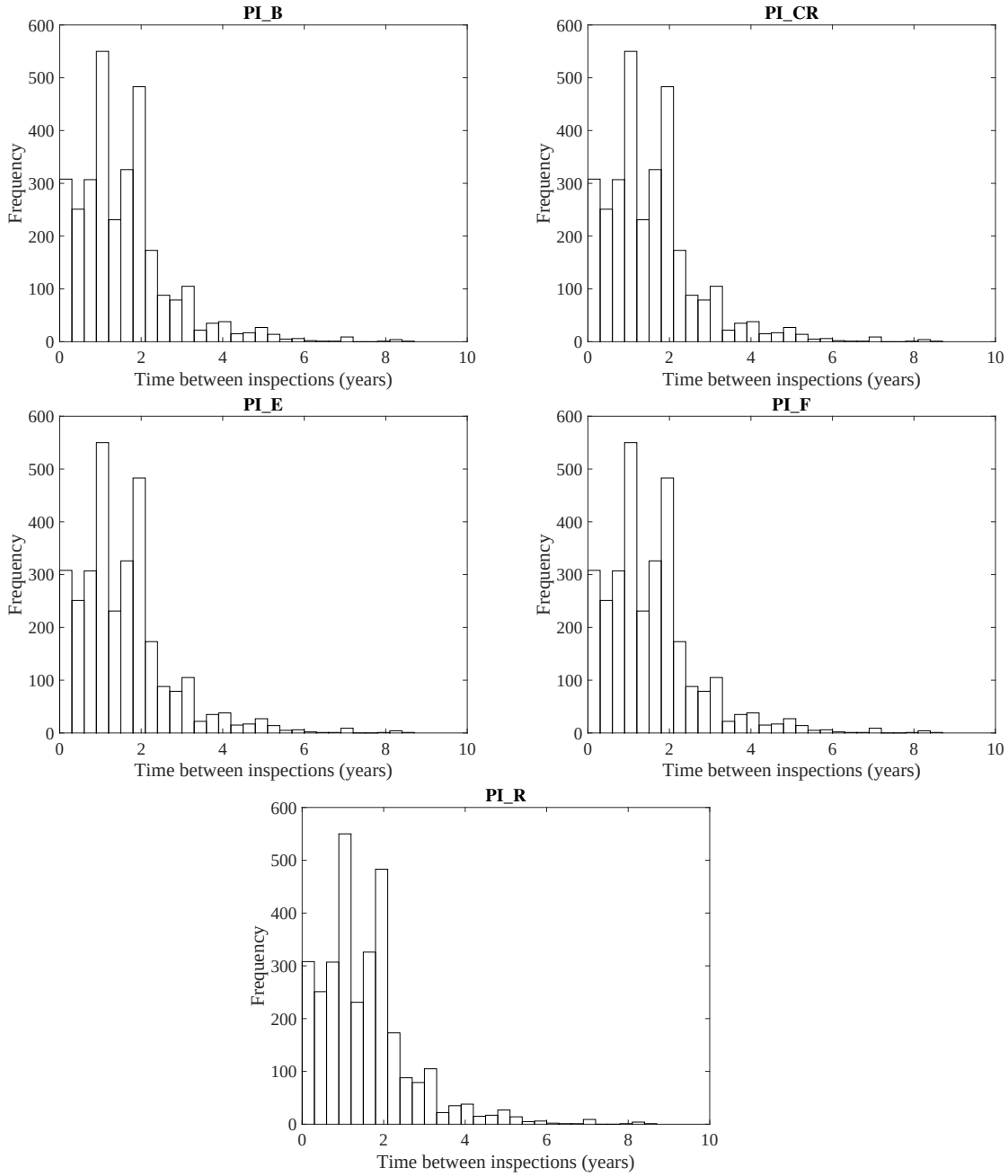


Figure 3.3: Mean time period between inspections for each indicator as measured in the LTPP database

growth rate of 3% was adopted, since this was the rate verified in several sections with more complete data from different States. ESAL values for years with missing data can then be calculated from years with available traffic data. Table 3.20 shows a sample of traffic data for two sequences of inspections for the same pavement section.

Regarding pavement structure, data of thickness and the structural number (SN) was retrieved from the LTPP database. The SN is an "abstract number" developed by AASHTO and is widely used worldwide to characterize pavement structure. In

Table 3.20: Sample of traffic data

Sequence	State	Shrp	Test date	Year	Yearly traffic (kESAL)	Accumulated traffic (kESAL)
	1	1001	08/08/1990	1990	171	0
	1	1001	03/04/1992	1992	181	283
1	1	1001	28/07/1992	1992	181	340
	1	1001	22/10/1992	1992	181	383
	1	1001	13/01/1993	1993	189	424
	1	1001	10/01/1996	1996	204	0
2	1	1001	27/01/1998	1998	216	418
	1	1001	06/04/2003	2003	251	1539

addition, information about the type of layers and respective thickness was collected in order to determine the SN for few cases with missing data. This was calculated according to Equations 3.18 and 3.19 and the coefficients proposed by the Massachusetts Highway Department (MassDOT, 2006), as shown in Table 3.21.

$$SN_{layer} = Layer\ Thickness * Layer\ coefficient \tag{3.18}$$

$$SN_{section} = \sum SN_{layers} \tag{3.19}$$

A correspondence between the layer material and the layer position/function as described in LTPP is indicated in Table 3.22, and these were the values used to determine the SN. Table 3.23 describes each material type. An example of a pavement structure, divided in its layers with the respective thickness and SN coefficient is illustrated in Table 3.24.

Table 3.21: Layer coefficients (per inch) for existing pavements (MassDOT, 2006)

Material type	Surface Course	Base Course	Sub-base
Hot Mix Asphalt	0.44	0.34	
Sand Asphalt	0.40		
Asphalt Treated Penetrated Stone		0.24	
Crushed Stone/Macadam; Sand bound Crushed Stone		0.14	
Sandy Gravel		0.07	
Crushed Stone (Dense Graded)			0.14
Gravel			0.11
Sand/ Sandy Clay			0.05 to 0.10

Table 3.22: Layers and respective coefficients for Structural Number

Material (LTPP code)	Overlay	Original Surface Layer	AC Layer Below Surface (Binder Course)	Base Layer	Subbase Layer	Friction Course
1	0.44	0.44	0.44			
2	0.44					0.44
22				0.07	0.11	
23				0.14	0.14	
24				0.14	0.05	
25				0.07	0.11	
26				0.07	0.11	
27				0.14	0.14	
28			0.44	0.34	0.34	
29			0.40	0.30		
30				0.30	0.30	
31				0.34	0.34	
32				0.30		
33				0.30	0.30	
34				0.34		
38				0.30	0.20	
41				0.14	0.14	
42				0.14	0.14	
43				0.14	0.14	
46				0.14		
49				0.07	0.05	
52					0.10	
53					0.10	

Having information about time, traffic and pavement structure, other related independent variables might be potential Markov parameters. For this thesis, seven parameters are explored, as follow:

1. **Time**. Time is perhaps the most intuitive variable to understand and use in Markov models to predict deterioration, since it is a process that occurs along time. The disadvantage comes when the same time-based model is being used to predict deterioration, for the same time horizon, for two or more pavement sections that significantly differ, for instance, in the amount of traffic load.

2. **Traffic**. Traffic volume is, indeed, the most important variable for pavement design, usually quantified in terms of ESAL referring to trucks traffic only. It is, then, possibly a good parameter for the pavement deterioration to be deduced from. There are, however, other factors that led to different deterioration curves

Table 3.23: Description of material type and its LTPP codes

LTPP code	Description
1	Hot Mixed, Hot Laid Asphalt Concrete, Dense Graded
2	Hot Mixed, Hot Laid Asphalt Concrete, Open Graded (Porous Friction Course)
22	Gravel (Uncrushed)
23	Crushed Stone, Gravel or Slag
24	Sand
25	Soil-Aggregate Mixture (Predominantly Fine-Grained Soil)
26	Soil-Aggregate Mixture (Predominantly Coarse-Grained Soil)
27	Soil Cement
28	Asphalt Bound, Dense Graded, Hot Laid, Central Plant Mix
29	Asphalt Bound, Dense Graded, Cold Laid, Central Plant Mix
30	Asphalt Bound, Dense Graded, Cold Laid, Mixed In-Place
31	Asphalt Bound, Open Graded, Hot Laid, Central Plant Mix
32	Asphalt Bound, Open Graded, Cold Laid, Central Plant Mix
33	Asphalt Bound, Open Graded, Cold Laid, Mixed In-Place
34	Recycled Asphalt Concrete, Plant Mix, Hot Laid
38	Lean Concrete (<3 sacks cement/cy)
41	Limerock, Caliche (Soft Carbonate Rock)
42	Lime-Treated Subgrade Soil
43	Cement-Treated Subgrade Soil
46	Sand Asphalt
49	Other
52	Sandy Clay
53	Silty Sand

for pavement sections with the same traffic. In this thesis, for matters relating traffic with deterioration, traffic is measured as the number of ESAL of trucks traffic.

3. **Normalized traffic**. For a pavement section, if the accumulated traffic is divided by its initial traffic volume (first year of records), it is somehow already taking into account the traffic level for which it was designed. This might allow using the same intensity matrix for pavement sections with different traffic realities.

4. **Traffic and thickness**. To consider both traffic and thickness within the same intensity matrix, the accumulated traffic at each historical record is divided by the respective pavement thickness. This normalization intends to allow the same intensity matrix to represent a thicker pavement section layer with more traffic as well as a thinner layer with less traffic.

Table 3.24: Scheme of a pavement section layers and respective SN

Layer no.	Description	Material	Mean thickness (in)	Coefficient	SN
1	Original surface layer	1	1.8	0.44	0.79
2	Base layer	34	4.6	0.34	1.56
3	Sub-base layer	23	5.0	0.14	0.7
4	Sub-base layer	25	5.0	0.11	0.55
5	Subgrade	52	n.a.	n.a.	
All					3.60

5. **Traffic and Structural Number (SN)**. Similar to the previous item, the normalization of traffic with the SN is more detailed since it captures the structural capacity of the different layers. It is expected to be more accurate.

6. **Normalized traffic and thickness**. This parameter considers not only the relative growth of traffic, but also the pavement thickness. Two dividing operations are needed to find its values, resulting in relatively low values which might risk losing significance of the considered components.

7. **Normalized traffic and Structural Number**. Similar to the previous item, but considering SN instead of thickness.

Considerations regarding the usage of some of the parameters are discussed in Section 4.4.

Chapter 4

Pavement performance prediction models

4.1 Introduction

Pavement performance prediction models (PPPMs) are a crucial part of a PMS, as explained in Section 2.2. The more accurate and detailed the PPPMs are, the more efficient the resource allocation is expected to be towards the pavement management along its life-cycle. Although the recognition of its importance had been noticed several decades ago, PPPMs keep being a subject of development in recent years (Wang and Liang, 2014; Porras-Alvarado et al., 2014; Neves et al., 2012). Despite not being the core of this thesis, they are an indispensable input to develop and test an optimization methodology, with strong influence in the optimization results. Thereby, adopting and adapting a pavement performance prediction model (PPPM) was part of this work.

Given the association of this thesis with the SustIMS project, Markov models were chosen for the PPPM, since the other highway assets in the scope of SustIMS were modelled in the same basis. Nevertheless, Markov chains have been predominantly used for PMSs in recent years and are relatively simple to implement. As main advantages, Markov models allow generalization of the deterioration process into the transition pattern among CSs, which is suitable for representing pavement performance and they can be used in the absence of historical data as the probability of observing future state depends only on the observed CSs at the present (Lethanh and Adey, 2012). More features of Markov models are described in Section 2.2, while specifications of its implementation in this work are presented in Section 4.2.

Historical data to develop these models were retrieved from the LTPP database and COST354 was the reference to classify pavement condition with performance indexes,

as explained in Chapter 3.

In this chapter, a theoretical explanation about Markov modelling is presented, followed by a demonstration of its implementation and assessment. This is made for the case where *Time* is the only parameter that influences pavement deterioration. Finally, in Section 4.4, an exploitation of the Markov models is performed, by comparing the results of using different parameters as the independent variable. Part of the work described in this chapter was published in an international journal (Moreira et al., 2016b).

4.2 Markovian approach

A Markov chain is a particular stochastic process with discrete states in which the state at one time epoch depends only on the state in the previous time epoch (Ching and Ng, 2006). The parameter, usually the *Time*, can be discrete or continuous. To ease the reading of this and next sections, *Time* is assumed to be the parameter. According to Mishalani and Madanat (2002) and Lounis and Madanat (2002) there are two deterioration models in discrete states processes: time based models and state based models, being the latter adopted in the present work. In a state based model, the probability for a pavement section to stay in the same CS or to move to a next state in a pre-defined period of time Δt is defined.

For the methodology presented in this thesis, Markov homogeneous models were adopted since it is intended to be generally applicable at a network level, so that the TPM is constant for all the prediction period. In fact, some experiences were performed in order to have different Markov models for sections with different traffic volumes, grouped in classes, but it proved to be unsuccessful. Based on a discrete performance scale, a constant probability of transition between states is defined by Equation 4.1:

$$\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_i \end{bmatrix}^T_{t+\Delta_t} = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_i \end{bmatrix}^T_{t} \times \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1j} \\ 0 & p_{22} & \cdots & p_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & p_{ij} \end{bmatrix}_{\Delta_t} \tag{4.1}$$

where $S_{t+\Delta t}$ and S_t are the state probability vectors at times $t+\Delta t$ and t, respectively. These vectors are defined as the probability of a structure or component being in each condition state, CS_i. P is the transition matrix, where P_{ij} defines the probability of the transition between state i to j from instant t to $t+\Delta_t$. The average condition state is then obtained by multiplying $S_{t+\Delta t}$ with the vector of the possible condition states:

$$\overline{CS}(t+\Delta t) = S_{t+\Delta t} * \begin{bmatrix} 1 \\ 2 \\ \vdots \\ i \end{bmatrix} \tag{4.2}$$

A continuous time Markov process is adopted for this work, since the intervals between inspections Δt (or other parameter) are not regular or similar for all pavement sections (Ng and Moses, 1998; Yang et al., 2009). Kalbfleisch and Lawless (1985) proposed the definition of a transition intensity matrix Q as shown in Equation 4.3 (Kallen and Van Noortwijk, 2006):

$$\frac{\partial}{\partial t} P = P \times Q \tag{4.3}$$

Solving this equation, the TPM is determined through equation 4.4:

$$P = exp\,(Q \times \Delta t) \tag{4.4}$$

The intensity matrix, Q, represents the instantaneous probability of transition between the state i to state $j \neq i$ (independently of Δt) and is directly correlated with any transition probabilities matrix P (Bladt and Sørensen, 2009).

Bearing in mind that the pavement deterioration is a natural and continuous process, instantaneous transitions can only occur between adjacent CSs and a pavement section cannot reduce its CS without the influence of a maintenance and rehabilitation (M&R) operation. Consequently, the matrix Q is null except for the main diagonal and the diagonal above that. The worst CS is designed as absorbing state since there are no transitions from it. For these reasons, all the elements in the last line of matrix Q are null. In this study, the intensity matrix Q is 5×5, as illustrated in Equation 4.5, as there are 5 different CSs for the road pavement performance classification,

$$Q = \begin{bmatrix} -\theta_1 & \theta_1 & 0 & 0 & 0 \\ 0 & -\theta_2 & \theta_2 & 0 & 0 \\ 0 & 0 & -\theta_3 & \theta_3 & 0 \\ 0 & 0 & 0 & -\theta_4 & \theta_4 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.5}$$

being,

$$\begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \end{bmatrix} = \begin{bmatrix} q_{1,2} \\ q_{2,3} \\ q_{3,4} \\ q_{4,5} \end{bmatrix} \tag{4.6}$$

where matrix Q satisfies the following conditions (Kalbfleisch and Lawless, 1985):

- $q_{i,j} \geq 0$ for $j - i = 1$
- $q_{i,i} = -\sum_{j \neq i} q_{i,j}$ with $i = 1, \cdots, k$, being k the total number of condition states
- $q_{i,j} = 0$ for $i > j$
- $q_{i,j} = 0$ for $j - i > 1$
- $q_{i,j} = 0$ for $i, j = k$

Applying Equation 4.4 with matrix Q as defined, the transition probabilities can be determined for any time interval between observations and, consequently, be used to predict the pavement performance at a given instant in the future with limited computational cost.

Initial estimates of matrices Q can be obtained through the calculation of the hazard rates, θ_i, based on the Jackson approach (Jackson, 2011) as presented in Equation 4.7:

$$\theta_i = q_{ij} = \frac{n_{ij}}{\sum \Delta_{t_i}} \tag{4.7}$$

where n_{ij} represents the number of elements that moved from state i to j and Δt_i is the time between observations where the initial CS is i. By using Equation 4.7, it is assumed that the inspection dates represent the exact transition moment in the Markov process (Jackson, 2011), which hardly happens in reality. The optimization of Q through the maximization of the log-likelihood defined by Equation 4.8 (Kalbfleisch and Lawless, 1985), is a step taken to consider that transitions take place at unknown occasions in between the inspection dates.

$$L = \sum_{pav=1}^{N} \sum_{transition=1}^{M} ln\left(P_{ij}\right) \tag{4.8}$$

where M is the number of inspections carried out for each pavement section (valid sequence as defined in Section 3.5.2), N is the number of analysed pavement sections (valid sequences) and P_{ij} is the probability of occurrence of observed transition, as predicted by the Markov model, according to Equation 4.4.

The log-likelihood value can be used as an indicator of the model quality, since the best deterioration model is the one resulting in higher probabilities of occurrence of the observed transitions. The higher L value is (closer to zero, because it assumes negative values), the better the model accuracy is. A value of $L = 0$ represents an ideal model.

4.3 Model design and assessment

The design of the Markov model is accompanied by a continuous assessment in order to understand whether or not the results are reasonable and to possibly explore other approaches of using data towards a better model.

4.3.1 Assessment metrics

In this thesis, the quality of the models are assessed through the log-likelihood value (equation 4.8), confusion matrices and its derivations and regression error characteristic (REC) curves. In addition, the analysis of the predicted time in each CS for all PIs is useful to assess the plausibility of the model.

Assuming the prediction of PIs as a classification problem, the calculation of confusion matrices can give an overview of the quality of the proposed models. More than a mere accuracy test, it shows which classes are classified properly and which are misclassified (confused) with other classes and in what degree. These matrices are relatively simple to understand for binary classifiers, becoming more and more complex as the number of classes, and consequently size of the matrix, grows (Susmaga, 2004; Hastie et al., 2009).

In fact, for a binary problem, a confusion matrix is a 2×2 matrix that quantifies the true positives TP, true negatives TN, false positives FP and false negatives FN, as illustrated in Figure 4.1. Given a classifier and an instance, if the instance is positive and it is classified (predicted) as positive, it is counted as a TP; if it is classified as negative, it is counted as a FN. If the instance is negative and it is classified as negative, it is counted as a TN; if it is classified as positive, it is counted as a FP. With n classes, the confusion matrix becomes an $n \times n$ matrix, where the diagonal represents the number of correct predictions, while the remaining cells represent incorrect predictions. Instead of managing trade-offs between TP and FP, there are n benefits and $n^2 - n$ possible errors (Fawcett, 2006).

For the pavement prediction model addressed in this work, as there are five possible condition states, the confusion matrix is a 5×5 matrix. However, for an easier overview of the model accuracy, a similar approach to a binary problem is done, as follows:

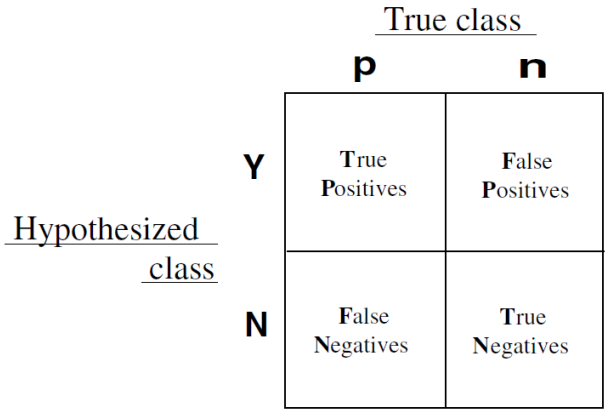


Figure 4.1: Confusion matrix for a binary problem (Fawcett, 2006)

- TP: if the model predicts a transition from a CS_i to a CS_j that actually happens, with $i \neq j$;
- TN: if the model predicts no change of CS, which is actually verified;
- FP: if the model predicts a transition from a CS_i to a CS_j that does not occur, with $i \neq j$;
- FN: if the model predicts no change of CS, when actually there is a transition for another CS.

A confusion matrix forms the basis for some interesting derivations such as the true positive rate (TPR), also known as recall, the false positive rate (FPR) or fall-out, the positive predictive value (PPV) or precision and the F_1 score, among others. The recall is the fraction of well predicted changes of CSs, among all observed transitions that actually revealed a change of CS, while the precision is the fraction of well predicted changes of CSs among all the transitions where a change of CS was predicted. F_1 score is the harmonic mean of precision and recall, being an aggregated performance score to evaluate the model, and its value increases as the number of FPs and FNs decreases in comparison with the TPs. These derivations are calculated according to Equations 4.9, 4.10, 4.11 and 4.12 (Fawcett, 2006).

$$TPR = \frac{TP}{TP + FN} \tag{4.9}$$

$$FPR = \frac{FP}{FP + TN} \tag{4.10}$$

$$PPV = \frac{TP}{TP + FP} \tag{4.11}$$

$$F_1 = 2\frac{PPV * TPR}{PPV + TPR} = \frac{2TP}{2TP + FP + FN} \tag{4.12}$$

TPR and FPR are also useful to build receiver operating characteristics ROC graphs. These are two-dimensional graphs in which TPR is plotted on the Y-axis and FPR is plotted on the X-axis, thus depicting relative trade-offs between TP and FP, as shown in Figure 4.2. Informally, it can be stated that a point in ROC space is better than another if it is located at an upper-left position (Fawcett, 2006).

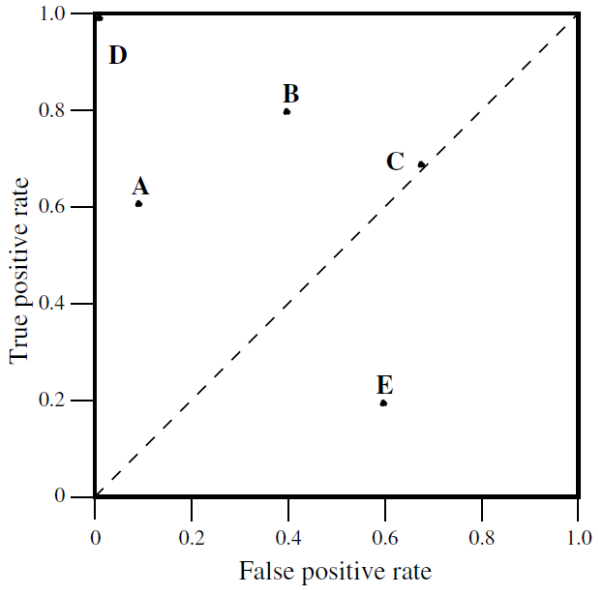


Figure 4.2: A basic ROC graph showing five discrete classifiers (Fawcett, 2006)

While ROC curves provide a powerful tool for visualizing and comparing classification results, REC curves generalize ROC curves to regression problems. These curves plot the error tolerance on the X-axis versus the percentage of points correctly predicted within the tolerance in the Y-axis, consisting in a trade-off between the error tolerance and the accuracy of the model (Bi and Bennett, 2003). In an ideal model, the curve is a vertical line, coincident with the Y-axis, meaning that 100% of predictions are accurate with no error. An example of REC curves can be seen in the next subsection in Figure 4.9.

4.3.2 Model development

The Markov model as presented in Section 4.2 was implemented in the computing software MATLAB using a self-developed script for this purpose. A function named $fmincom$, which is a non-linear programming solver, is used in order to optimize Q through the maximization of the log-likelihood. The start point given as input for this optimization is the group of θ_i calculated with Equation 4.7.

The accuracy of the PPPM to be developed depends on the way data are considered and filtered, as briefly resumed in the following items:

- Model 1: all available data are used;
- Model 2: transitions of more than one CS are considered outliers and predictions are always made from the immediately previous record;
- Model 3: consecutive records in the same CS are disregarded;
- Model 4: transitions of more than one CS are outliers, and the first available record is considered as the reference point for all the predictions.

These four approaches are tested and compared in order to determine the most reasonable one.

Model 1

Table 4.1 indicates the optimal θ_i and the respective log-likelihood (L) values obtained after training the model with all the database as presented in Section 3, using the parameter *Time* as the independent variable. It is observed on Table 4.1 that the hazard

Table 4.1: θ and L values for each performance index (model 1)

	PI_B	PI_CR	PI_E	PI_F	PI_R
θ_1	0.0192	0.1046	0.0670	0.2885	0.1101
θ_2	0.0336	0.3102	0.0395	0.3503	0.0407
θ_3	0.0498	0.5473	0.0518	0.1811	0.0453
θ_4	0.0534	0.6413	0.0627	0.0925	0.0435
L	-410	-1180	-942	-522	-969

rates for PI_CR and PI_F are significantly higher than for the other PIs, suggesting a faster deterioration as mentioned in chapter 3 in the analysis of Table 3.19. In order to visualize the evolution of the PIs, the average CS is calculated, as indicated in Equation 4.2, for every year for a period of 100 years and plotted in Figure 4.3. It is, indeed, observed that PI_F and PI_CR deteriorate significantly faster than other indicators. In opposition, a pavement section with the best possible condition for bearing capacity indicator would never achieve the worst condition within 100 years.

Although the model is able to predict continuous values for the PIs, these are usually classified by discrete CSs in management systems at a network level, as well

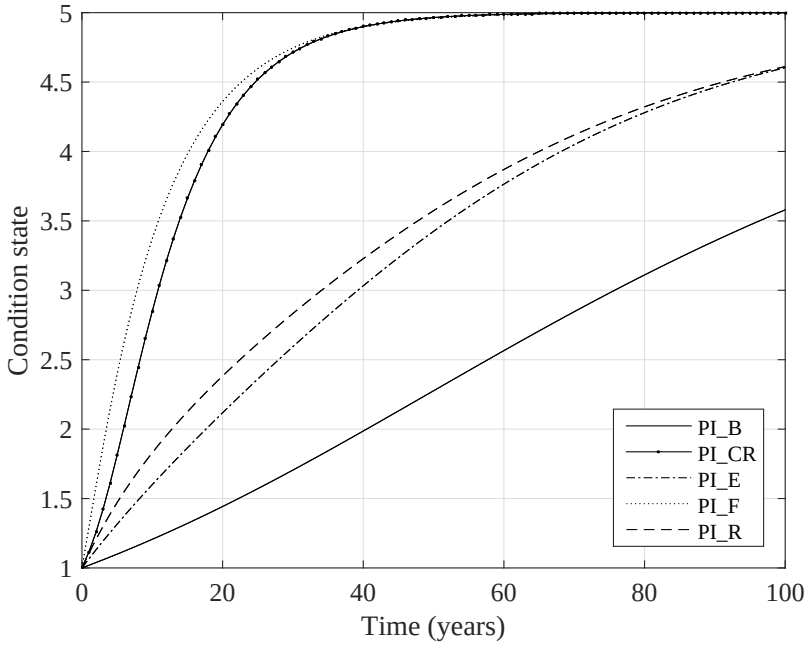


Figure 4.3: Individual PIs evolution for a period of 100 years (model 1)

as the trigger values and/or minimum quality requirements. Similarly, the effects of M&R operations can be quantified as the number of reduced CSs as a function of the actual CS. The initial condition of a pavement from where the Markov model starts the performance prediction is also an integer value. Therefore, the predicted condition should also be rounded to integer values, so that $CS = round(\overline{CS})$.

Bearing this fact in mind, Figure 4.3 shows that a pavement section in the CS 1 for the friction indicator (PI_F) needs less than 2 years to advance for CS 2. For PI_E, the necessary time for the same transition is approximately 8 years. Figure 4.4 summarizes the time in which a performance indicator remains in the same CS, according to its initial condition.

It fact, the necessary time for PI_CR and PI_F to deteriorate in one condition state are short comparing to the life expectancy for which a pavement is designed. This modelled results can be partially explained by the fact of having some consecutive records in the database where a change of two or more CSs occurs in a short period of time, as it can be noticed in Figure 4.5 where the number of deteriorated CSs for PI_F is plotted against the time between consecutive inspections. Similar scatters could represent the data for the other PIs. Furthermore, in the original database, it was noticed that some of those records were followed by a quality improvement without the existence of a M&R operation, suggesting eventual missing data and/or errors in the database. For these reasons, it was decided to consider transitions of more than

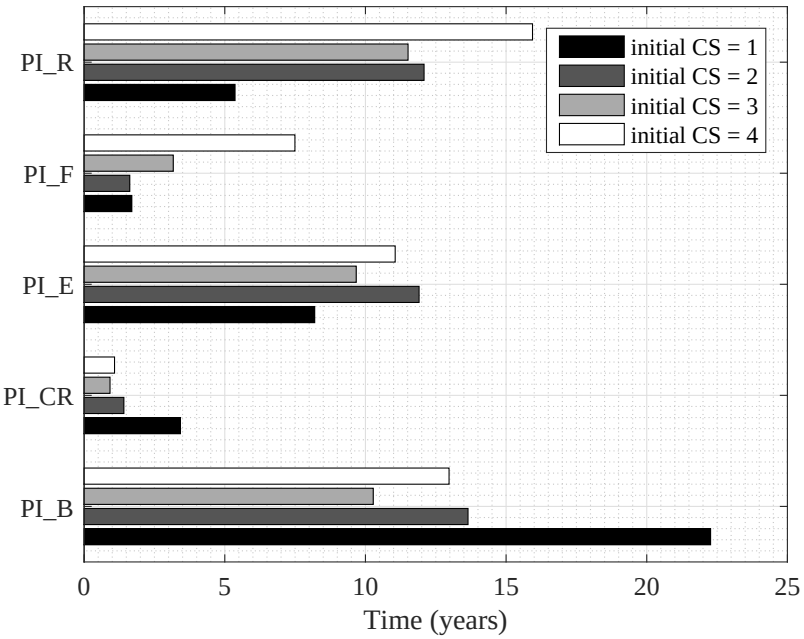


Figure 4.4: Necessary time for each PI to change to the next condition state (model 1)

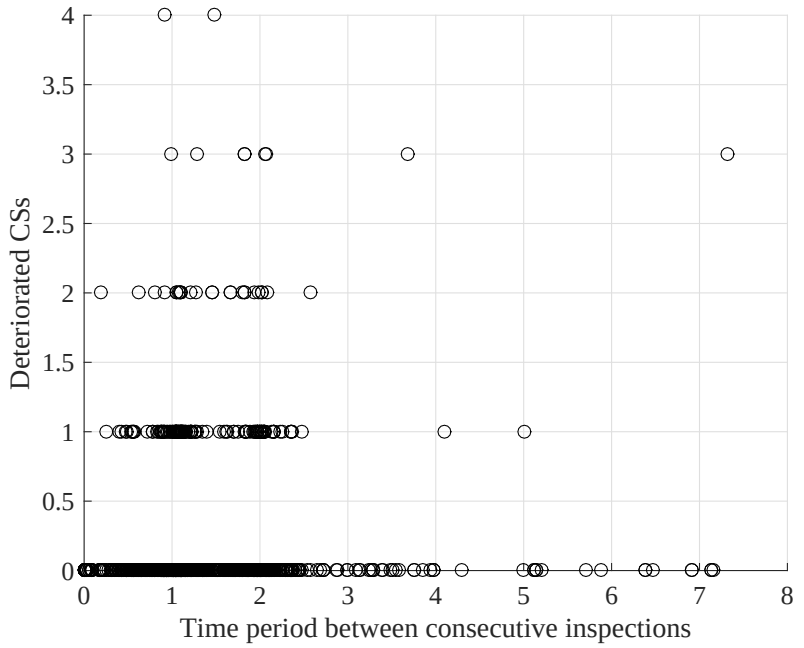


Figure 4.5: Time period between consecutive inspections VS deteriorated CSs for PI_F

one condition state between consecutive inspections as outliers, and thus remove them from the database. The new number of sequences and records are indicated in Table 4.2.

Table 4.2: Number of valid sequences and records after removing outliers from the database

	PI_B	PI_CR	PI_E	PI_F	PI_R
No. sequences	670	652	663	472	695
No. records (model 1)	3090	2411	4160	1691	3794
No. records (model 2)	3079	2100	4155	1598	3785

Model 2

Considering the new database after filtering the outliers to train the model, the resulting optimal θ_i and L are as indicated in Table 4.3. It is noticed that PI_CR and PI_F

Table 4.3: θ and L values for each performance index (model 2)

	PI_B	PI_CR	PI_E	PI_F	PI_R
θ_1	0.0186	0.0736	0.0671	0.1773	0.1084
θ_2	0.0256	0.1178	0.0390	0.2108	0.0395
θ_3	0.0113	0.1777	0.0489	0.1071	0.0443
θ_4	0.0420	0.3542	0.0743	0.0765	0.0378
L	-375	-678	-936	-360	-952

are still the ones with higher hazard rates, although its values are not as high as in the model 1 as expected, suggesting a lower deterioration rate.

Metrics of global accuracy, precision, recall, F1 score and the fall-out for this model are presented in Table 4.4, from where it is observed a very good accuracy, but bad performance regarding the other metrics. For instance, the recall for PI_F is only 2%, meaning that from all the observed changes of CS (296 cases), the model correctly predicted only 2% (5 cases). On the other hand, from all the cases the model predicted a change of CS (17 cases), 29% (5 cases) are correct, so the precision equals 29%. The 90% of global accuracy represent the percentage of correctly predicted transitions between inspections. In fact, the significant majority of records in the database do not reveal a change of CS and the model is good in predicting such event. Not a number (NaN) cells exist when the metric cannot be calculated due to a null denominator.

The difficulty the model has to predict the moment when a change of CS occurs is well illustrated in the example on Figure 4.6. The predicted CS only jumps to CS 2 after such event is observed. Indeed, the predicted value depends only on the most

Table 4.4: Accuracy metrics (model 2)

	PI_B	PI_CR	PI_E	PI_F	PI_R
Global accuracy (%)	96	83	92	88	90
Precision, PPV (%)	NaN	59	0	10	29
Recall, TPR (%)	0	14	0	1	2
F1 score (%)	NaN	22	NaN	1	3
Fall-out, FPR (%)	0	2	0	1	0

recent observed CS, which explains the fact of not noticing a continuous growth of the predicted values represented with a + in the Figure. Having so short intervals between inspections, the model will hardly indicate a change of CS.

Facing these difficulties, it was decided to filter the database in order to consider, for each sequence of inspections, only the first and last records, as well as transitions where a change of CS is observed.

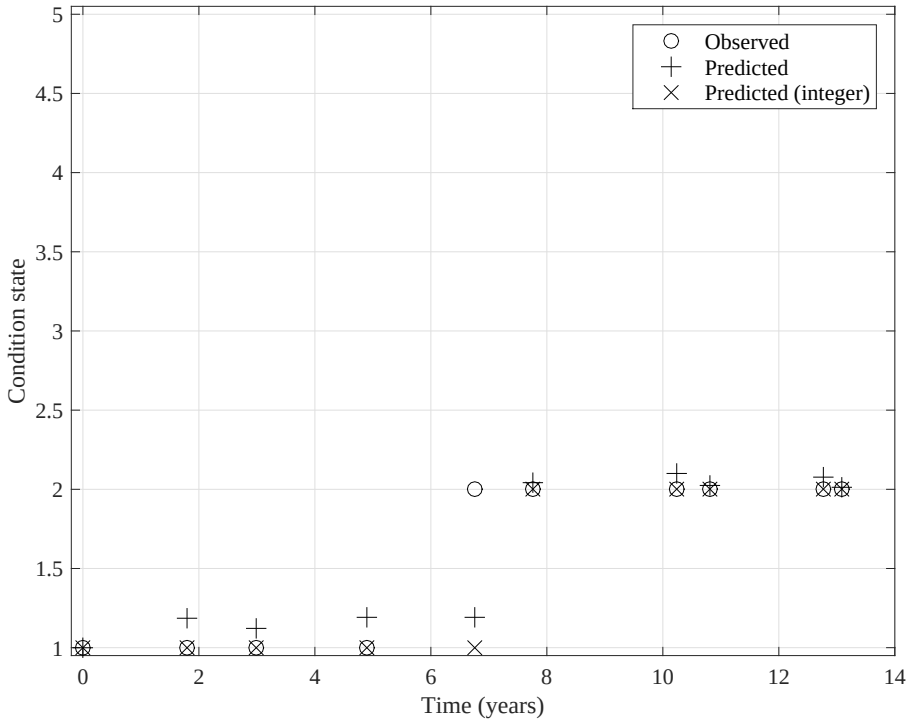


Figure 4.6: Observed and predicted condition state for PI_R for section 12_4106 (model 2)

Model 3

Due to the difficulties of predicting changes of CSs, model 3 was trained with a database where there are no consecutive records in the same CS except for the first and the last one of the sequence, thus the number of records is much less, as indicated in Table 4.5. The respective θ_i and L are indicated in Table 4.6.

Table 4.5: Number of valid sequences and records after removing outliers and transitions with no change of CS from the database

	PI_B	PI_CR	PI_E	PI_F	PI_R
No. sequences	670	652	663	472	695
No. records (model 1)	3090	2411	4160	1691	3794
No. records (model 2)	3079	2100	4155	1598	3785
No. records (model 3)	1268	1211	1471	871	1551

Table 4.6: θ and L values for each performance index (model 3)

	PI_B	PI_CR	PI_E	PI_F	PI_R
θ_1	0.0191	0.0919	0.0772	0.2746	0.1252
θ_2	0.0232	0.0854	0.0363	0.2367	0.0387
θ_3	0.0097	0.1856	0.0338	0.1099	0.0373
θ_4	0.0504	0.3850	0.0439	0.0762	0.0316
L	-307	-527	-650	-289	-726

The most noticeable difference comparing to model 2 is the higher values of θ_1 for all PIs, since a considerable part of the deleted records represented consecutive observations in the CS 1. The same metrics presented for model 2 are shown for this case in Table 4.7. An increase of precision and recall is well noticed in this model. In opposition, the global accuracy decreases for values as 50% in the case of PI_CR, for instance. Nevertheless, the major drawback of model 3 is the relatively high percentage of fall-outs, i.e., the relative frequency of predicted changes of CS that actually do not happen. For instance, from all the 560 observed transitions where there is no change of CS, the model predicts a change in 21% (116) of the cases, thus overestimating the pavement deterioration. This fact is partially related to the optimization of Q that increases the hazard rate for CS 1. Furthermore, to disregard such a high amount of reliable data from the original database might be a questionable assumption.

Table 4.7: Accuracy metrics (model 3)

	PI_B	PI_CR	PI_E	PI_F	PI_R
Global accuracy (%)	86	50	57	62	59
Precision, PPV (%)	50	46	27	33	36
Recall, TPR (%)	1	37	19	19	22
F1 score (%)	2	41	22	24	27
Fall-out, FPR (%)	0	38	25	18	21

Model 4

Bearing in mind the drawbacks of models 2 and 3, model 4 was thought to mix both approaches but avoiding their disadvantages. Model 4 is trained with the same database as model 2, i.e., the whole data excluding transitions of more than one CS, so that θ_i and L are equal. However, the application of the model considers the CS and moment of the first available record as the reference point to start the prediction, ignoring all the observed CS meanwhile, unless the observed CS changes. In such case, the moment it changed and the new condition form the new reference point. In a way, this consideration is giving memory to the Markov model.

Table 4.8 indicates the metrics for model 4, showing that the recall is always higher than the fall-out percentage and the global accuracy is generally good, except for the PI_CR

Table 4.8: Accuracy metrics (model 4)

	PI_B	PI_CR	PI_E	PI_F	PI_R
Global accuracy (%)	96	64	83	80	81
Precision, PPV (%)	0	22	10	15	14
Recall, TPR (%)	0	39	16	16	19
F1 score (%)	NaN	28	12	15	16
Fall-out, FPR (%)	0	30	12	12	13

By giving memory to the model, its ability to predict the moment when a change of CS occurs increases. Figure 4.7 compares observed and predicted values for the same indicator and section previously presented in Figure 4.6. It is, indeed, verified a continuous increase of the PI_R from year 0, disregarding the observed values until the 5^{th} record when the observed CS changes. The model successfully predicted that change as well. Nevertheless, the 5^{th} record becomes the new reference point from

which future predictions are performed.

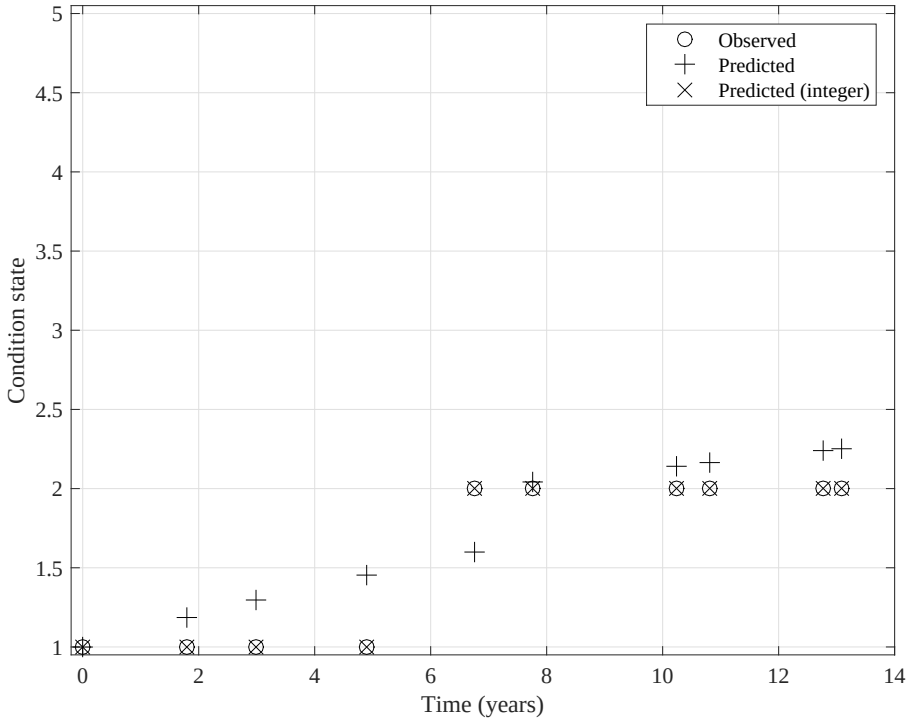


Figure 4.7: Observed and predicted condition state for PI_R for section 12_4106 (model 4)

Models comparisons

In order to select one of the presented models, a comparison of the assessment metrics is illustrated in Figure 4.8.

The PI_B bar chart is inconclusive because the original database barely contain transitions of more than one CS and the deterioration is very slow for all the models. The higher precision of model 2 lacks of meaning, for that 50% represent 1 TP among the total of 2 predictive positive.

The global accuracy is higher for model 2 and 4, because most of observed data do not change CSs and the models are good in predicting it.

The precision for model 4 is lower than for model 3 in all the cases, which is partially explained by the significantly higher number of FPs, even though the number of TPs is similar for both models. This happens because the database for model 4 contains a lot more records where there is no change of CS. The recall is very low for model 2 and is similar for both models 3 and 4. Thus, F1 score is slightly better for model 3, indicating a better balance among recall and precision.

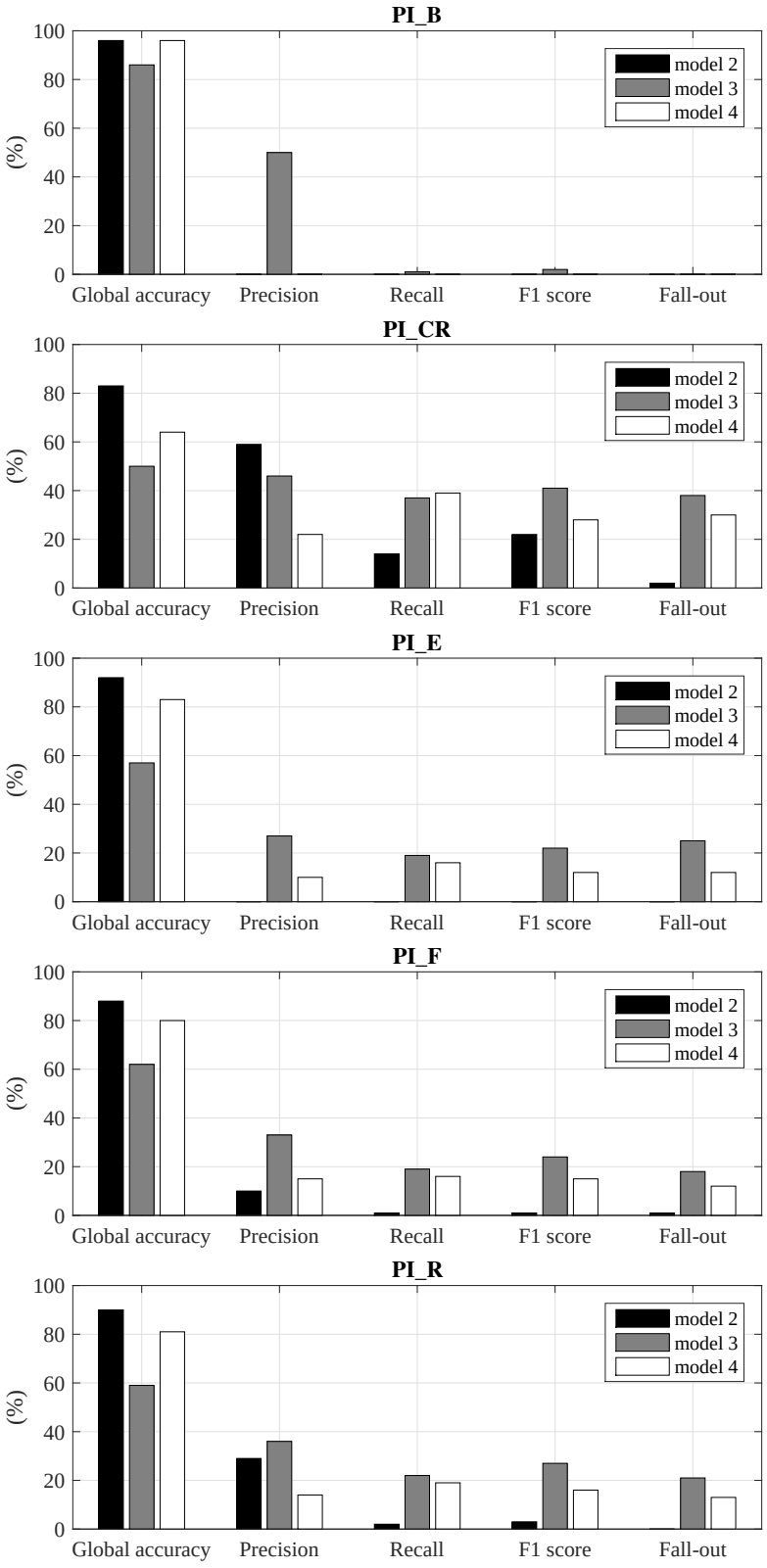


Figure 4.8: Comparison of metrics for models 2, 3 and 4

Model 3 is the one expected to over-predict the CS in a more significant amount of times.

In order to complement the comparison of the most promising models, 3 and 4, REC curves are illustrated in Figure 4.9. These are useful because they can represent the continuous values of PIs rather than only the integer ones as used for the aforementioned metrics. It can be seen that for an absolute deviation of 1 CS, both models have

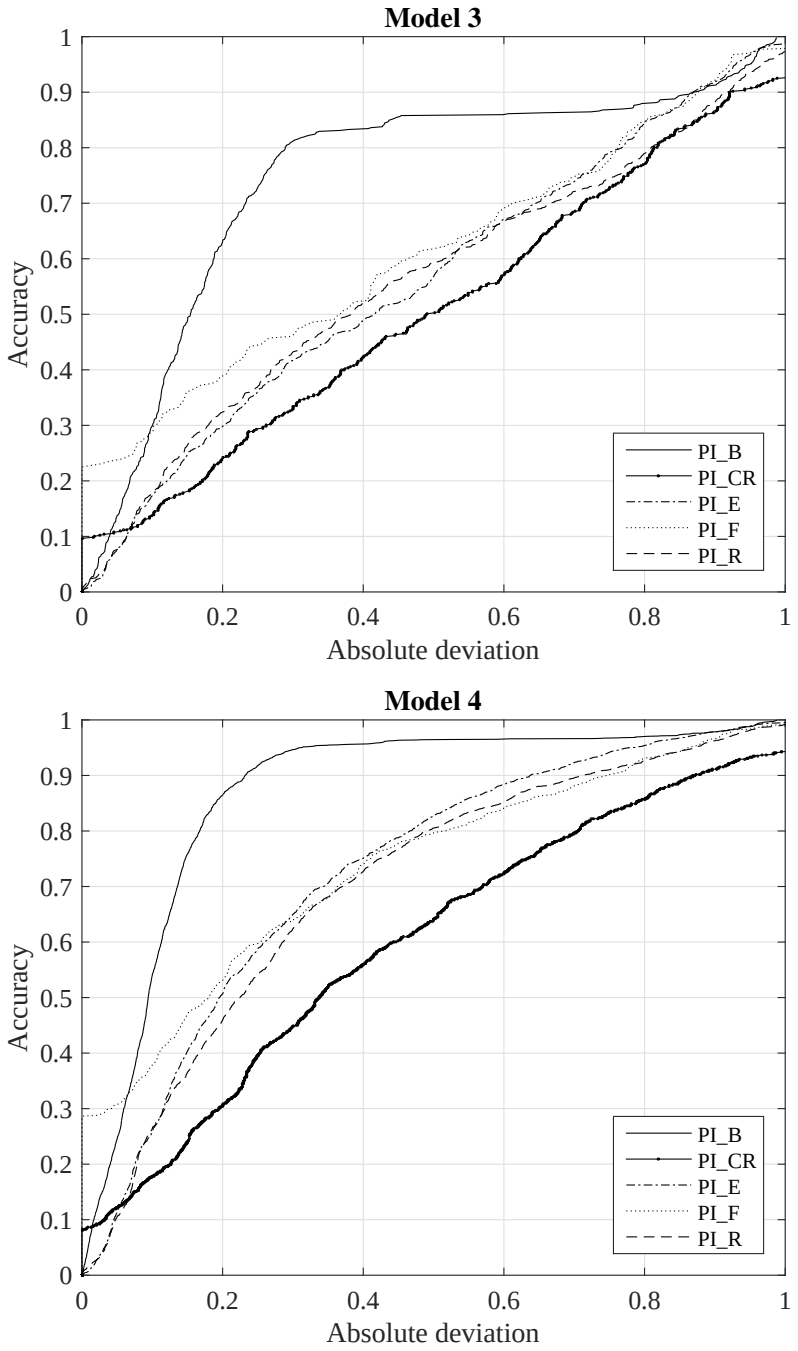


Figure 4.9: REC curves for models 3 and 4

similar accuracy. However, for lower absolute deviations, model 4 is more accurate. For example, for an absolute deviation of 0.2, model 4 is about 55% accurate, while accuracy for model 3 is near 40%.

Considering all the relative advantages and drawbacks of the models, the model 4 is the selected one to be the used further in this work. The main reasons for its selection are:

- It is trained with as most reliable data as possible, excluding outliers as defined in model 1, but not removing all the consecutive inspections with no change of CS as for model 3;
- It is not the best nor the worst in most of the metrics, hence it is a balanced model to have reasonable values for all the metrics at the same time;
- Although the model has the same matrix Q as model 2, it uses memory in its application, by considering always the first record, or the record when a change of CS is verified, as the reference point to start the prediction.
- The REC curves suggest a more accurate model than model 3.

Results and analysis of model 4

For a deeper analysis of the model, a full confusion matrix for all PIs is presented in Table 4.9, and Figure 4.10 shows a scatter plot comparing predicted with observed CSs for PI_E as an example.

In the confusion matrix, the correct predictions are represented in the main diagonal. For instance, from all the 1617 observed cases that achieved CS_2 for PI_E, the model correctly predicted 1417 (88%), it under-predicted 133 (8%) and over-predicted 67 cases (4%). There is a general tendency to under-predict the PI values, as noticed by the higher percentages on the diagonal above the main one, comparing to the one below. Over-predictions for CS_1 are, however, frequent for all PIs except for PI_B.

The scatter plot allows representing continuous values that fit within each class indicated in the confusion matrix, so it gives an idea of the absolute deviation from the integer CS. Considering the average of predictions, the differences between the predicted and the observed CSs are small, except for CS_4. An over-prediction trend happens for CS_1, since all the predicted values are necessarily higher than 1, and for CS_2. For worst conditions, the model tend to under-estimate the pavement deterioration regarding PI_E. The dispersion of points is also due to the fact that whereas

Table 4.9: Confusion matrix of the prediction models for each of the PIs

			Observed condition state				
			CS_1	CS_2	CS_3	CS_4	CS_5
Predicted condition state	PI_B	CS_1	1821 (100%)	67 (14%)	0	0	0
		CS_2	0	406 (86%)	15 (15%)	0	0
		CS_3	0	0	84 (85%)	1 (8%)	0
		CS_4	0	0	0	12 (85%)	2 (67%)
		CS_5	0	0	0	1 (8%)	1 (33%)
	PI_CR	CS_1	535 (64%)	92 (32%)	0	0	0
		CS_2	282 (34%)	162 (56%)	39 (34%)	0	0
		CS_3	18 (2%)	32 (11%)	54 (47%)	14 (23%)	0
		CS_4	0	1 (0%)	21 (18%)	39 (65%)	14 (9%)
		CS_5	0	0	1 (1%)	7 (12%)	137 (91%)
	PI_E	CS_1	1256 (81%)	133 (8%)	0	0	0
		CS_2	304 (19%)	1417 (88%)	74 (26%)	0	0
		CS_3	0	67 (4%)	201 (71%)	14 (56%)	0
		CS_4	0	0	8 (3%)	11 (44%)	2 (29%)
		CS_5	0	0	0	0	5 (71%)
	PI_F	CS_1	33 (54%)	13 (10%)	0	0	0
		CS_2	28 (46%)	67 (54%)	28 (11%)	0	0
		CS_3	0	45 (36%)	193 (74%)	33 (10%)	0
		CS_4	0	0	40 (15%)	282 (87%)	33 (9%)
		CS_5	0	0	0	10 (3%)	322 (91%)
	PI_R	CS_1	509 (64%)	112 (7%)	0	0	0
		CS_2	282 (36%)	1490 (89%)	93 (20%)	0	0
		CS_3	0	72 (4%)	372 (78%)	28 (22%)	0
		CS_4	0	0	9 (2%)	101 (78%)	6 (27%)
		CS_5	0	0	0	0	16 (73%)

predicted PIs are continuous values, the observed PIs are already divided into classes and thus plotted only on vertical lines from integers.

Figure 4.11 shows the probabilities for a transition from CS_i to CS_j to occur for the friction indicator, as a function of time. If the initial CS is 2, it is observed that after 5 years the PI_E is more likely to be in CS_3 than in CS_2 and the probability of being in CS_4 is around 15%. The probability of staying in the same CS is continuously decreasing, while the probability of changing to the worst CS is continuously increasing. For other transitions, the probability increases for a period, decreasing afterwards.

The deterioration over time of all PIs and CPIs for 50 years are illustrated in Figures 4.12 and 4.13, providing the initial CS is 1 for all PIs and considering the average

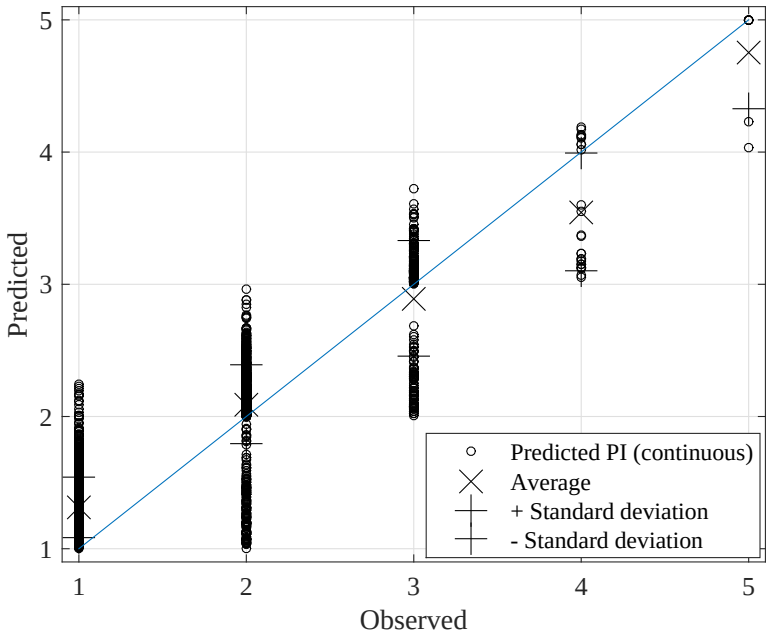


Figure 4.10: Scatter-plot of PI_E for model 4

condition state ($\overline{CS}$) as determined using Equation 4.2. It is clear that PI_B deteriorates very slowly, for it is most likely to deteriorate just 1 CS in 50 years. PI_F is the indicator with faster deterioration. Regarding combined indicators, the one for satefy (CPI_SFT) evolves much faster than the comfort indicator (CPI_COM). Although the structural quality of a pavement depends on PI_B, the combined performance indicator for structure (CPI_STR) also depends on indicators for cracking, evenness and rutting, and so it deteriorates significantly faster than the PI_B itself. Being a combination of all CPIs, the GPI is the indicator that first achieves the worst CS.

To complement the analysis, the probability of a PI to achieve or not the worst CS is presented in Table 4.10, providing that the initial CS is 3. From its understanding, it is sure that a pavement section will achieve the worst CS for PI_CR in 40 years. On the other hand, if 100 pavement sections are considered, probably 81 of them will still not be in CS_5 regarding PI_B after 40 years.

A generalization to consider the probabilities of not achieving the worst condition state as a function of time and initial CS, is illustrated in Figure 4.14 for PI_CR. It is seen that after 10 years, if the initial condition is CS_1, there is nearly 6% chance of achieving the worst condition, whereas if the initial condition is CS_3, the probability increases to almost 70%. This statements are in line with the transition probability matrix (TPM), calculated through Equation 4.4 and resulting as indicated in Table 4.11.

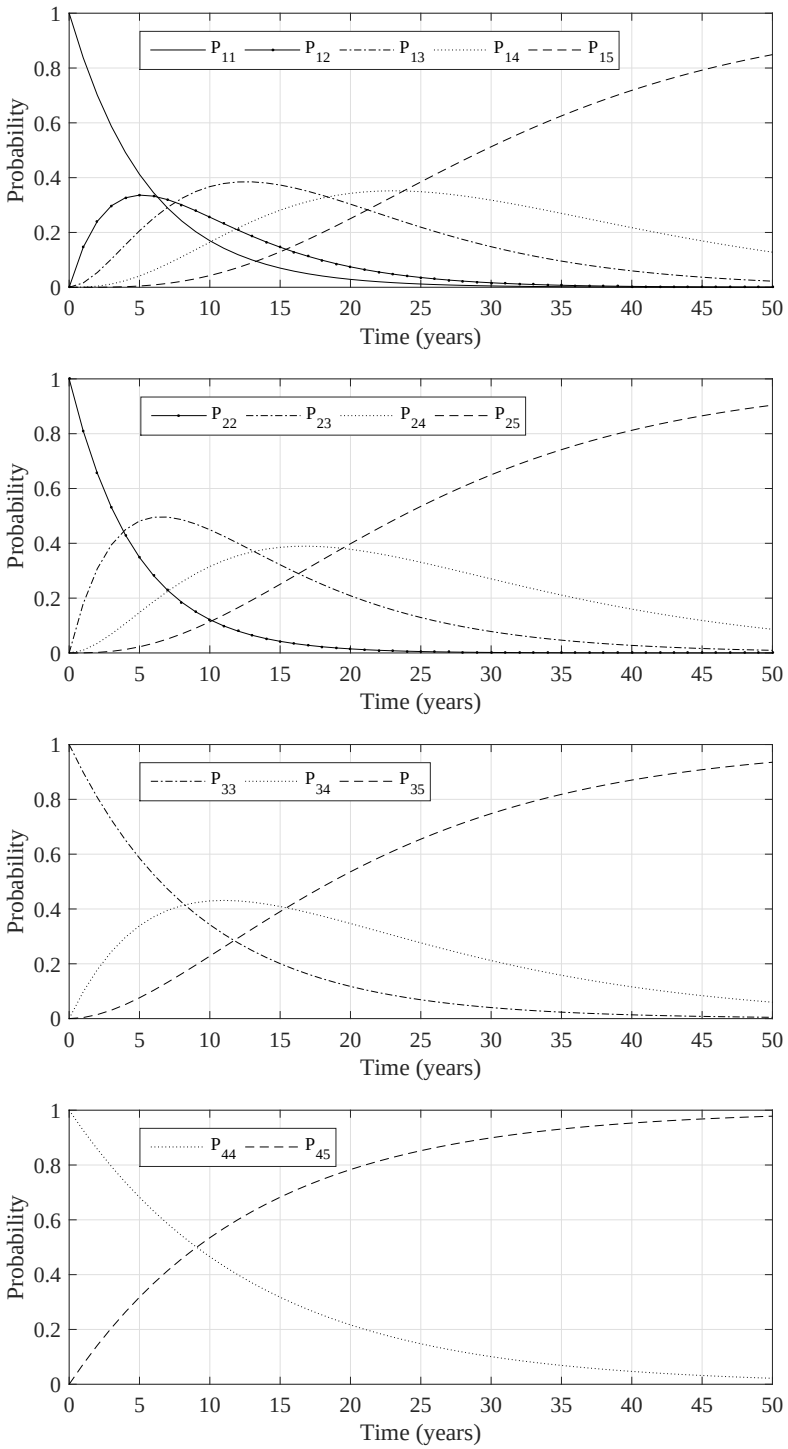


Figure 4.11: Evolution of P_{ij} for PI_F for a period of 50 years using model 4

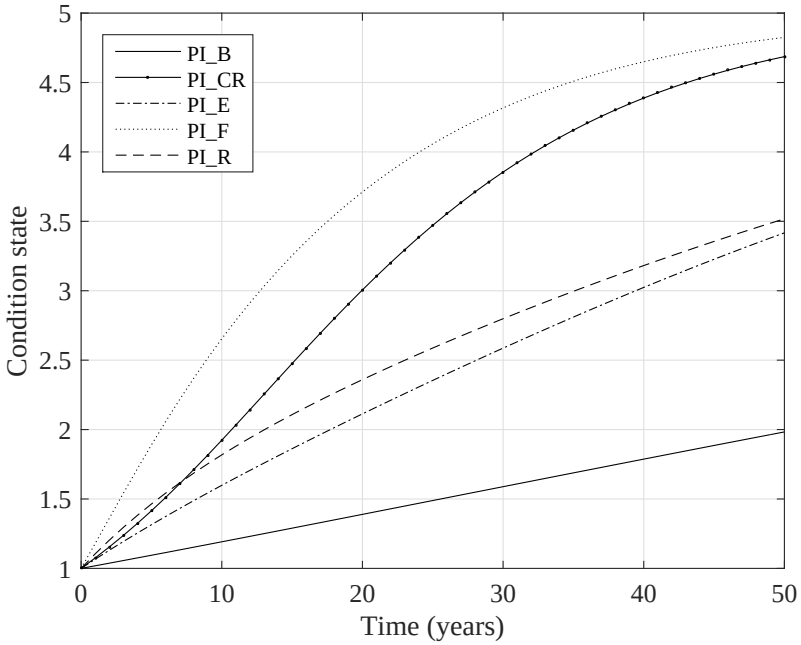


Figure 4.12: PIs evolution for a period of 50 years using model 4

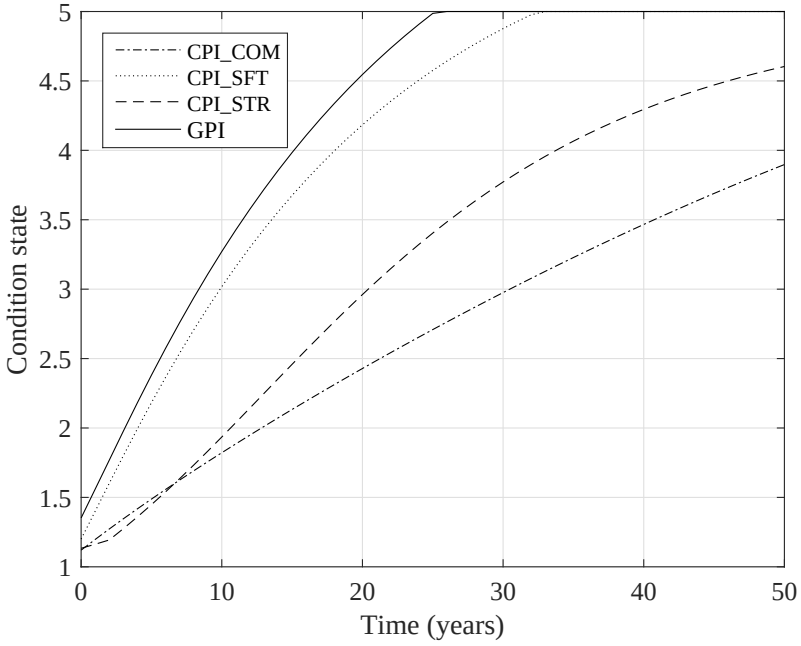


Figure 4.13: CPIs and GPI evolution for a period of 50 years using model 4

Table 4.10: Probabilities of not achieving CS_5 from CS_2

Time(years)	Probabilities (%)				
	PI_B	PI_CR	PI_E	PI_F	PI_R
10	98	36	90	80	95
20	94	7	69	49	82
30	88	1	49	27	67
40	81	0	33	14	53
50	74	0	22	7	41

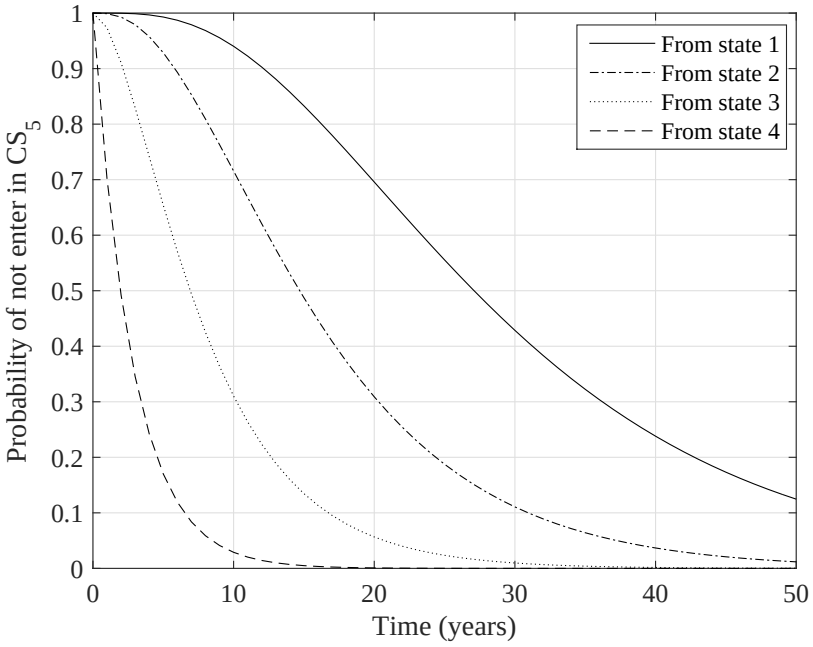


Figure 4.14: Probability of PI_CR not achieving CS_5

Table 4.11: Transition probability matrix for PI_CR, for a period of 10 years.

From/To	CS_1	CS_2	CS_3	CS_4	CS_5
CS_1	0.4788	0.2851	0.1296	0.0467	0.0598
CS_2	0	0.3080	0.2729	0.1347	0.2844
CS_3	0	0	0.1692	0.1411	0.6897
CS_4	0	0	0	0.0289	0.9711
CS_5	0	0	0	0	1.0000

4.4 Consideration of other Markov parameters

Until this point, *Time* has been referred as the parameter for the Markov model, i.e., the independent variable from which intensity matrices are deduced. As pavement deterioration depends on other variables such as traffic or its thickness, for instance, the use of more parameters might result in more accurate models. In this work, seven parameters (or combination of parameters) were tested: (1) time; (2) traffic; (3) normalized traffic; (4) traffic and thickness; (5) traffic and structural number (SN); (6) normalized traffic and thickness; (7) normalized traffic and SN. The description and obtaining process of these parameters was already explained in Section 3.5.3.

As the most promising parameters were traffic - measured in thousands of equivalent single axle load (kESAL) of trucks - and traffic divided by the SN (hereinafter referred to as *Traffic/SN*), besides the *Time*, only these are presented in this section. The metrics presented in Section 4.3.1 are used to assess and compare these models as well. The model is trained and applied as described in the development of model 4 in Section 4.3.2, just differing on the parameter.

To have an idea about the order of magnitude and range of these parameters, an histogram of accumulated traffic and traffic-SN between inspections for PI_E, after filtering the database, is presented in Figure 4.15. Relevant information to retrieve from the histogram is that a very high percentage of inspections is done for relatively similar interval of traffic or traffic/SN. There are, though, few cases for which a much higher traffic or traffic/SN passed between inspections, which might cause some bias on the development of Markov models. Nevertheless, those cases are considered so that the used data are the same as for the model 4 presented before.

A graphical comparison of the assessment metrics is presented in Figure 4.16. For PI_B, all metrics related with predicting changes of CS are null or nearly null, because the models predict a very slow deterioration of this indicator. It is worth noting, however, that the model using traffic/SN as the Markov parameter is the only one with some recall and precision. The global accuracy is similar for all the models, except for the indicator PI_CR in which the one using the parameter *Time* shows worst accuracy. In the other hand, the *Time* based model is generally better for all the other metrics, except for the PI_F where *Traffic/SN* based model results in better metrics. The *Traffic* based model does not has the best results in any metric, except for the global accuracy to PI_R.

The difference of the models is more noticeable for the PI_CR. For instance, from all 262 observed changes of CS, *Time*, *Traffic* and *Traffic/SN* based models correctly predicts it 102, 43 and 48 times, respectively. In opposition, the models wrongly predict

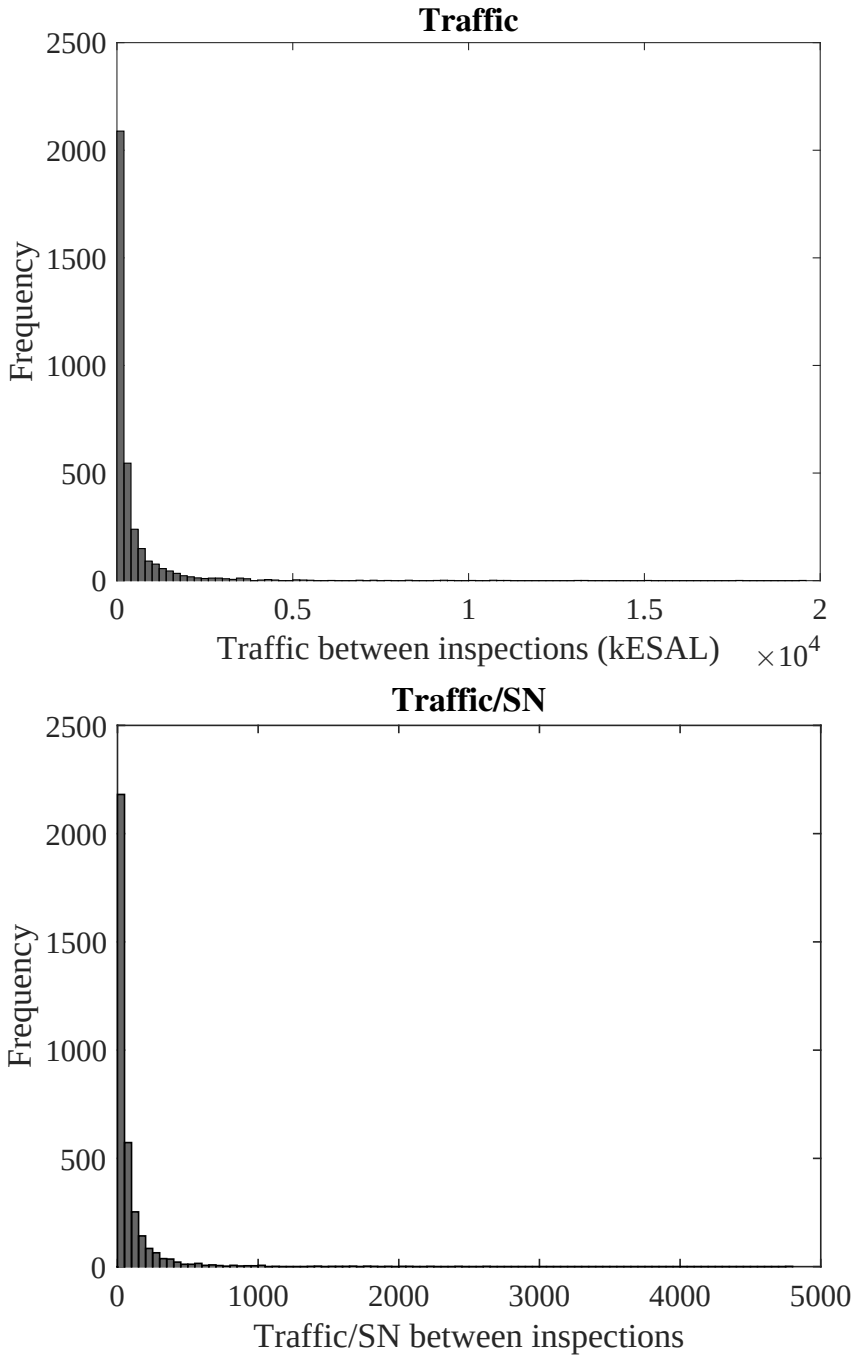


Figure 4.15: Mean accumulated traffic and traffic/SN between inspections for each indicator as measured in the LTPP database

the change of CS in 361, 220 and 199 cases, respectively. Indeed, it is verified that models with a better recall are usually those with higher percentage of fall-out.

The comparison of models is complemented with the illustration of REC curves, separately plotted for each PI in Figure 4.17. It is observed that until some absolute deviation, traffic and traffic/SN based models provide more accuracy. For higher

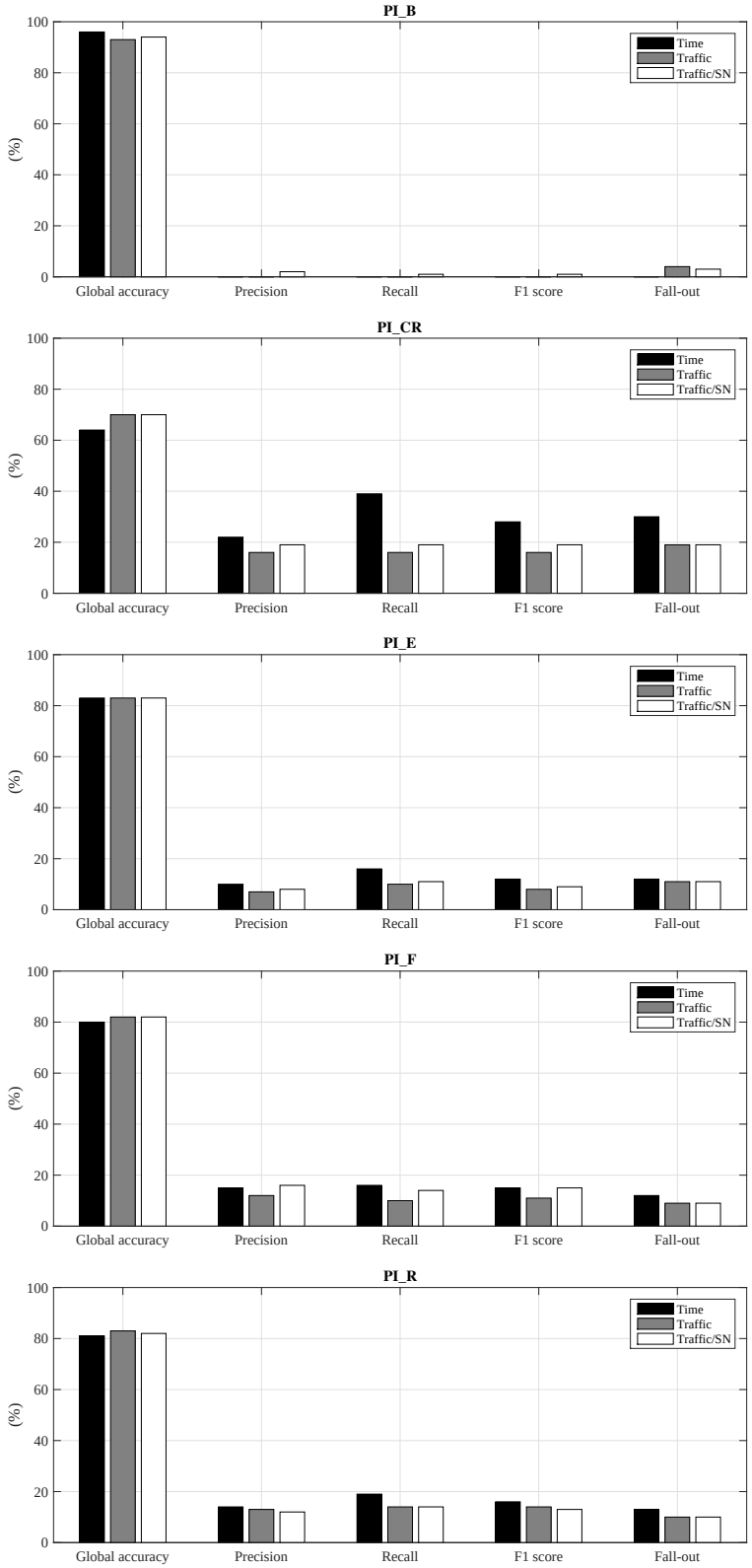


Figure 4.16: Comparison of metrics for models based on *Time*, *Traffic* and *Traffic/SN*

deviation, *Time* based model is the most accurate, suggesting that the observed and predicted values by the *Traffic* and *Traffic/SN* based models can achieve larger disparities. Such fact occurs only for a few percentage of cases. Taking PI_E as an example, if a deviation of 0.1 is accepted, the *Time* based model is accurate in about 25% of the cases, whereas the other models are accurate in more than 50%. However, a difference of more than 1 between the observed and predicted CSs is more likely to happen for the *Traffic* and *Traffic/SN* based models.

These differences can be seen in a scatter plot as shown in Figure 4.18. The higher dispersion of points in the traffic and traffic/SN based model is clear. Nevertheless, the average and standard deviation are similar, for the most disperse points are just a very low percentage of the total. The exception happens for the observed CS_1, in which the standard deviation is significantly lower for the *Time* based model.

Failing the prediction of the pavement condition in two or more condition states is, indeed, an error that has significant impact in the decision making process. As observed in the scatter plots, this do not occur for the *Time* based model only, which is partially explained by the fact of having a lower range of time periods between inspections when compared to the range of accumulated *Traffic* and *Traffic/SN*. There are, in fact, records of cases in which an high amount of accumulated traffic does not cause a change of CS, as well as there are other cases with few accumulated traffic between inspections that actually reveal a deterioration of CS. The inclusion of the structural number was an effort to reduce this problem, as it is expected that pavement sections with higher traffic are also designed to have an higher structural number. It was a beneficial addition to the model as proven by the better results on the assessment metrics and by the lower standard deviation for CS_1. Nevertheless, few significant prediction errors are still present.

In conclusion, the *Time* base model seems to be the one that causes less significant errors. In terms of accuracy, the *Traffic/SN* based model performs sometimes better than the *Time* based model. The most important aspect that justifies the consideration of other parameters besides the *Time* is the ability to predict different deterioration processes for different pavement sections in diverse real environments. Figure 4.19 illustrates the deterioration of two sections with different traffic load and structure as indicated in Table 4.12. For simplification reasons, the assigned traffic is considered equal for all the years, since this fact does not interfere with the purpose of the Figure.

According to Figure 4.19, if only time is considered, the pavement section is likely to not achieve the CS_4 for both sections. If traffic loading is considered, then section A deteriorates much slower than section B. While the latter achieves CS_4 after 10 years, the former never deteriorates so much during the whole 50 years. This exaggerated

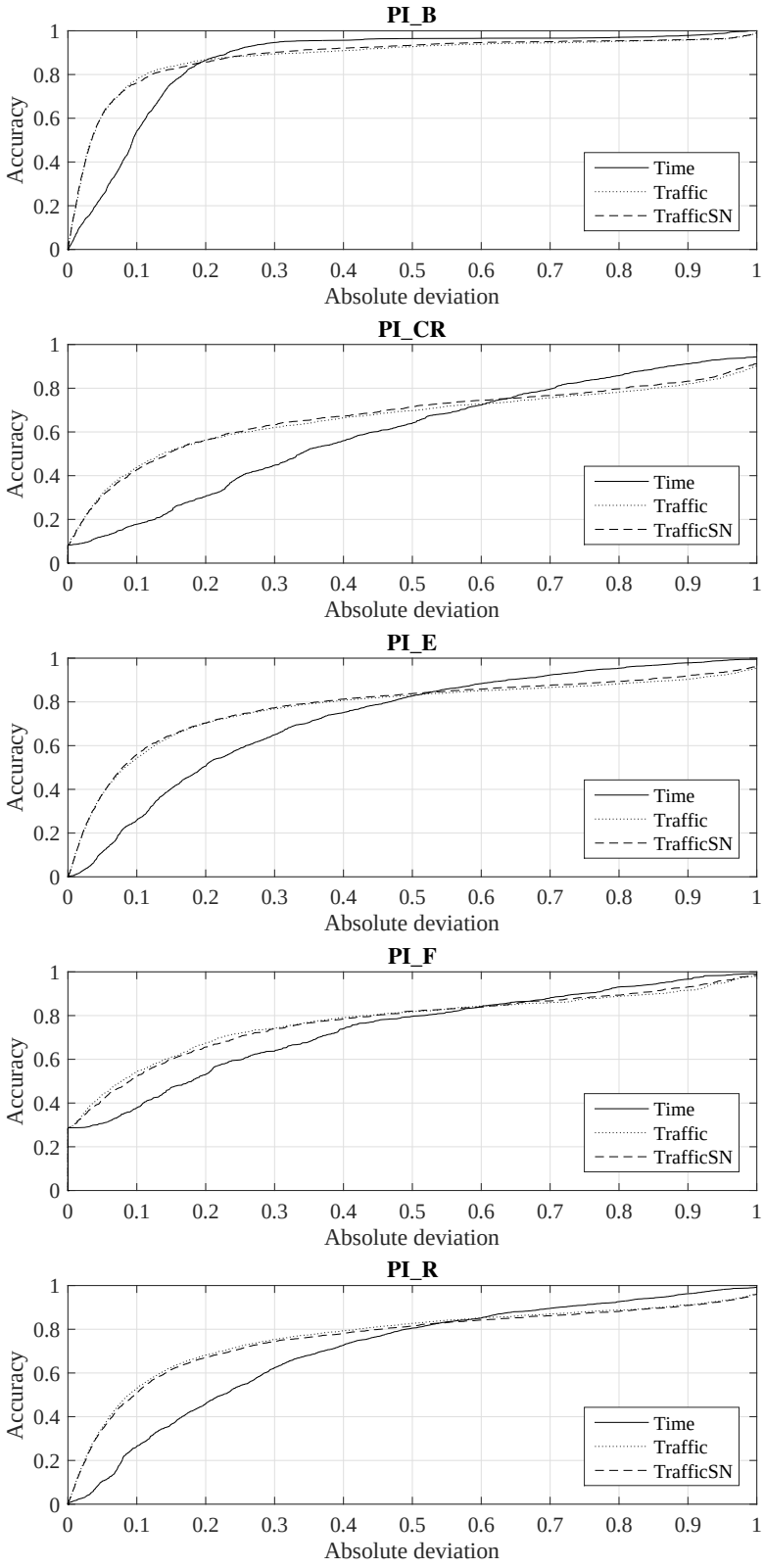


Figure 4.17: Comparison of REC curves for models based on *Time*, *Traffic* and *Traffic/SN*

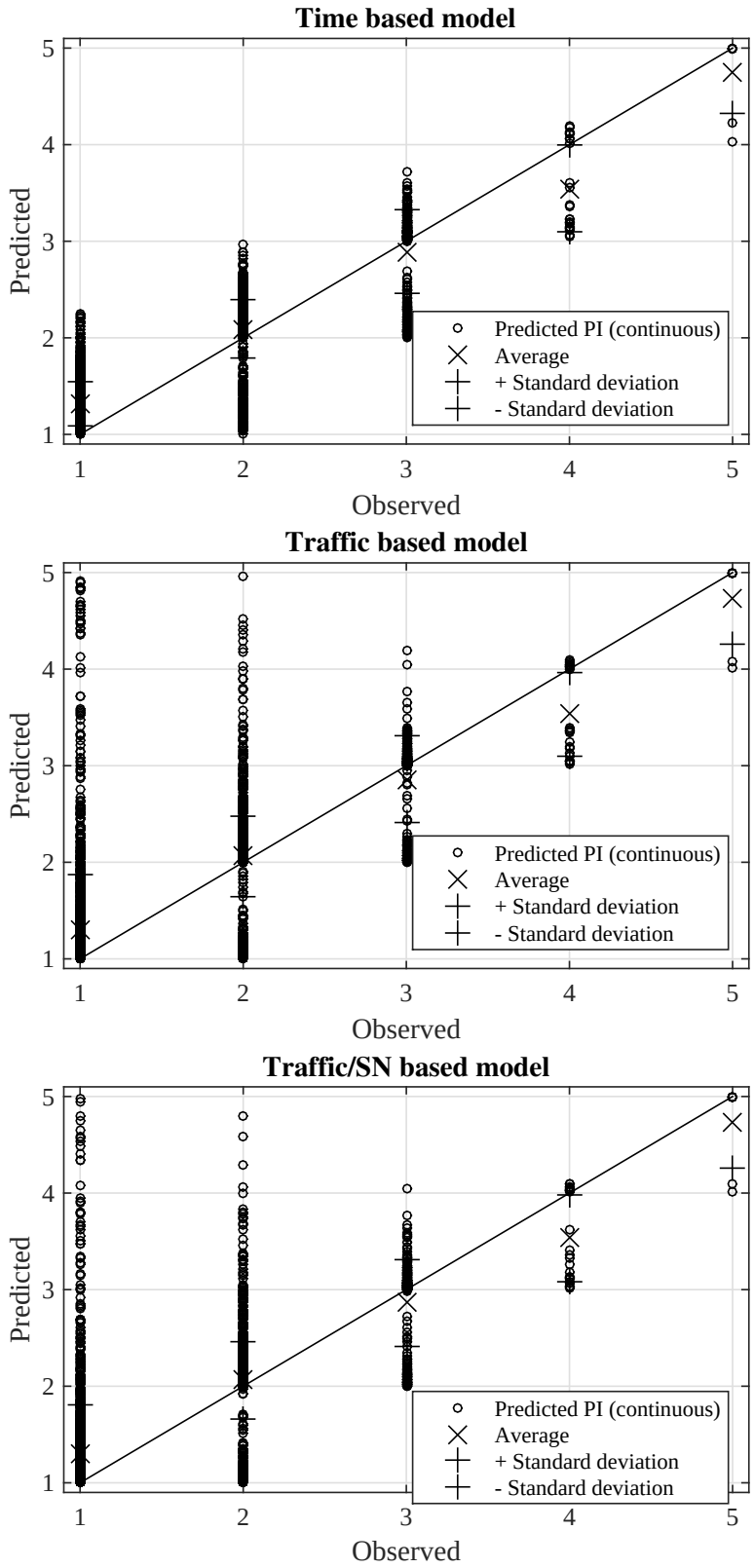


Figure 4.18: Scatter-plot of PI_E for *Traffic* and *TrafficSN* based models

Table 4.12: Traffic and SN of two different sections

Section	LTPP_id	Yearly average traffic (kESAL)	SN	Traffic/SN
A	1_1001	211	5	42.7
B	4_1003	1569	9.9	158.5

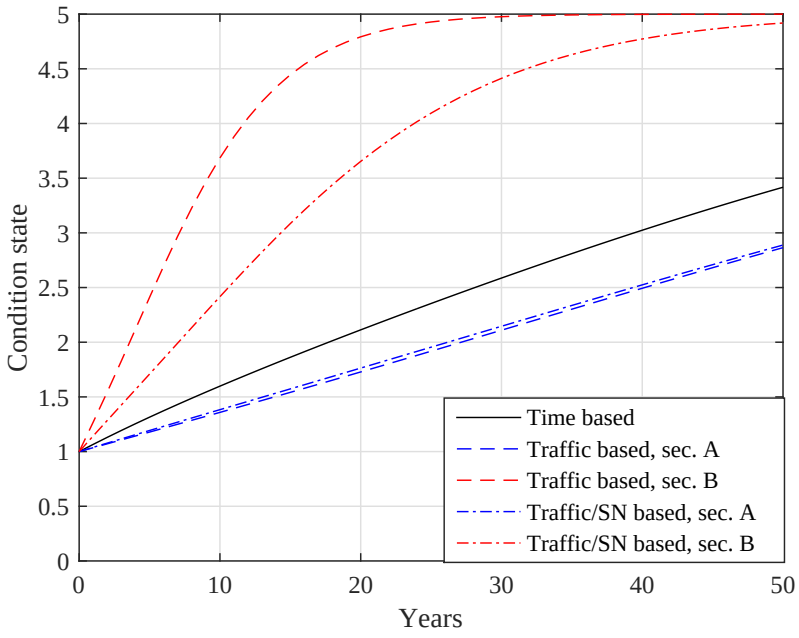


Figure 4.19: Comparison of PI_E evolution of two sections for a period of 50 years

difference is reduced if the influence of SN is considered, as the structure of section B is stronger than A. Considering the *Traffic/SN* based model, after 20 years, the PI_E for section A is in CS_2 while for section B it is in CS_3. From this practical example, which could be generalized for many other cases within the LTPP database, the parameter *Traffic/SN* seems to be a better option to use rather than only the accumulated traffic, as this parameter can led to extreme prediction results more often.

For illustration purposes, and in coherence to what was shown for the *Time* based model in Section 4.3.2, a confusion matrix is presented in Table 4.13, and Figures 4.20, 4.21 and 4.22 present the $\overline{CS}$ deterioration as a function of accumulated *Traffic/SN*.

The confusion matrix confirms the fact of having a few percentage of predictions that overpass the observed CS in more than 1 unit, namely for the PI_CR. As for the *Time* based model, the indicator with fastest deterioration is PI_F, while the slowest one is PI_B. From Figure 4.22, it is observed that even after a value of 1000 accumulated

Table 4.13: Confusion matrix for the *Traffic/SN* based model for each of the PIs

		Observed condition state				
		CS_1	CS_2	CS_3	CS_4	CS_5
Predicted condition state						
PI_B	CS_1	1762 (97%)	66 (14%)	0	0	0
	CS_2	52 (3%)	402 (85%)	15 (15%)	0	0
	CS_3	5 (0%)	5 (1%)	84 (85%)	1 (8%)	0
	CS_4	2 (0%)	0	0	11 (85%)	2 (67%)
	CS_5	0	0	0	1 (8%)	1 (33%)
PI_CR	CS_1	649 (78%)	111(39%)	0	0	0
	CS_2	108 (13%)	145 (51%)	41 (36%)	0	0
	CS_3	36 (4%)	24 (8%)	60 (52%)	21 (35%)	0
	CS_4	23 (3%)	6 (2%)	13 (11%)	31 (52%)	22 (15%)
	CS_5	19 (2%)	1 (0%)	1 (1%)	8 (13%)	129 (85%)
PI_E	CS_1	1310 (84%)	142 (9%)	0	0	0
	CS_2	196 (13%)	1376 (85%)	68 (24%)	0	0
	CS_3	30 (2%)	85 (5%)	206 (73%)	14 (56%)	0
	CS_4	16 (1%)	12 (1%)	9 (3%)	11 (44%)	2 (29%)
	CS_5	8 (1%)	2 (0%)	0	1 (0%)	5 (71%)
PI_F	CS_1	43 (70%)	16 (13%)	0	0	0
	CS_2	13 (21%)	86 (69%)	27 (10%)	0	0
	CS_3	4 (7%)	17 (14%)	207 (79%)	33 (10%)	0
	CS_4	1 (2%)	6 (5%)	27 (10%)	265 (82%)	33 (9%)
	CS_5	0	0	0	27 (8%)	322 (91%)
PI_R	CS_1	643 (81%)	126 (8%)	0	0	0
	CS_2	119 (15%)	1423 (85%)	93 (20%)	0	0
	CS_3	20 (3%)	111 (7%)	366 (77%)	28 (22%)	0
	CS_4	7 (1%)	12 (1%)	14 (3%)	100 (78%)	6 (27%)
	CS_5	2 (0%)	2 (0%)	1 (0%)	1 (1%)	16 (73%)

Traffic/SN, there is still some probability for a pavement section to be in a CS other than the worst.

4.5 Monte Carlo simulation

Up to this point, the CS has been referred to the average condition state ($\overline{CS}$) calculated with Equation 4.2. This is a deterministic way to determine the CS once the intensity matrices Q are known. However, Markov models are probabilistic, so that the pavement deterioration is ruled by some stochasticity.

For this thesis, Monte Carlo simulation is used to impose such stochasticity, un-

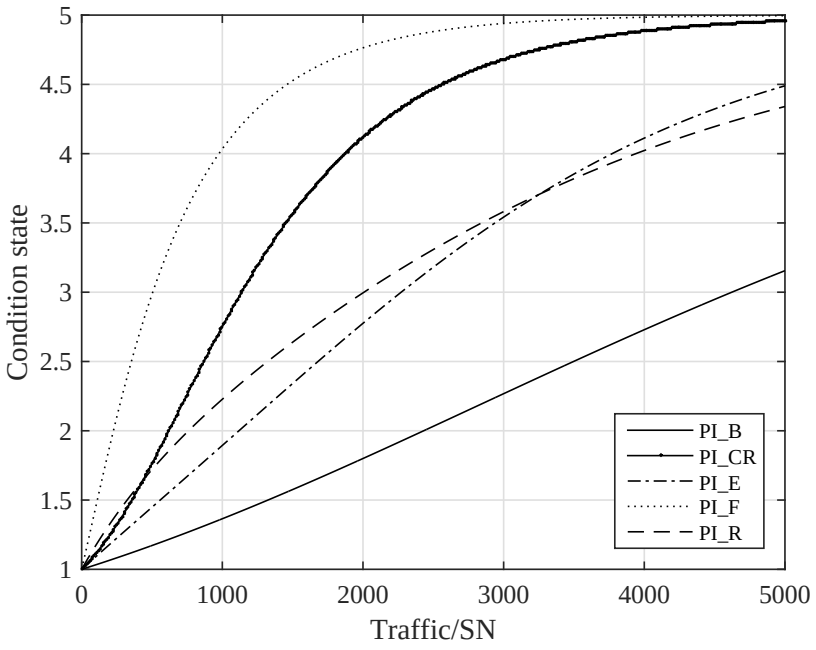


Figure 4.20: PIs evolution as function of accumulated traffic/SN

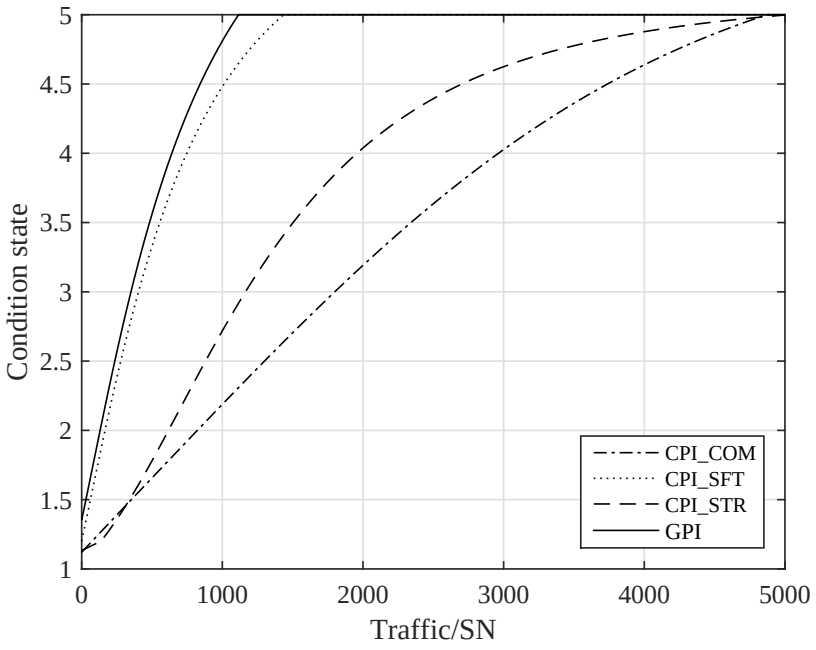


Figure 4.21: CPIs and GPI evolution as function of accumulated traffic/SN

certainty and, ultimately, to perform a risk analysis. It consists of sampling from probability distributions defined by the prediction models, thereby enabling the translation of the input uncertainties into uncertainties in the results. For a given instance of time (or amount of accumulated traffic or *Traffic/SN*), each PI is characterized by

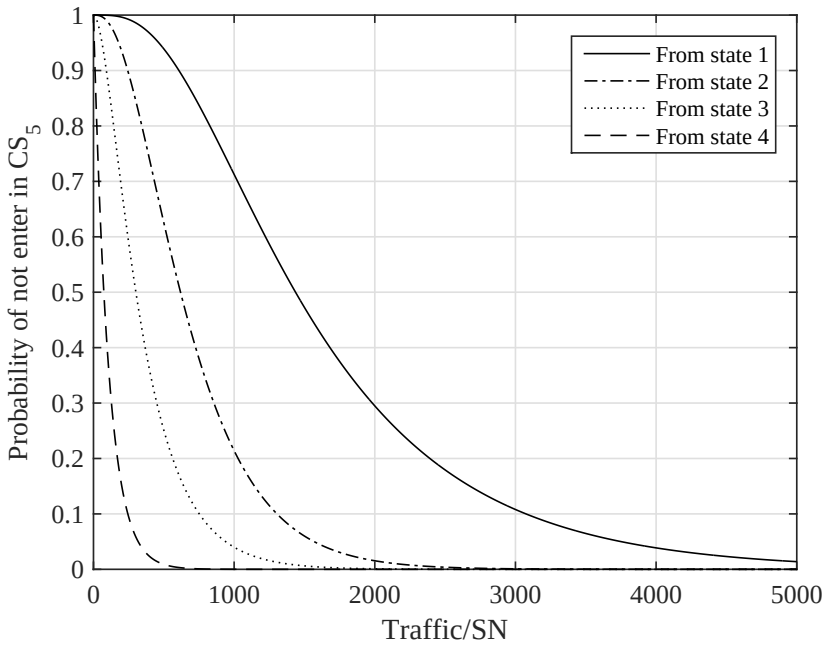


Figure 4.22: Probability of PI_CR not achieving CS_5 as function of accumulated traffic/SN

a sample of PI estimates that represents the probability distribution. The value of the corresponding PI is estimated by the mean value of the sample. The higher the number of sampling simulations is, the closer the mean value is to the value of ($\overline{CS}$) calculated with Equation 4.2 (Denysiuk et al., 2017).

Given the CS value i in time t, the CS value i' in time $t+1$ is computed using the probability vector corresponding to the i^{th} row of the transition probability matrix (TPM). For instance, if a pavement section is currently in the CS_2, the 2^{nd} row of the TPM is the considered probability vector. Then, a random number $u \sim U(0,1)$ is generated and the next CS is determined as indicated in Equation 4.13:

$$i' = \begin{Bmatrix} 1 & \text{if} & u < \sum_{j=1}^{1} p_{ij} \\ 2 & \text{else if} & u < \sum_{j=1}^{2} p_{ij} \\ 3 & \text{else if} & u < \sum_{j=1}^{3} p_{ij} \\ 4 & \text{else if} & u < \sum_{j=1}^{4} p_{ij} \\ 5 & \text{else if} & u < \sum_{j=1}^{5} p_{ij} \end{Bmatrix} \tag{4.13}$$

where p_{ij} is the element of the TPM positioned in the line i, corresponding to the actual CS, and in the column j. The value of i' is always equal or greater than i (Denysiuk et al., 2017).

As an example, Figure 4.23 shows the deterioration process of PI_CR of a pavement section, considering *Time* as the Markov parameter, for 3 Monte Carlo simulations, for the average of 100 simulations and for the deterministic approach. A different deterioration pattern is observed for simulations A, B and C after the 5^{th} year. While the condition state remains unchangeable for simulation B, the pavement section achieves the worst CS in the case of simulation C. The average of 100 simulations approximates very well the deterministic results. This proximity is more and more certain as the number of simulations to determine the average increase.

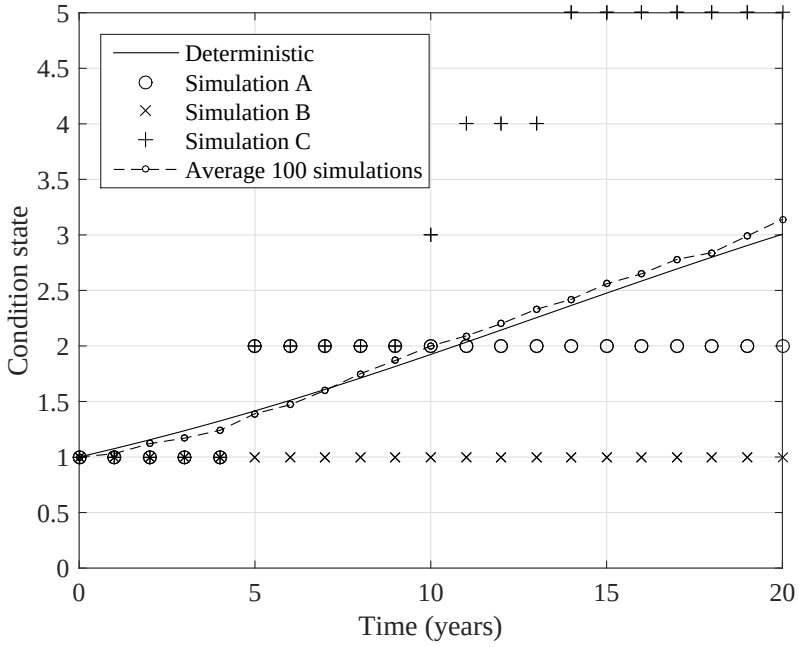


Figure 4.23: CPIs and GPI evolution as function of accumulated *Time*

By performing several simulations, it is possible to observe and quantify the number of times a certain CS was achieved for a certain year in the time horizon, thus a risk analysis can be done. Such analysis is presented in Table 4.14 for the average of 100 simulations illustrated in Figure 4.23. By observing Table 4.14, it can be said that there is a 71% chance for a pavement section to remain in the CS_1 after 5 years, and a 31% chance of being in the worst CS after 20 years. In other words, if the deterioration prediction is made for a road network of 100 pavement sections, 31 of them would be in the worst condition state after 20 years.

Summing up, the use of Monte Carlo simulations allow the decision maker to visu-

Table 4.14: Frequency that a CS is achieved in 100 simulations for specific times

CS	Time(years)			
	5	10	15	20
1	71	42	26	15
2	22	34	31	28
3	4	12	20	16
4	3	6	7	10
5	0	6	16	31

alize the uncertainties in the results, allowing the decision about the M&R strategies to be risk-based, where pessimist and optimistic scenarios can be balanced.

4.6 Preservation model

The preservation model consists in defining the effects of the maintenance and rehabilitation (M&R) operations on the CS of the performance indicators for a pavement section. The list of M&R operations in use for this work are part of a more extensive list provided by a major Portuguese highway administration. Its costs and effects were quantified by some experts from the road sector. For the case studies to be presented in Chapter 6, the M&R list is adapted to meet practical aspects of each case study. Furthermore, some particularities about the optimization methodology were important to define the final effects of M&R operations, as these strongly influence the results given by the optimization algorithm.

In fact, some operations of the extensive list merely differ in the thickness of the pavement layer to be added/replaced due to reasons only noticed at a project level analysis, such as the depth of cracking for instance. However, they produce similar numerical effects to the PIs, and the optimization algorithm always gives preference to the cheaper M&R operation among those with equal effects. As the developed optimization methodology is not able to consider all project level aspects, operations with intermediate thicknesses and unit costs were selected.

When a M&R operation is applied, its effect on the pavement can be modeled as:

1. Improvement of performance, i.e., reduction of CS in one or more unit for specific PIs;

2. Change of the deterioration rate for a period of time. This change either intends

to accelerate or reduce the rate comparing to the initial rate or the one verified after the previous improvement of CS.

A single M&R operation can produce just one of the described effects or a combination of both.

A description of all the considered M&R operations for this work, and its average, minimum and maximum costs are presented in Table 4.15 . In fact, the variation of costs depends on project related options, which are out of the scope of a network-level analysis. For the optimization process, the average values are used, however a lower and upper bound of overall M&R costs for a certain analysis period are indicated for decision making purposes, to account with uncertainties at the project level. The action of doing nothing is also included in the table as it is a necessary input for the optimization methodology. All M&R operations are to be applied to the whole area of a pavement section, except for the case of crack sealing that is applied to the cracked area only, which differs in accordance to the value of PI_CR as previously defined by Equation 3.3.

Table 4.15: Description and cost of M&R operations

ID	Description	Cost (€/m^2)		
		min.	mean	max.
1	Do nothing		0.0	
2	Crack sealing	3.51	3.70	3.89
3	Milling ($\leq$ 5cm) + TC + RC	14.25	15.00	15.75
4	TC + overlay	13.40	15.30	16.90
5	Milling ($\leq$ 5cm) + TC + SC	19.10	21.00	22.30
6	Milling (5-10cm) + TC + BC + TC + SC	37.80	41.55	44.70
7	Milling (>10cm) + TC + BaseC + TC + BC (5-10cm) + TC + SC	63.60	68.90	73.30
8	Milling (5cm) + TC + SAMI + SC	32.60	34.50	35.80
9	Milling (5-10cm) + TC + SAMI + BC + TC + SC	15.30	55.05	58.20
10	Milling (>10cm) + TC + SAMI + BaseC + TC + BC (5-10cm) + TC + SC	77.10	82.40	86.80
11	Surface shot blasting	2.56	2.70	2.84
12	Surface treatments	5.32	5.60	5.88

Notes: BaseC = Base Course; BC = Binder Course; RC = Regulating Course; SAMI = stress absorbing membrane interlayer; SC = Surface Course; TC = tack coat.

For reading convenience, only effects for M&R ID 6 are presented within the text body, in Table 4.16. Effects of all M&R operations can be found in Appendix A.

Table 4.16: Effects of M&R ID 6 on all PIs

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
PI	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
PI_B	–	1	2	2	–	–	–	–	–	–	–	0	0	0	–
PI_CR	–	1	2	3	4	–	per.	per.	per.	per.	–	50	60	70	80
PI_E	–	1	2	3	–	–	–	–	–	–	–	0	0	0	–
PI_F	–	1	2	3	4	–	–	–	–	–	–	0	0	0	0
PI_R	–	1	2	3	–	–	per.	per.	per.	–	–	30	40	50	–

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

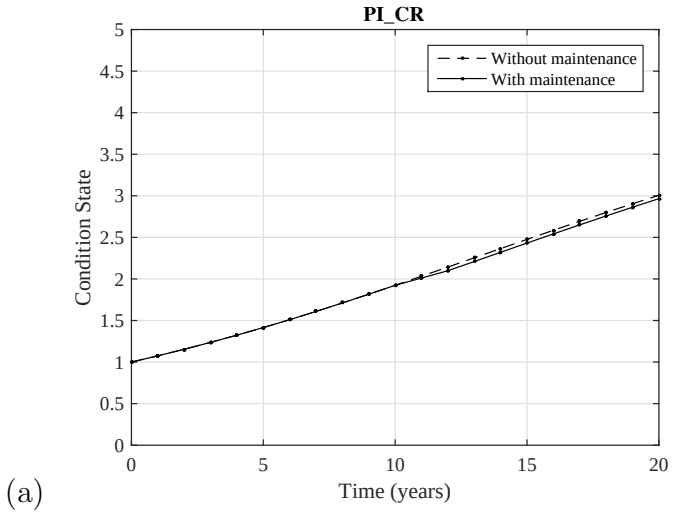
The effects depend on the CS at the moment of its application. For instance, a pavement section with PI_R in CS_2 reduces the CS in 1 unit if the M&R ID 6 is applied. Then, the deterioration rate is 30% higher for the remaining period until another operation with effects on rutting is performed. The effects on PI_E consist only in the improvement of a CS but it does not affect the deterioration rate. Figure 4.24 (b) and (c) makes use of the proposed Markov models to illustrate the mentioned effects. Figure 4.24(a) refers to a crack sealing applied on the 10^{th} year, causing a reduction of 20% in the deterioration rate of PI_CR for two years, after which the previous rate is effective again. Although M&R effects can be uncertain, they are expected to produce the theoretical effects results when applied, thus these are considered as deterministic values for the optimization methodology.

4.7 Conclusions

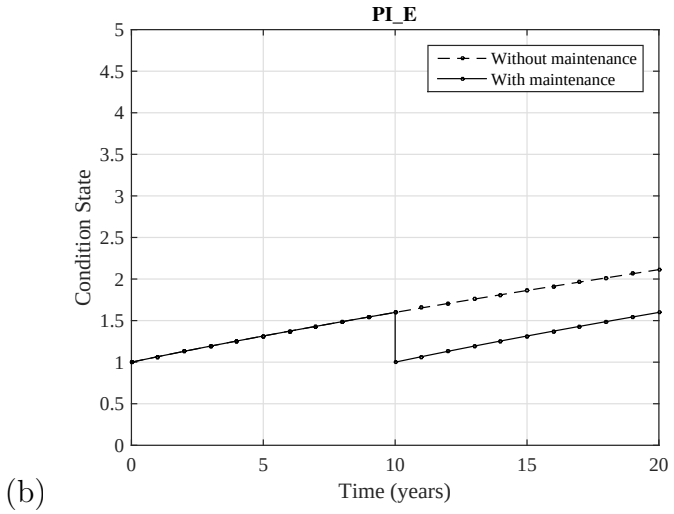
In this chapter, some basic theoretical explanation about Markov models was presented, as well as its training and assessment of different approaches of considering data and applying the model. At last, its stochastic character was illustrated and the preservation model to be used in the optimization methodology was presented.

Regarding the development of Markov models, consecutive inspections denoting a change of more than 1 condition state were not considered, as most of them seemed to be outliers and they represent a low percentage of all historical data.

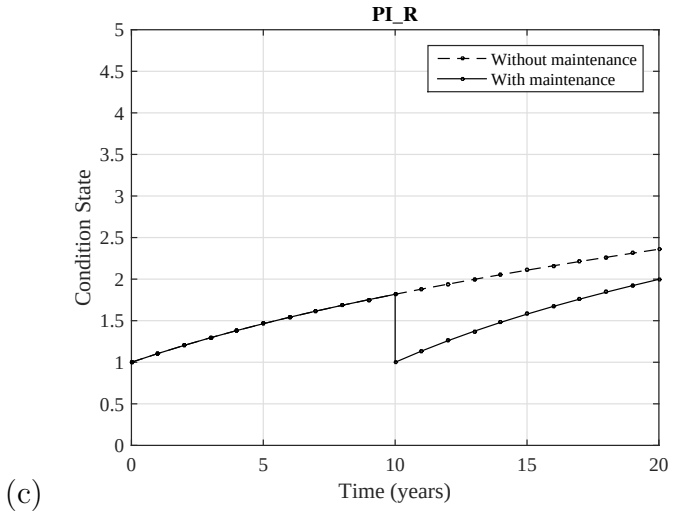
From the several approaches to consider data (model 1 to 4), it was decided to use the one with the most amount of available data to train the model, and then to give memory, in a way, in the application of the model. This was done by considering the beginning of a pavement section service life or the moment when a change of



(a)



(b)



(c)

Figure 4.24: Graphical representation of M&R effects: a) reduction of the deterioration rate; b) improvement of PI; c) improvement of PI and change of deterioration rate

CS is observed as the reference to start counting the accumulated *Time* (or other parameter). The main goal is to avoid the problems originated by the fact of considering the observed CS as an integer value and of restarting the counting of *Time* (or other parameter) when an inspection that does not reveal a change of CS occurs.

Time has been the most common parameter in use to predict pavement deterioration with Markov models. However, as this parameter cannot differentiate sections with different real conditions, the consideration of traffic and structural number were explored. Results shown the traffic/SN can be an appropriate parameter. However, it requires the existence of historical data of traffic and pavement structure that might not be available for several road administrations. If only traffic data are available, the traffic based model can be used, although it must be complemented by predicting with the *Time* based model in order to understand if the traffic based model is not over or under predicting the CS exaggeratedly.

For the case studies further presented in this thesis, the suitability of both the *Time* and *Traffic/SN* based models is assessed in order to select the most promising prediction model to be used in the optimization methodology.

Chapter 5

Development of the optimization methodology

5.1 Introduction

In this chapter, all features of the developed optimization methodology are presented, including explanations to justify the choice of alternative approaches.

First, the quantification of optimization variables representing pavement quality, administration, user and environmental costs are detailed. These can be seen as constraints or objective functions by the optimization algorithm.

Theoretical explanations about multi-objective optimization and genetic algorithms are presented in the following two sections, indicating some of its characteristics in more detail, thus complementing what was already written in the literature review chapter. As theoretical explanations are still not enough to define the favourite optimization method and algorithm to use, a comparison between two promising ones for the particular problem of this thesis was carried out and it is presented in Section 5.5.

The biggest section, 5.6, refers to the implementation of multi-objective genetic algorithm, which was elected as the favourite one for the methodology. The influence of considering user/environmental costs in the decision making process is then analysed. Within the same section, three different approaches of simultaneously considering more than one pavement sections for optimization are compared: two different ways of a "global" or single-stage approach in Subsection 5.6.3 and a two-stage approach in Section 5.6.4. In this sequence, a coordination of three conflicting objectives through optimization of different pairs in two levels is presented in Subsection 5.6.5, with application in a hypothetical case study where pavement quality, administration costs and society costs are the conflicting objectives. Finally, an uncertainty analysis

is performed in the last subsection.

Conclusions of this chapter are presented at the end of the chapter.

5.2 Optimization variables

5.2.1 Pavement quality

For this thesis, pavement quality is assessed by performance indicators (PIs) proposed by the COST354 Action as presented in Section 3.3. The evolution of each PI along a time period is defined according to the prediction models and the M&R operations as presented in the previous chapter. Knowing all PIs for each year, CPIs and GPI can be obtained. For optimization purposes, any of these indicators might be used in order to define constraints and/or objective functions.

The value of "pavement quality" to be used in this work is directly related to the GPI, as this is a global measure that accounts for all the pavement indicators and emphasizes the one in worst condition. Some ways of using the GPI in the objective function of quality to be optimized could be considered, such as, for instance, the minimization of: (1) the area under the GPI graph, (2) the sum of the annual values of GPI at the beginning of the year or (3) the maximum value of GPI for the whole period. These objective functions are mathematically written in Equations 5.1, 5.2 and 5.3.

$$f = min \int_0^t GPI \tag{5.1}$$

$$f = min \sum_0^{t-1} GPI \tag{5.2}$$

$$f = min(max\ GPI) \tag{5.3}$$

Figure 5.1 illustrates the evolution of GPI for a given M&R plan, indicating its yearly value with black circles, highlighting the area under the curve with grey colour and the maximum value of GPI with a black cross. The objective functions results for Equations 5.1, 5.2 and 5.3 would be 50.7, 49.1 and 3.5, respectively. Although the first two values are similar, the $\int GPI$ is a preferable metric as it is able to capture with more precision the evolution of GPI within a year. Naturally, this value increases with the period of analysis. In opposition, the maximum GPI is independent of the number of years in analysis, which is an advantage for the decision maker to have a more constant basis to compare the optimization results, regardless of the time horizon. However,

some preliminary simulations showed that optimizing a preservation plan through the minimization of the maximum GPI leads to less diversity of results than through the minimization of $\int GPI$. For this reason, Equation 5.1 was selected as the objective function to optimize the pavement quality.

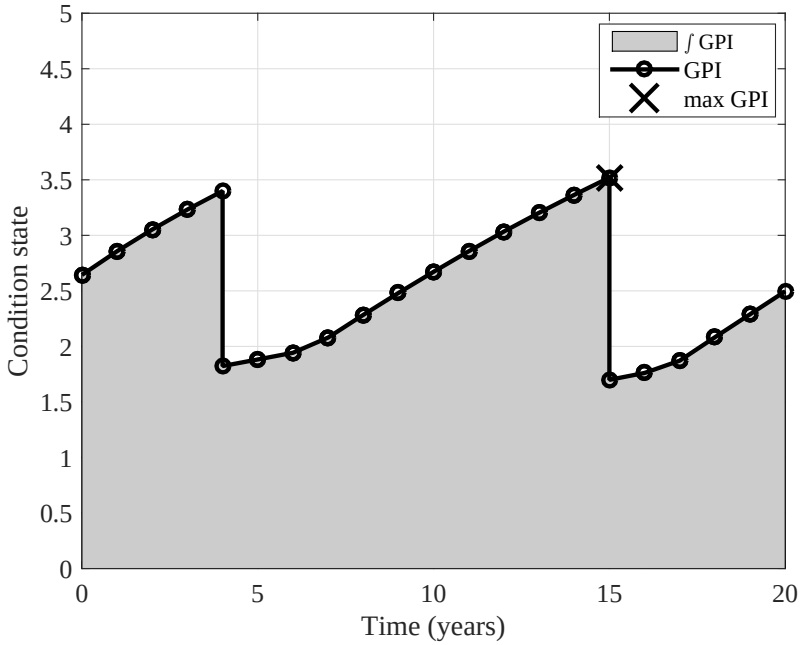


Figure 5.1: Evolution of GPI and quantification of pavement quality

Regarding the constraints, these are often imposed according to the pavements quality control, which can be under supervision of other entities rather than the road agency. Limits are usually imposed to technical parameters or individual PIs as they can be directly measured or calculated. The main goal is to assure pavements keep a certain level of comfort and safety, so that the imposition of limits to the respective combined indicators is also a plausible option to support decision making.

Calculation process

As the quality of the pavement is to be calculated an enormous amount of times during the optimization process, a systematic routine was developed in order to determine the value of each PI for all the years of a period analysis, given a M&R plan. A simplified flowchart illustrating the routine implemented in MATLAB is shown in Figure 5.2. The conditional statements are needed to account with the variety of effects a M&R can produce, as exposed in Figure 5.1. When there is no M&R operation, or this has no impact on a certain PI, the conditional statement is important to verify whether or not the current deterioration behaviour is different than the previous one. The vector

$refProb$ changes every year and forms the basis to determine the PI for the next year. $refProb$ is, initially or immediately after a M&R operation, a vector of 5 elements, being 4 of them null and one with the number "1" on the position corresponding to the current CS of the PI. As the years pass by, $refProb$ is a transition probability vector that depends on its previous values, rather than on the integer value of the CS, so the next value for the PI depends on all the time passed since the initial moment (or moment of the last M&R operation). This is a way to introduce memory on the deterministic version of Markov models.

5.2.2 Administration costs

Administration costs (C_A) as considered in this thesis depend exclusively on the cost of M&R operations planned for the analysis period. For a given year, the cost is equal to the unitary cost of the selected M&R, as indicated in Table 4.15, times the area of the pavement section (A_{sec}). Exception is made for the case of crack sealing (M&R ID 2), as this is applied only to specific cracks. For calculation purposes, the percentage of cracked area is given by the technical parameter for cracking (TP_{cr}). This is equivalent to the variable CR in Equation 3.3 of Subsection 3.4.1. Therefore, the area (A_{cs}) to be accounted to determine the crack sealing cost is given by Equation 5.4.

$$A_{cs} = \frac{PI_CR/0.16}{100} \times A_{sec} \tag{5.4}$$

In order to compare different M&R plans into the same basis, C_A are converted to the net present value (NPV) for an analysis period T. A discount rate d is used to reflect the time value of money, considering the net cost of capital and the inflation rate (Branco et al., 2005). C_A is determined by Equation 5.5,

$$C_A = \sum_{t=0}^{T} \frac{C_{A,t}}{(1+d)^t} \tag{5.5}$$

where $C_{A,t}$ is the administration cost for year t regardless the discount rate. Administration costs can be used for an objective function as well as for constraints, by defining an annual or multi-annual budget.

5.2.3 User and GHG emissions costs

For the present thesis, user and environmental costs rely only on the fuel consumption, which depends on the pavement roughness, because it affects the fuel consumption factor (FCF) as explained in Subsection 2.4.3. Thus, the evolution of PI_E is decisive

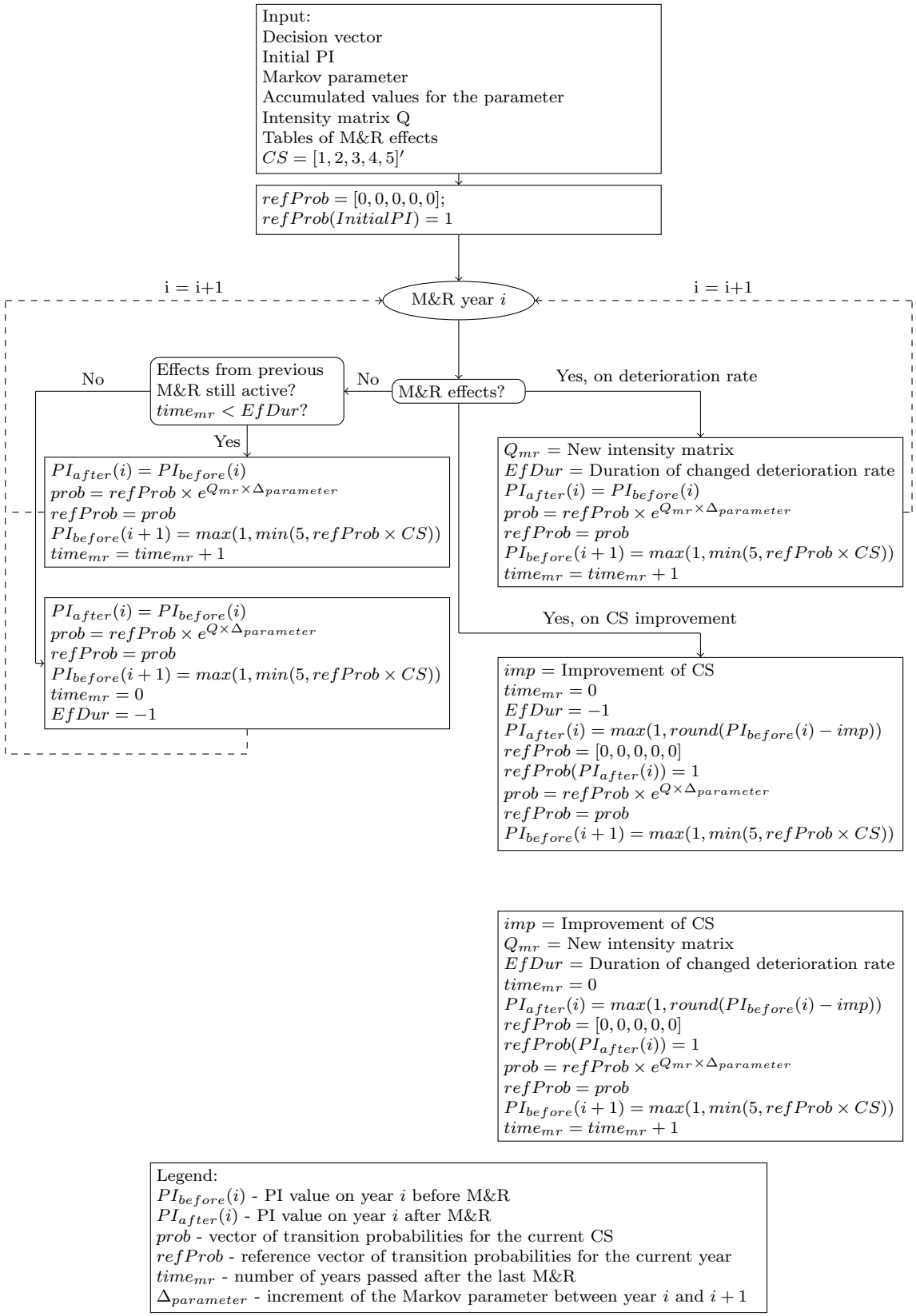


Figure 5.2: Flowchart to calculate PI values for each year

to quantify these costs. For each year i, the average value of IRI is calculated according to Equation 5.6, and the FCFs for medium cars and heavy trucks are determined by Equations 5.7 and 5.8 (based on Figure 2.14), respectively:

$$IRI_{average}(i) = \frac{(PI_E_{after}(i) + PI_E_{before}(i+1))/2}{0.816} \tag{5.6}$$

$$FCF_i = 7.377 * 10^{-}3 * IRI_{average}(i) + 0.993 \tag{5.7}$$

$$FCF_i = 2.163 * 10^{-}2 * IRI_{average}(i) + 0.953 \tag{5.8}$$

where $PI_E_{after}(i)$ is the value for the performance indicator on year i after the occurrence of a M&R operation, if applicable, and $PI_E_{before}(i+1)$ is the PI value on the next year before a possible M&R operation takes place.

In the reference work from where the FCF equations were deduced, Chatti and Zaabar (2012) assume that all cars use petrol engines and all trucks use diesel engines, with consumptions of 0.10785 litre/km (speed of 112 km/h) and 0.44731 litre/km (speed of 88 km/h) respectively. In Portugal, as well as in many other countries, diesel engines for medium cars are more popular than petrol engines. Passenger and commercial medium cars sales in Portugal from 2008 to 2014 account for 75% of diesel cars and 25% of petrol cars (ACAP and Auto Informa, 2015). A factor of 0.866 is used to convert the petrol consumption to diesel (U.S. Department of Energy, 2017a). The average consumption values used in this chapter are:

- Medium cars (diesel): 0.09491 litre/km
- Medium cars (petrol): 0.10785 litre/km
- Trucks (diesel): 0.44731 litre/km

From all petrol cars, only 7.5% are 98 octane petrol (DGEG, 2015), so that it is assumed for this chapter that all petrol is of 95 octanes. Such consideration is also reasonable because the difference of prices of the two petrol types would not be significant to influence the decision making process for pavement preservation. All the results on this chapter are based on the average fuel prices of 2016 in Portugal (maisgasolina.com, 2017):

- Diesel: 1.191 €/litre
- Petrol 95: 1.442 €/litre

The quantification of environmental costs in this thesis is made through the allocation of a cost per each tonne (ton) of CO_2e, as explained in Subsection 2.4.2. Several prices

were presented, varying from country to country. A value of 8 €/ton CO_2e is used in this chapter, because it is approximately the adopted carbon tax for Portugal (refer to Figure 2.12). The combustion of a litre of petrol and diesel releases 2,3477 and 2,6893 Kg of CO_2, respectively (EPA, 2014). As CO_2 constitutes 97% for the GWP of fuel combustion from vehicles, the following unitary emissions of CO_2e are adopted:

- 2.3477/0.97 = 2.420 Kg of CO_2e per litre of combusted petrol;
- 2.6893/0.97 = 2.772 Kg of CO_2e per litre of combusted diesel;

In addition, the equivalent energy in killowatt-hour (kWh) can also be determined assuming that a litre of petrol and diesel correspond to 9 and 11 kWh Carbon Trust (2011). Although the developed optimization methodology does not consider this unit of measurement to affect user costs, its importance might increase in the next decades as electric engines start replacing the conventional ones.

In this thesis, Equations 5.9, 5.10 and 5.11 are used to calculate user costs:

$$AT_{x,f,t} = ratio_{x,f,t} * AT_{x,t} \tag{5.9}$$

$$FC_{x,f,t} = FCR_{x,f} * FCF_{x,t} * AT_{x,f,t} \tag{5.10}$$

$$C_U = \sum_{t=0}^{T} \frac{G_{price} * (FC_{C,G,t} + FC_{Tr,G,t}) + D_{price} * (FC_{C,D,t} + FC_{Tr,D,t})}{(1+d)^t} \tag{5.11}$$

where $AT_{x,f,t}$ is the annual traffic in $vehicle * km$ for year t of vehicles of the type x, running on fuel of the type f, FC is the fuel consumption in litres, FCR is the fuel consumption rate and FCF is the fuel consumption factor. C_U represents the user costs, in euros, for the whole analysis period T, C and Tr stand for cars and trucks, while G and D stand for gasoline and diesel, respectively. d is the discount rate.

The CO_2e emissions and respective costs are determined through Equations 5.12 and 5.13:

$$CO_2e_{emis,t} = CO_2e_G * (FC_{C,G,t} + FC_{Tr,G,t}) + CO_2e_D * (FC_{C,D,t} + FC_{Tr,D,t}) \tag{5.12}$$

$$CO_2e_{cost} = \sum_{t=0}^{T} \frac{CO_2e_{emis,t}/1000 * CO_2e_{price}}{(1+d)^t} \tag{5.13}$$

where $CO_2e_{emis,t}$ is the amount of CO_2e emissions in kg and the CO_2e_{price} is given per tonne of CO_2e emissions.

User costs (C_U) are directly related to the money spend by individuals in fuel. Environmental costs are associated with the price of CO_2e at national level, so that they

can ultimately be related to a cost to be supported by the society, besides road users. For this reason, user and environmental costs can either be considered individually or summed as society costs (C_S):

$$C_S = C_U + CO_2e_{cost} \tag{5.14}$$

They can be used to define objective functions to be minimized, but cannot be considered as constraints, as it is very ambiguous and hard, if not impossible, to define limits for user or society costs, despite the existence of global goals to reduce CO_2e emissions.

5.3 Multi-objective optimization

5.3.1 General concepts

All the variables presented in the previous section can constitute objective functions. The developed optimization methodology is able to consider one, two or even the three objective functions in the same optimization problem. As these are conflicting within each other, the problem is multi-objective. In fact, the multi-objective problem truly arises when the optimum value for each of the objective functions is different when considered individually. Formally, a multi-objective problem is formulated as

$$\begin{aligned} \text{Minimize:} \quad & f(x) = (f_1(x), f_2(x), ..., f_s(x)) \\ \text{Subject to:} \quad & g_j(x) \geq 0, \quad j = 1, ..., J \\ & h_k(x) = 0, \quad k = 1, ..., K \\ & x_i^l \leq x_i \leq x_i^u, \quad i = 1, ..., n \end{aligned} \tag{5.15}$$

where the integer $s \geq 2$ is the number of objective functions, x, $f(x)$, $g(x)$ and $h(x)$ are the vectors of decision variables, objective functions, inequality constraints and equality constraints, respectively. The i^{th} variable varies in the range $[x_i^l, x_i^u]$.

In a problem where two objective functions are to be minimized, if a decision vector minimizes one objective function, but not the other one, then the objectives are conflicting. In such cases, several solutions are regarded as the optimal one, if they are non-dominated solutions. A solution x dominates a solution y if it is no worse in all objectives and it is strictly better in at least one objective. If there is no solution in the search space that dominates x, then x is a non-dominated solution, also known as a Pareto solution. The Pareto frontier contains all the non-dominated solutions of a multi-objective problem, meaning that none of them is numerically better than another.

In mathematical terms, a solution x is said to dominate a solution y if Equation 5.16 is verified. An illustration of a Pareto frontier, where all functions are to be minimized, is shown in Figure 5.3.

$$\forall i \in 1, ..., s: \ f_i(x) \leq f_i(y) \wedge \exists j \in 1, ..., s: \ f_j(x) < f_j(y) \tag{5.16}$$

Solutions can be grouped in different Pareto fronts according to the concept of dom-

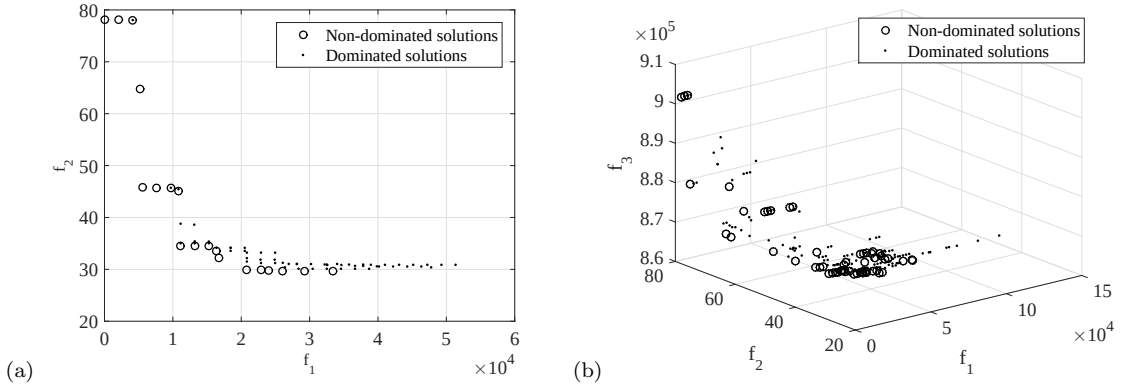


Figure 5.3: Example of a Pareto frontier: (a) two objectives; (b) three objectives

inance. The graduation of Pareto fronts is an important aspect in the efficiency of most multi-objective optimization algorithms. Figure 5.4 illustrates some solutions for a minimization of two objective functions, so that solutions a and b constitute the 1st front, i.e., the optimal one.

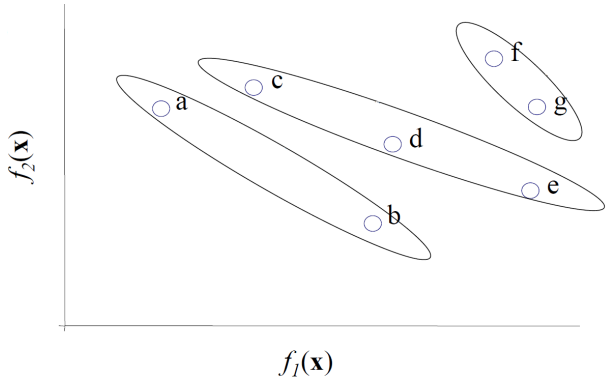


Figure 5.4: Graduation of Pareto fronts (adapted from Costa and Oliveira (2003))

In the objective space, it is possible to define an ideal objective vector and a nadir objective vector. They represent the *supremum* and the *infimum* of all objective functions, as indicated in Figure 5.5. The determination or estimation of their values are useful to improve the efficiency of some scalarization methods for optimization.

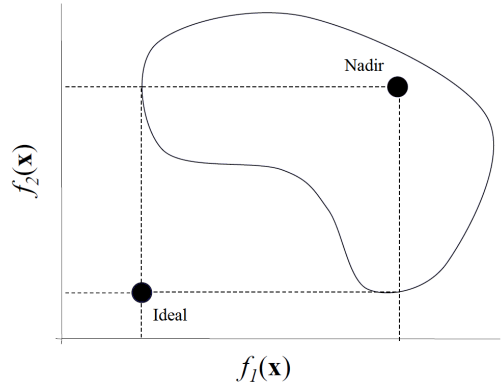


Figure 5.5: Ideal and nadir points (adapted from Costa and Oliveira (2003))

The convexity of Pareto frontiers is another important feature that influences the possibility of some optimization algorithms to find Pareto optimal solutions. Example of a convex and a non-convex frontier are shown in Figure 5.6.

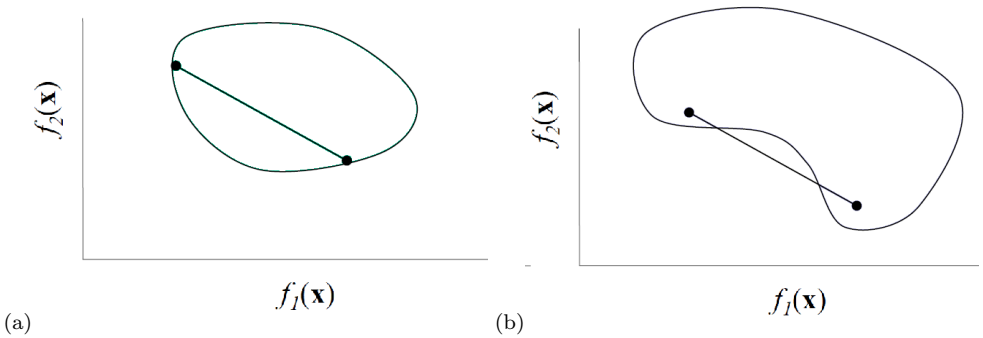


Figure 5.6: Convexity of Pareto frontier: (a) convex; (b) non-convex (adapted from Costa (2007))

Methods to solve multi-objective problems can be classified according to the moment when the decision maker introduces his own preferences to the optimization process, regarding the relative importance of each objective, for instance. They can be *a priori*, if preferences are given before starting the optimization, *a posteriori*, if no preferences are explicated before the end of the process, and progressive, if preferences are introduced iteratively during the optimization process. *A priori* definition of preferences is specially relevant when scalarization methods are used to combine two or more objective functions into a single one that can be minimized with single-objective algorithms. One of this methods is the min-max method, known as the Tchebycheff method, which is explained in the next subsection (5.3.2) and applied in Section 5.5. The election of this scalarization method relies on its capacity to find solutions in non-convex Pareto frontiers.

5.3.2 Tchebycheff framework

The Tchebycheff method, also known as min-max method, is a variant of weighted metric methods. These are scalarization methods that reformulate the multi-objective problem into a single-objective by weighting the metrics. The goal is to minimize the distance between a reference point and the feasible objective region, formally defined as

$$\text{minimize} \quad \left(\sum_{i=1}^{s} w_i |f_i(x) - F_{ref}|^p \right)^{1/p} \tag{5.17}$$

where p is a parameter with great influence on the obtained solutions. The Tchebycheff method consists in adopting the infinite norm, i.e., $p = \infty$, formally resulting in the expression 5.18

$$\text{minimize} \quad max_{1 \leq i \leq s}[w_i |f_i(x) - F_{ref}|] \tag{5.18}$$

For 5.17, with $p \neq \infty$, convexity is needed to guarantee that all Pareto optimal solutions can be found, whereas for 5.18, if the reference point F_{ref} is well positioned, any Pareto optimal solution can be found regardless of the problem convexity. Figure 5.7 illustrates the mentioned differences. Solutions given by 5.18 might be weak, i.e., dominated, if

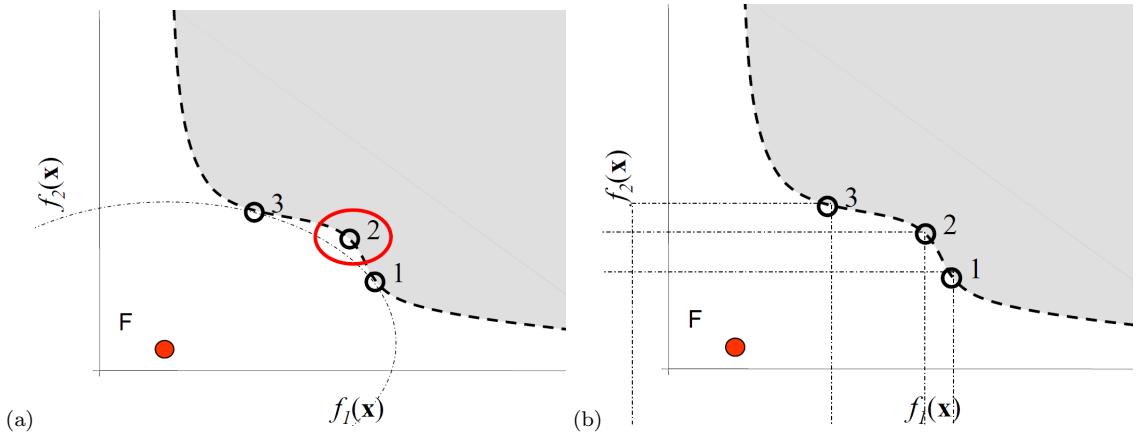


Figure 5.7: Pareto solutions found by: (a) weighted metric method; (b) Tchebycheff method (adapted from Costa (2007))

all the weights are positive. This fact can be avoided by giving a slight slope to the contour of the metric. The augmented problem is then formally defined as

$$\text{minimize} \quad max_{1 \leq i \leq s}[w_i |f_i(x) - F_{ref}|] + \rho \sum_{i=1}^{s} |f_i(x) - F_{ref}| \tag{5.19}$$

where ρ is a sufficiently small positive scalar (Miettinen, 2001).

Ideally, the reference point F_{ref}, represented in Figure 5.7 as a red dot with label F,

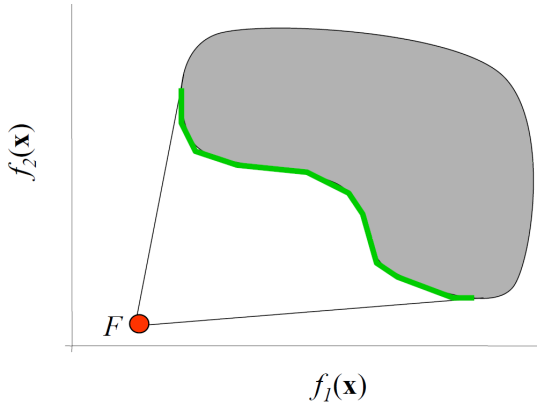


Figure 5.8: Positioning the reference point for the Tchebycheff method (adapted from Costa (2007))

is coincident with the *Ideal point* (Figure 5.5). As the ideal point is often unknown in real optimization problems, it is desirable that the reference point is positioned somewhere below the expected optimal values of all objective functions. This is necessary to allow the Tchebycheff method to find solutions in all the Pareto frontier, as shown in Figure 5.8.

It is also important to have the objective functions quantified in the same order of magnitude, as much as possible, in order to improve the diversity of non-dominated solutions. Indeed, having the Pareto frontier at similar distances from all objectives' axis allow the combination of weights to reach a wider variety of regions in the frontier. This can be done by reducing or increasing the scale of the objective functions accordingly.

In summary, the choice of the reference point and axis scale has great influence on the obtained solution. Several weights must be tested in order to find several solutions, although each combination demands the resolution of an optimization problem. The Tchebycheff formulation results in non-differentiable problems, which requires a compatible optimization algorithm, such as the case of GA.

5.4 Genetic algorithms

Genetic algorithms (GAs) play an important role in the developed methodology, because they were the elected optimization algorithm to use. The relative advantages that lead to this choice and several references of its use in the context of decision making and PMS were highlighted in the literature review chapter. Recapitulating, GAs are efficient in producing good solutions for difficult combinatorial optimization problems, capable of converging to the Pareto optimal set as a whole with low prob-

ability of solutions converging to local minima. There is no need to express objective functions, constraints, or any other problem parameters in a mathematical form, because GA uses objective function information rather than derivatives or other auxiliary knowledge, which is a significant advantage for the problem addressed in this thesis.

As the name suggests, GA is a meta-heuristic optimization technique based on the mechanics of natural selection and evolution. The search for an optimal solution starts from an initial population of solutions and evolves from generation to generation towards a final population with better results, considered as the optimal solution. Indeed, as with any heuristic, the true optimality of the solution is not always guaranteed, but GAs are likely to render relatively close to the optimum.

The basics of GAs rely on some concepts, such as population, selection, crossover, mutation, stopping criteria, elitism and crowding, as defined in the following paragraphs. A flowchart of the working of a GA is shown in Figure 5.9.

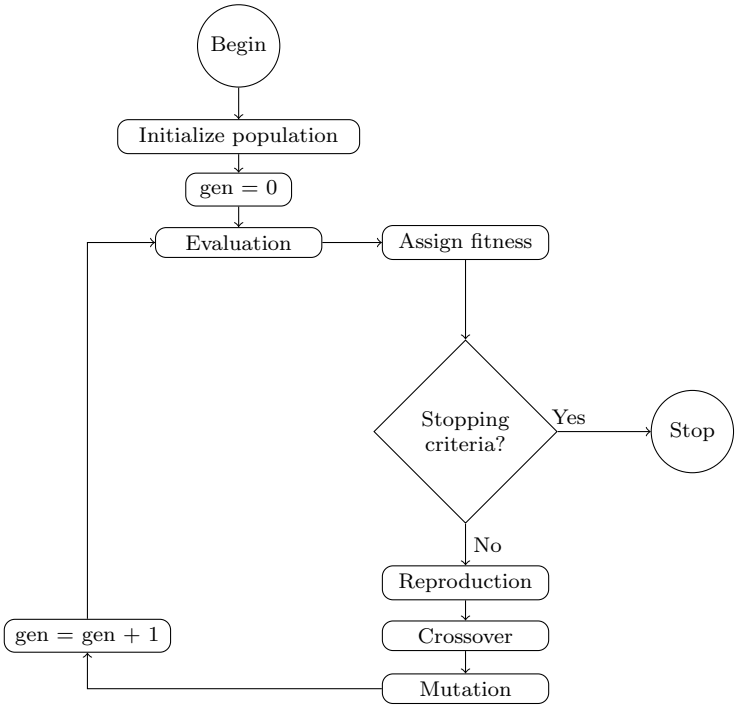


Figure 5.9: Flowchart of the working principle of a GA (adapted from Deb (2008b))

Population

A population is a group of individuals, each representing a candidate solution that is evaluated according to the value of the objective function for that solution. This value is known as the fitness of a solution. Typically, solutions are coded in a binary string, so that individuals are said to carry a genetic code that is passed and transformed

between generations of populations. Population size depends on the problem to be solved, but it usually contains several hundreds of individuals, i.e., solutions. The initial population is (1) either randomly created or (2) defined by the user if an area of the search space likely to generate optimal solutions is known. The option (1) allows the consideration of a whole range of solutions, whereas option (2) narrows the search space, risking to miss some optimal areas, but it is expected to converge faster.

Selection

This step consists in selecting part of the population that is reproducing for the next generation of individuals. Likewise the natural selection, fitter solutions, as evaluated by the objective function, are more likely to survive and be selected. It is also important to select less fit solutions in order to preserve diversity of solutions. The group of selected individuals is known as parents that reproduce to create children through the operators of crossover and mutation, although there are other operators not commonly used.

Crossover

This is the traditional process that creates a child by combining the genetic code (or genotype) of parents. The division of the ascendant's genotype can be made in different ways as defined by a crossover function. In the example of Figure 5.10, crossover is made through the selection of a single-point to divide the genotypes. The population of the most recent generation is expected to have a better average fitness.

Mutation

Mutation is an operator with low probability of occurrence and its main goal is to impose some variation on the population in order to avoid the algorithm to be trapped in a local minimum. In the example of Figure 5.10, mutation occurs in one allele of the genotype of both children.

Stopping criteria

The generation of new populations stops when a pre-established criterion is achieved, such as, for instance:

- Number of generations;
- Computation time;

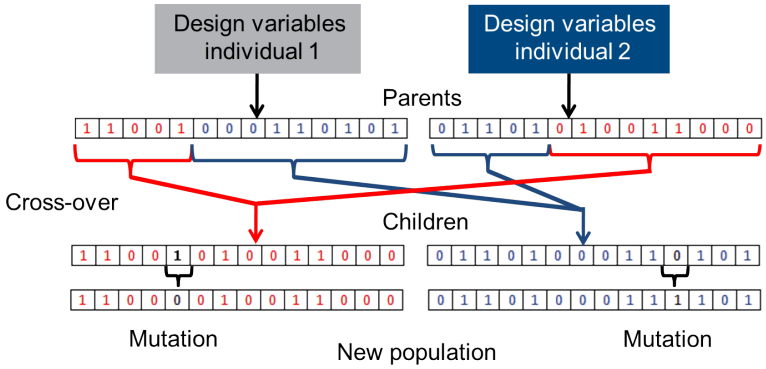


Figure 5.10: Genetic algorithm operators (Design Methods, 2012)

- Fitness value;
- Change of average fitness between generations is less than a specific value;
- Average change in the spread of Pareto solutions is less than a specific value.

Elitism

Elitism is a feature that keeps some of the fittest solutions unchanged to the next generation, which might increase the performance of the algorithm by avoiding this to waste time re-discovering previously discarded optimal solutions. Solutions preserved by elitism can also be used as parents, as schematically presented in Figure 5.12.

Problems with several optimal solutions, such as multi-modal and multi-objective problems, require additional features of GAs in order to preserve diversity solutions, ensuring that the solution space is adequately searched so that the algorithm finds many solutions in a region of Pareto front and only few in other region, as illustrated in Figure 5.11. Among others, crowding is a method to maintain diversity, by eliminating the most similar individuals when a new one enters a sub-population (Gupta and Ghafir, 2012). Diversity is directly related to the spread of Pareto solutions and the respective stopping criteria.

Non-dominated sorting genetic algorithm II

The Non-dominated sorting genetic algorithm-II (NSGA-II) (Deb et al., 2002) is one of the most well known and used implementation of GAs for multi-objective optimization problems. It uses an elite-preservation strategy as well as a diversity-preserving mechanism that differentiates it from others, as there is no need to have parameters to control diversity. Figure 5.12 shows a scheme of the NSGA-II procedure. It is observed

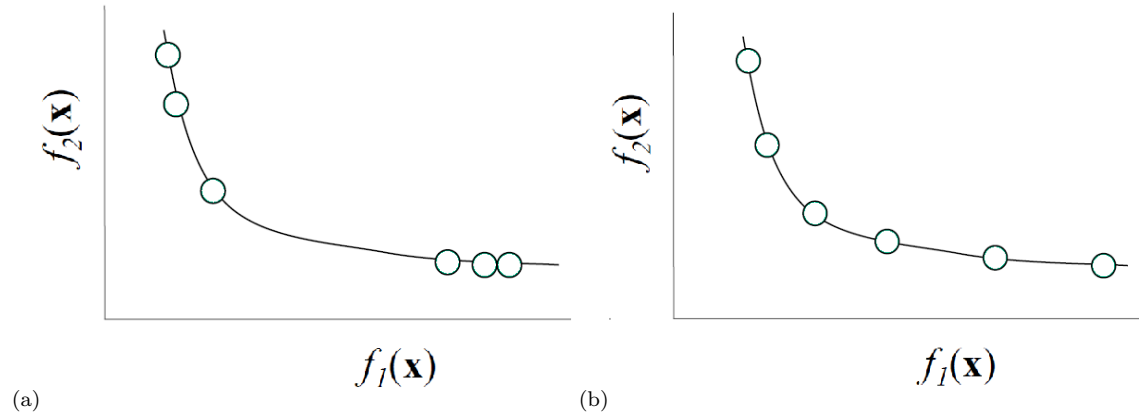


Figure 5.11: Pareto front: (a) less diversity of solutions; (b) more diversity of solutions (adapted from Costa (2007))

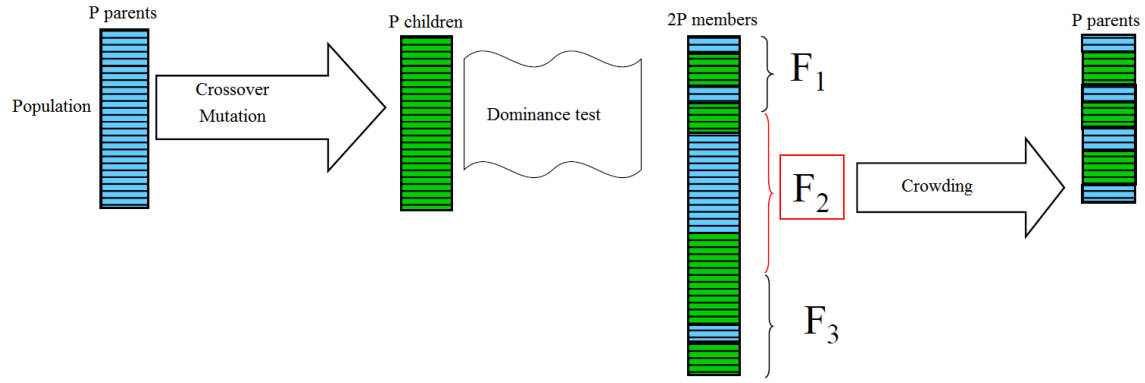


Figure 5.12: Schematic of the NSGA-II procedure (adapted fromCosta (2007))

that Pareto fronts F1, F2 and F3 include all parents and children, ranked together, thus elitism is assured. Then, the following population of parents include all individuals from F1 and some individuals of F2, selected by crowding, i.e., giving preference to the most widely spread solutions by using the crowding distance values in F2. This distance is given by the average side-length of a cuboid using the nearest neighbours of the solution being evaluated as its vertices. For a deeper understanding, readers should refer to Deb (2008b).

Constraint handling techniques

As formally indicated in Equation 5.15, optimization problems usually have constraints to be respected, either regarding the decision variables or functions of them. For constrained problems, the goal is to find feasible solutions that are optimal in terms of the objectives. For this thesis, three constraint handling techniques were studied and tested in order to elect the most suitable for the problems to be addressed. One of the techniques verifies whether the constraints are satisfied or not after the optimization

process finishes, i.e., *a posteriori*, while the other two methods impose constraints before the optimization process, i.e., *a priori* (Moreira et al., 2016a).

Using the *a posteriori* technique, solutions are generated as if the problem to solve was unconstrained. Then, for each Pareto solution x, the constraint function values are calculated and compared with the imposed limits to check the solution feasibility. The production of several solutions which are later considered infeasible might be a drawback if that causes the solver to search for less solutions in the feasible space.

On the other hand, if a constraint function is considered before optimizing the problem (*a priori*), the solution space is directly narrowed, so that every time the solver finds a solution, this is immediately classified as feasible or infeasible, helping the solver to converge towards a feasible solution space. At the end, all provided solutions respect the constraints. Another *a priori* technique to constrain the problem consists in applying a penalty function which adds a penalty value to the objective values whenever constraints are violated. This method does not confine the solution space, hence it worsens potential optimal solutions which do not respect the constraints, reducing the likelihood of those being part of the final population. The choice of penalty functions should be carefully made, because it can affect the convergence and the optimality of feasible solutions. The penalty function adopted for this study penalizes the objectives' values as more as the constraints' violations $g_j(x)$ and $h_k(x)$ are larger, alike to what is described in Deb (2008b). The objective function value $F(x)$ is then calculated according to Equations 5.20:

$$F_i(x) = f_i(x) + R_i \left[\sum_{j=1}^{J} g_j(x) + \sum_{k=1}^{K} h_k(x) \right] \tag{5.20}$$

where R is a user defined penalty parameter.

A comparison of the effectiveness of all three constraint handling techniques is presented in Section 5.5

5.5 Comparison of two genetic algorithms based optimization approaches

5.5.1 Problem definition and implementation options

The comparison of two optimization approaches (Tchebycheff method + GA *vs* Multi-objective GA) and constraint handling techniques is performed for a two-objective problem for a 20 years period, considering only one pavement section of one lane (3.5 m)

with 1 km length. At the beginning of the analysis period T, all individual PIs are assumed to be in condition state 2 (CS_2). Time is used as the Markov parameter, i.e., the variable that rules the prediction model. The problem consists in finding optimal M&R plans in order to maximize the pavement quality and to minimize administration costs with M&R, as defined by Equations 5.1 and 5.5, respectively. Figure 5.13 illustrates a flowchart with the general process until defining optimal solutions.

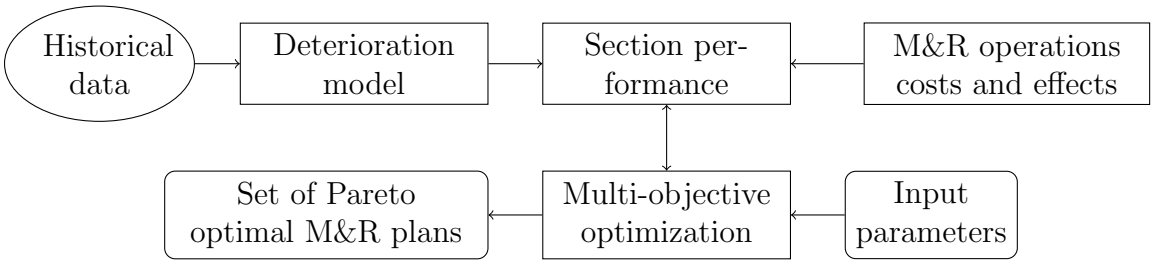


Figure 5.13: Flowchart of interactions among modules of one pavement section optimization (adapted from Denysiuk et al. (2017))

In order to test the performance of different ways to impose constraints in both optimization methods, several sub-problems with distinct constraints were created, as indicated in Table 5.1.

Table 5.1: Constraints for each problem and respective handling method

Problem no.	Constraints	Handling method
0	None	–
1.1	$C_A < 20000 € * T$	Constraint function
1.2		Penalty function
2.1	$GPI \leq 3$	Constraint function
2.2		Penalty function
3.1	$(CPI_COM,\ CPI_SFT,\ CPI_STR) \leq 3$	Constraint function
3.2		Penalty function
4.1	$(PI_B,\ PI_CR,\ PI_E,\ PI_F,\ PI_R) \leq 3$	Constraint function
4.2		Penalty function

Regarding the implementation of the Tchebycheff method, 11 combinations of weights (w_1 vs w_2) were used to transform both objective functions into a single one, so that several Pareto solutions can be found. These combinations starts from attributing no importance to the 1st objective, which is gradually increasing in intervals of 10% until it assumes 100% of importance, as indicated in the matrix of Equation 5.21. Each column of the matrix originates a weighted function that is to be minimized using a GA.

$$W = \begin{bmatrix} 1 & 0.9 & 0.8 & \cdots & 0.1 & 0 \\ 0 & 0.1 & 0.2 & \cdots & 0.9 & 1 \end{bmatrix} \tag{5.21}$$

For a period of 20 years, administration costs are higher than $\int GPI$ by four orders of magnitude, thus its respective objective function is divided by 10000 in order to get a better diversity of solutions in the Pareto frontier. The administration costs are then calculated back and illustrated in the Figures to follow in their normal order of magnitude.

The point (0,20) was chosen as the reference point F_{ref}, because the minimum cost for administration can be 0 and the pavement quality measured by $\int GPI$ is always more than 20, since 1 is the best possible CS that GPI can assume in each year. This point is the best known approximation of the *ideal point.*

Regarding the implementation of GA, each element of a decision vector is an integer value within the interval [1;12], corresponding to the M&R indicated in 4.15. Other relevant options for the algorithm are as follows:

- Population size: 200;
- Initial population: randomly generated;
- Elite count: 5% of population size;
- Crossover fraction: 80%;
- Crossover function: Scattered when there are no linear constraints, and intermediate when there are linear constraints;
- Mutation: Gaussian for unconstrained problems and adaptive feasible otherwise;
- Stopping criteria: Minimum generations = 50; maximum generations = 2000; Function tolerance = 1e-6.

The implementation of the Multi-objective GA require some different steps, thus the definition of some other options, as follows:

- Population size: 200;
- Initial population: randomly generated;
- Crossover fraction: 80%;
- Crossover function: Intermediate;
- Mutation: Gaussian for unconstrained problems and adaptive feasible otherwise;
- Distance measure function: distance crowding;

- Pareto front population fraction: 0.35;
- Stopping criteria: Minimum generations = 100; maximum generations = 2000; Function tolerance = 1e-4.

Most of the options are the default indicated by the software. Some preliminary experiences in changing some options were made, but the results suggested that a great increase on computational cost was needed for just slight improvements on the solutions optimality. For single-objective GA, all the tests with the mentioned options terminated because the average change in the fitness function value was less than the defined function tolerance, while for multi-objective GA the average change in the spread of Pareto solutions was the relevant stopping criteria, i.e., they both achieved the desirable level of convergence.

Because GAs are stochastic algorithms, different runs might lead to different results, due to differences in the initial population and other random processes along the reproduction process. Therefore, three runs were executed for each problem and the non-dominated solutions of the whole group of results were the selected as the final ones.

5.5.2 Results and comparison of the simulated problems

In this subsection, comparisons of optimization results using both methods and the various constraint handling techniques are presented. For that purpose, several Figures containing layers of results from different processes are shown. The Tchebycheff method with GA is abbreviated as TCGA and the multi-objective GA is abbreviated as MOGA. All optimization runs were made in a computer with 16.0 GB of RAM memory and 3.20 GHz processor.

Problem 0 - unconstrained

This problem addresses the particular case when no constraints are imposed by the decision maker, so the costs can achieve very high values as well as the pavement can get into a poor preservation state. Figure 5.14 shows the solutions found by both the MOGA and the TCGA methods for a 20 years period, after three optimization runs. In the figure, the non-dominated solutions which constitute the approximation to the Pareto frontier are highlighted with bigger marks (circles). To interpret the legends, ND stands for non-dominated solution and D stands for dominated solution. The distinction between ND solutions and D solutions within each optimization method serves only to illustrate all the solutions given by the three runs.

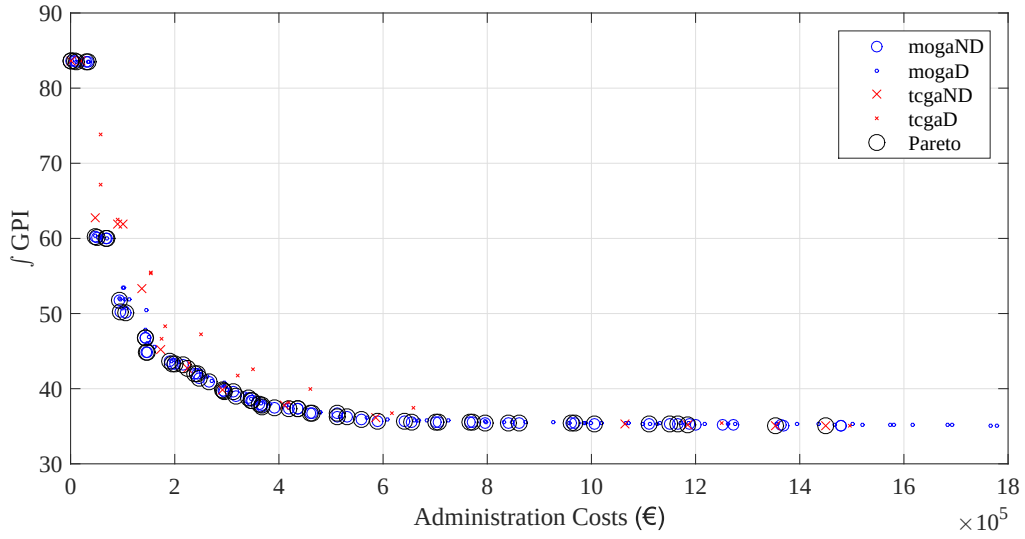


Figure 5.14: Results from MOGA and TCGA for problem 0

It is observed that MOGA provides better results in terms of objective fitness and number of optimal solutions, though the TCGA gives 6 non-dominated solutions, from which 4 are located near extreme regions of the Pareto frontier, representing solutions with very high cost or poor pavement quality. The running time for MOGA and TCGA were 76 and 691 minutes, respectively, evidencing the greater computational cost of using the TCGA method. The differences on the results and processing time become less significant for shorter analysis periods, but for typical pavement preservation planning periods with no constraints, the advantages of MOGA are well noticed (Moreira et al., 2016a). Nevertheless, it is important to assess if similar conclusions are obtained for constrained problems.

Problem 1 - limited budget

Problem 1 is constrained by the total budget available for the analysis period, so that one of the objective functions is being directly limited in its result. After observing the unconstrained results, the overall available budget was set to be 400 000 € for 20 years, because it appeared to be a reasonable value to shrink the amount of feasible solutions. Figures 5.15 and 5.16 show the solutions found by both methods.

Once again, it is observed the higher variety of solutions provided by MOGA, containing more Pareto solutions than the TCGA in absolute number. On the other hand, among the non-dominated solutions of TCGA, several are part of the Pareto frontier (6 out of 11 in problem 1.1 and 9 out of 11 in the problem 1.2), both at the extreme and in the middle of the frontier, thus being potential solutions to be chosen

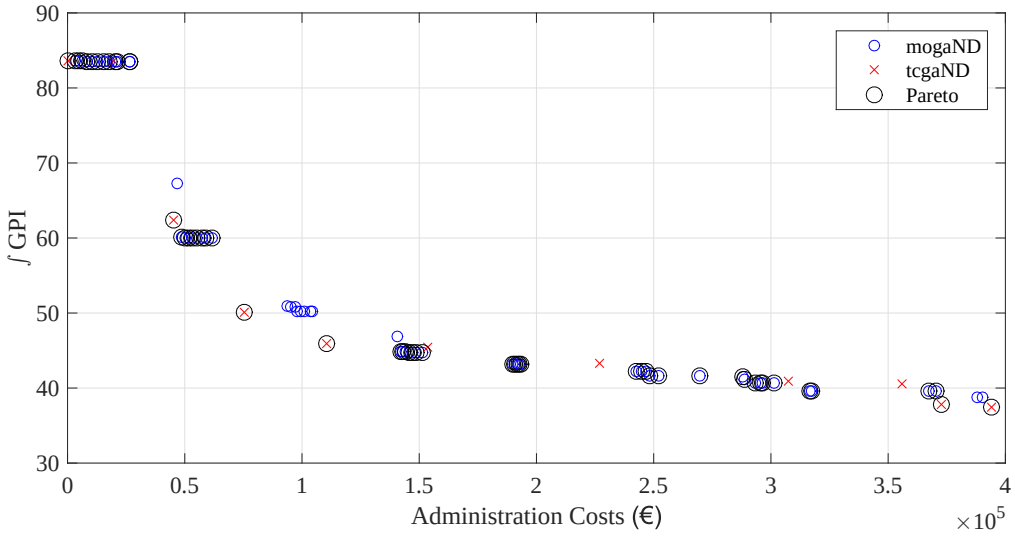


Figure 5.15: Results from MOGA and TCGA for problem 1.1

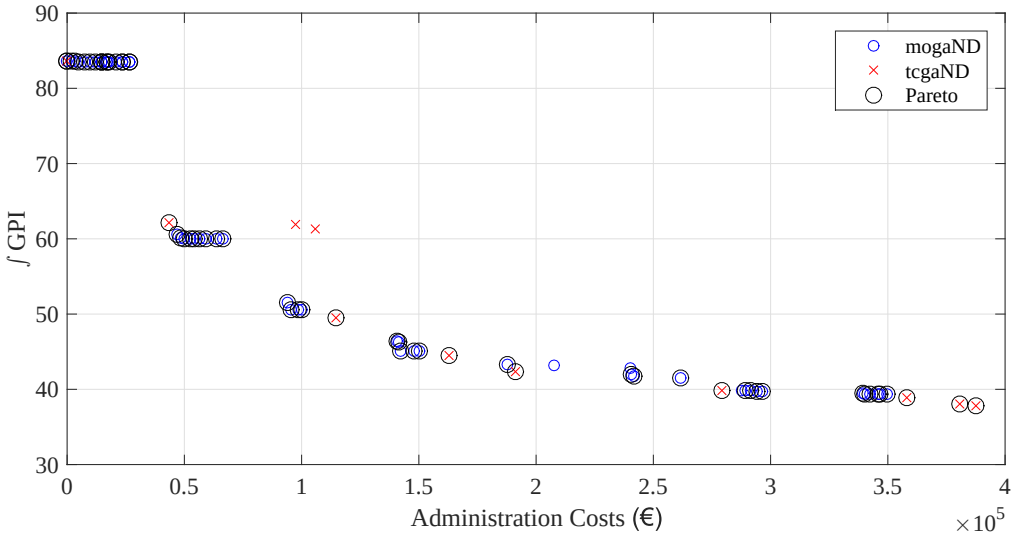


Figure 5.16: Results from MOGA and TCGA for problem 1.2

by a decision maker. In order to compare the effectiveness of the constraint handling methods, solutions of both methods are illustrated together for problems 0, 1.1 and 1.2 in Figures 5.17 and 5.18.

Using MOGA, solutions given by both constraint handling methods are not significantly different: the *prblm1.1* contributes with 23 solutions for the Pareto frontier, and *prblm1.2* contributes with 28 (Pareto frontier is not highlighted to avoid visual density of markers). The former used 135 minutes to find those solutions, while the latter used 71 minutes. Solutions from the unconstrained problem are also similar within the feasible solution space, i.e., for the region to the left of the red dashed line

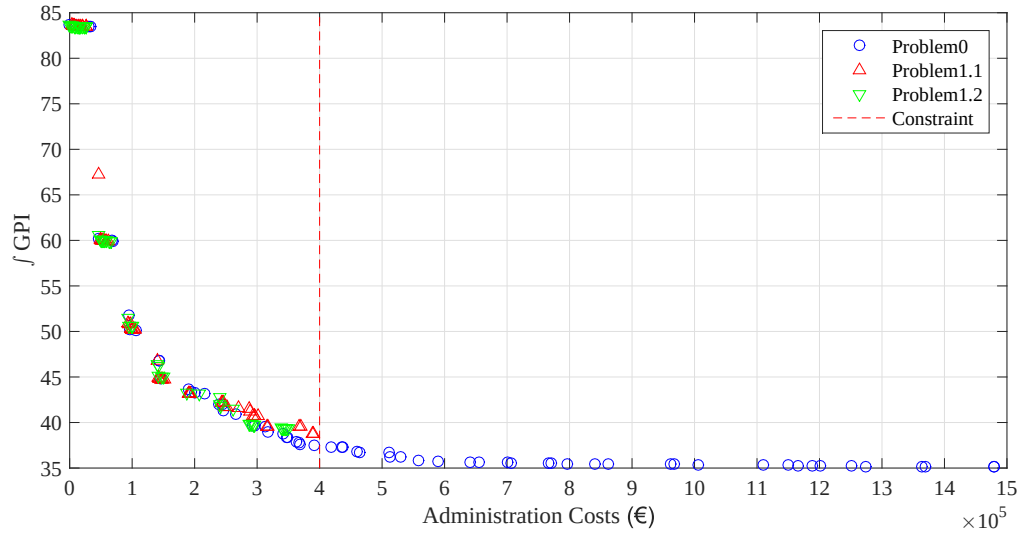


Figure 5.17: Results from MOGA for problems 0, 1.1 and 1.2

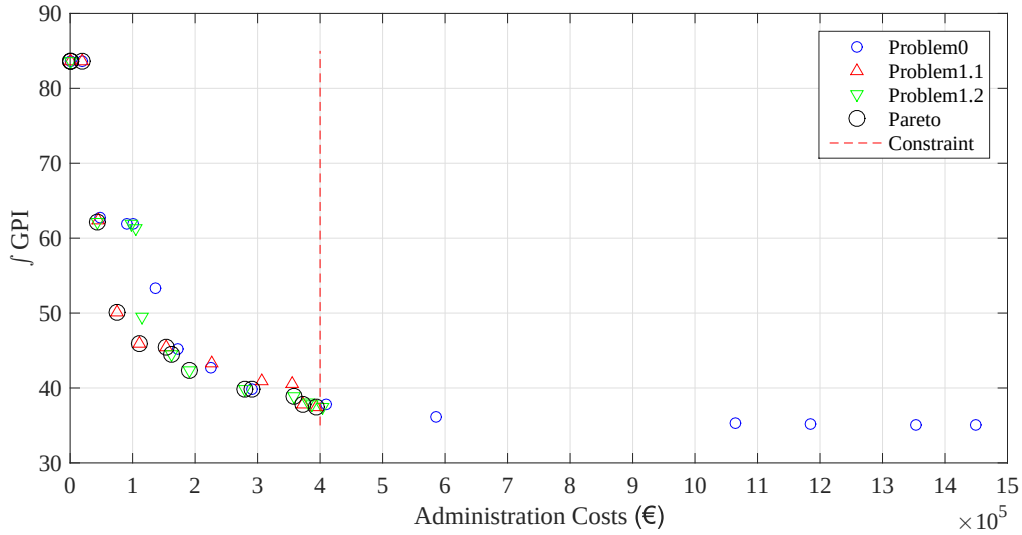


Figure 5.18: Results from TCGA for problems 0, 1.1 and 1.2

(*administration costs* $\leq$ 400 000). In this region, the number of solutions provided for problem 0, problem 1.1 and problem 1.2 are 35, 59 and 48 respectively, denoting some advantages of applying constraints *a priori*. The fewer results given for problem 0 was expected because the algorithm spreads the solutions by all the unconstrained solution space.

Regarding the optimization with TCGA, Pareto optimal solutions provided by both constraint handling methods are different, but it is hard to say which ones are better. However, the optimization using the penalty function is much faster to obtain the Pareto solutions than using the constraint function: 676 minutes against 954 minutes.

Based on the illustrated results and other simulations for different periods, it was concluded that when the value of an objective function is constrained, the solutions from different constraint handling methods do not differ significantly. The processing time, however, is much slower when a constraint function is used. If the constraint is applied *a posteriori*, there are less number of feasible solutions, which is the unique disadvantage of this technique for the illustrated example.

Problem 4 - PIs constrained

The constraints imposed in problems 2, 3 and 4 intend to limit the pavement deterioration by imposing maximum admissible values for the performance indicators, as stated in Table 5.1. The results obtained for problem 4 lead to similar conclusions as for problems 2 and 3, so only illustrations and analysis regarding problem 4 are presented.

The considered problem imposes a maximum admissible condition state of 3 (CS_3) for all individual PIs. For a better understanding of further graphs, Figure 5.19 illustrates the PIs evolution for a M&R plan that does not respect the constraints. All the time a PI is above CS_3, it is considered to be violating the constraints. Indeed, the area painted with red colour (Figure 5.19) is the added penalty to the objective functions fitness. The darker red area is summed up twice, as it represents the violation of two constraints simultaneously. Due to the impossibility of visualizing PI values in the objective function graphs, in the next Figures, black crosses will be used to identify results originated by infeasible solutions.

Figures 5.20 and 5.21 illustrate the results given by MOGA and TCGA, either using the constraint function or the penalty function. Several comparisons are made regarding the effectiveness and feasibility of the results, including a comparison with the unconstrained solutions.

It can be seen in Figure 5.20 that the TCGA results are considerable better than the MOGA ones when a constraint function is applied. Figure 5.21 shows that when constraints are imposed through the application of a penalty function, the amount of results is much higher for the MOGA and they all are non-dominated, in opposition to what is verified for TCGA. Solutions for problem 4.1 are all feasible because the solution space is narrowed, while for problem 4.2 some solutions might violate the constraints, but are still shown with penalized fitness. These are marked with black crosses in Figure 5.21.

Then, it is important to compare the behaviour of the same optimization methods under different constraint handling methods. Figures 5.22 and 5.23 compare the results obtained by using the two *a priori* constraint handling methods, for MOGA and TCGA

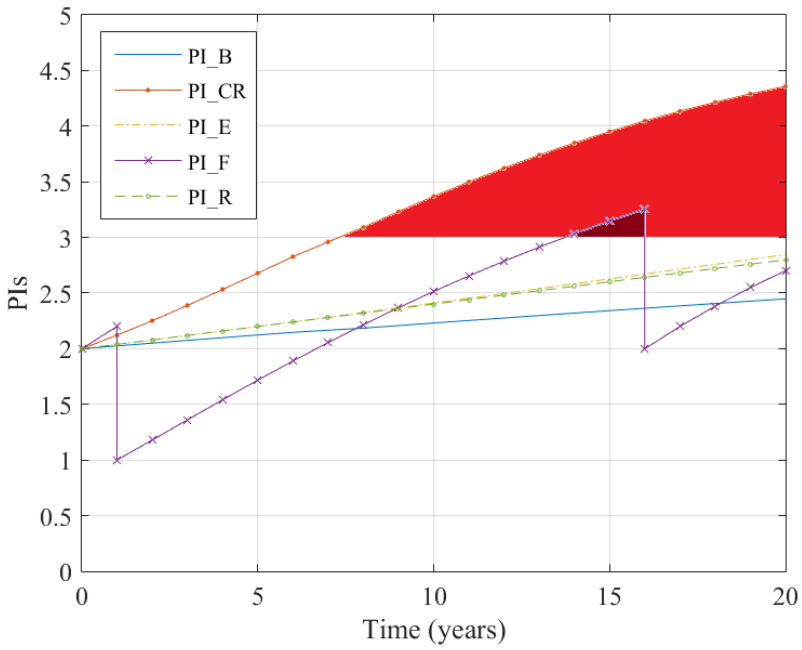


Figure 5.19: Evolution of PIs given a non-feasible M&R strategy

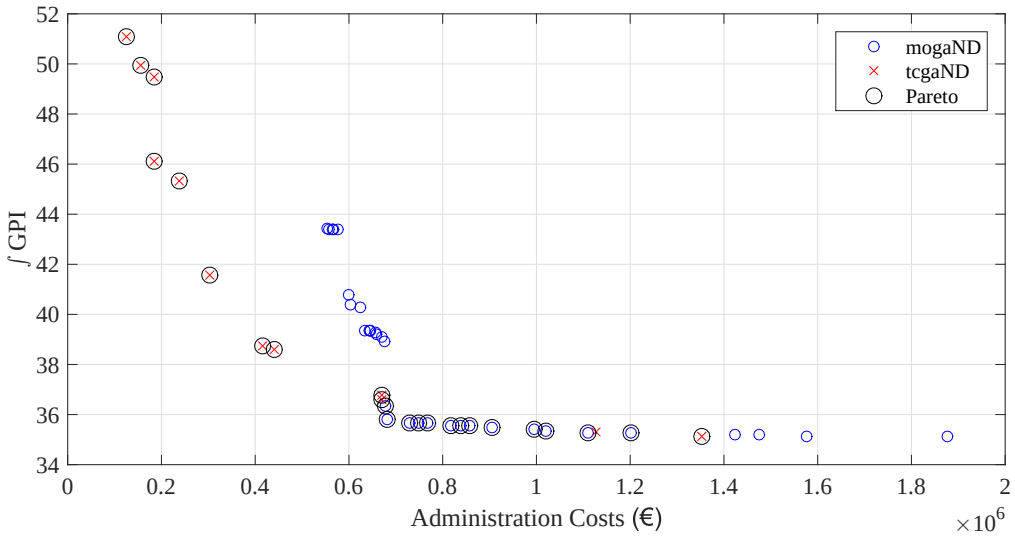


Figure 5.20: Results from MOGA and TCGA for problem 4.1

approach, respectively. Considering the feasible solutions of those Figures, the ones emerging from the application of a penalty function with MOGA are significantly better than when using a constraint function. Regarding the TCGA results, they are similar for both constraint handling methods, although some dominance is noticed for those obtained with the penalty function technique.

Optimization results from both the algorithms and constraint handling methods

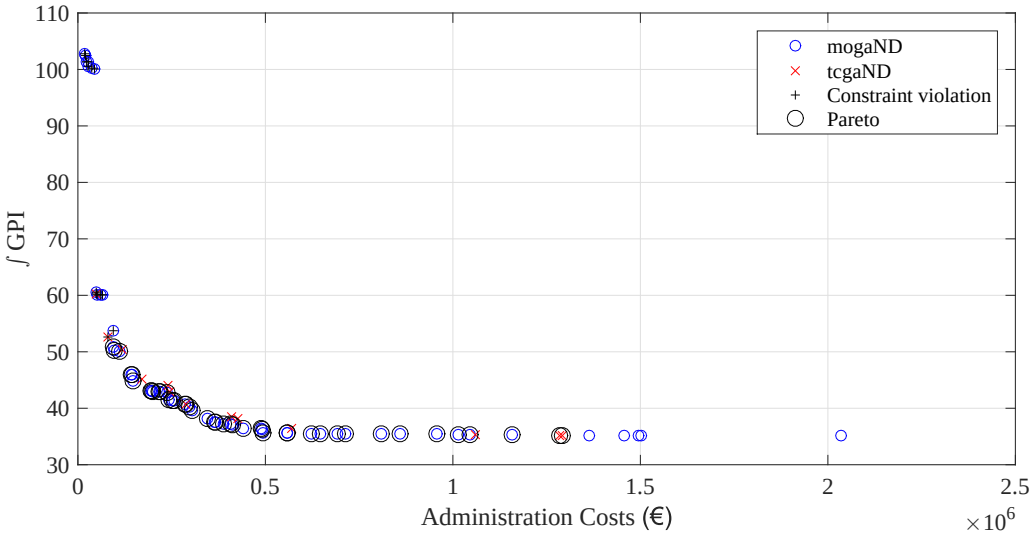


Figure 5.21: Results from MOGA and TCGA for problem 4.2

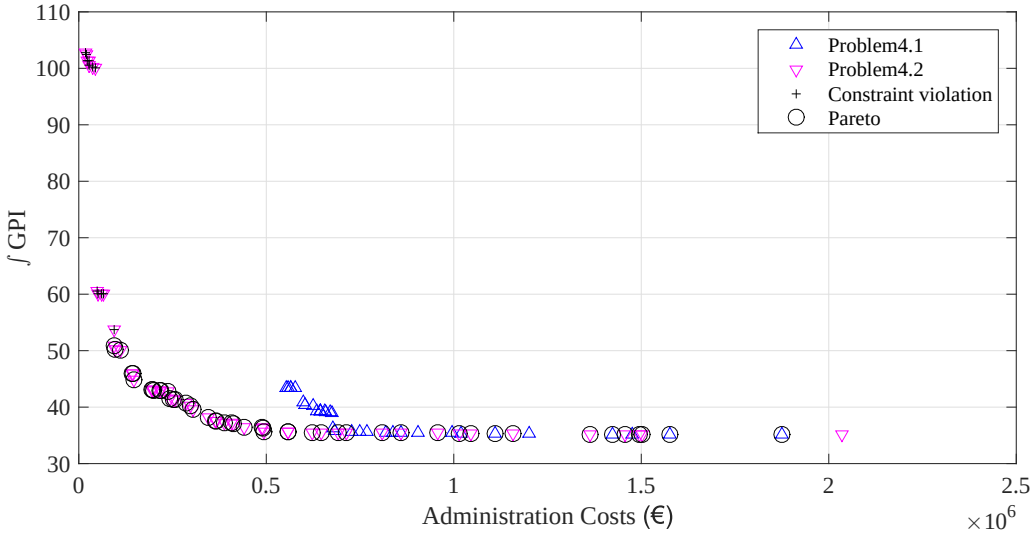


Figure 5.22: Results from MOGA for problem 4.1 and 4.2

are compared with the results obtained when no constraint is imposed *a priori* (see Figure 5.24 to Figure 5.27). By analysing Figure 5.24, it can be clearly concluded that the optimization results with *a posteriori* implementation of constraints are better than those obtained when a constraint function is applied. In contrast, when the penalty function method is used (Figure 5.25), the feasible results are quite similar, with both problem 0 and problem 4.2 having similar non-dominated solutions (approximations to the Pareto frontier). In this particular example, the unconstrained problem resulted in 10 infeasible and 57 feasible solutions, while problem 4.2 originated 12 infeasible and 45 feasible solutions. When considered together, problem 0 and 4.2 provide 23 and

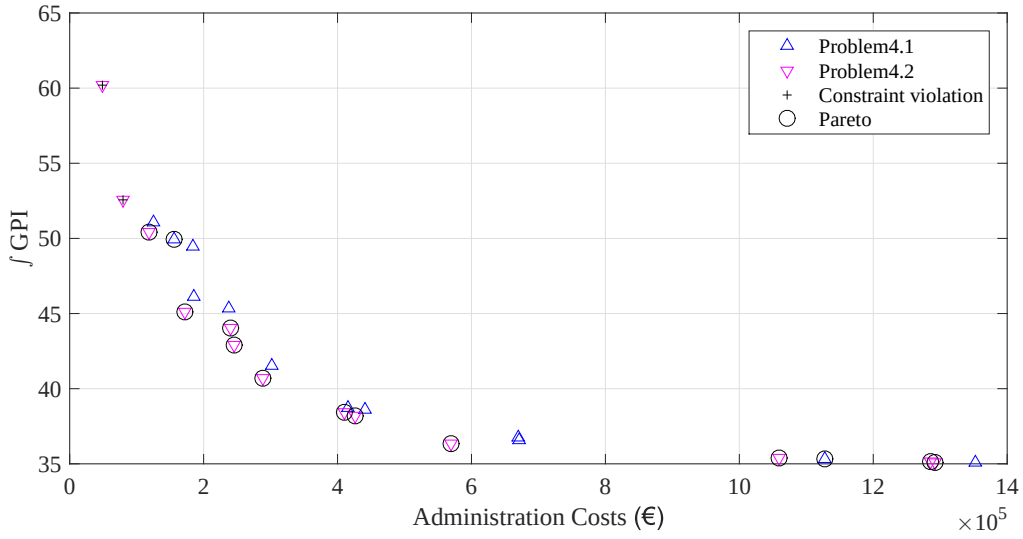


Figure 5.23: Results from TCGA for problem 4.1 and 4.2

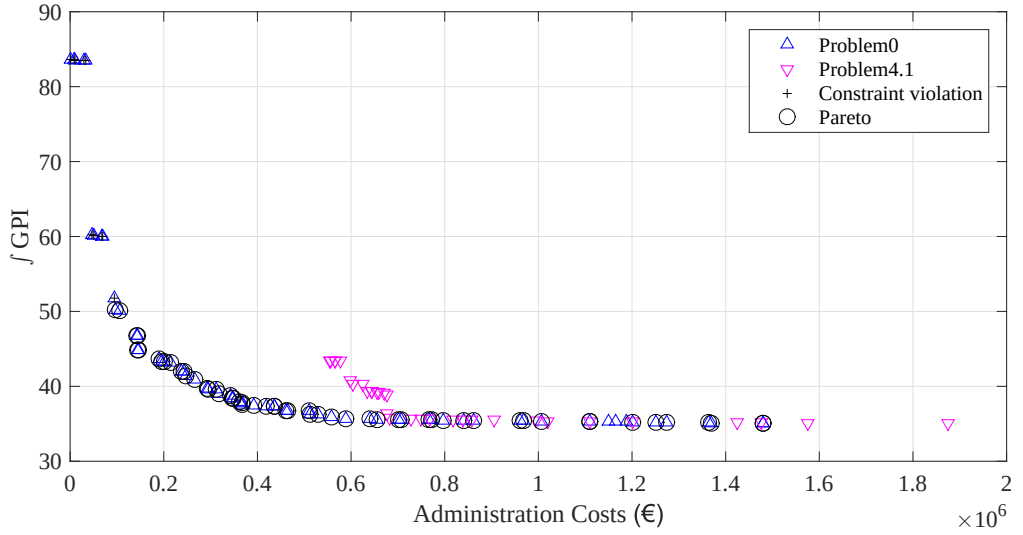


Figure 5.24: Results from MOGA for problem 0 and 4.1

35 non-dominated solutions, respectively, denoting a slight advantage for the penalty function technique. The processing time was similar: 76 minutes for problem 0 and 79 minutes for problem 4.2.

Figures 5.26 and 5.27, related to the TCGA method, indicate similar effectiveness on obtaining feasible solutions, whether the optimization process is carried out before or after imposing the constraints, for both constraint handling methods.

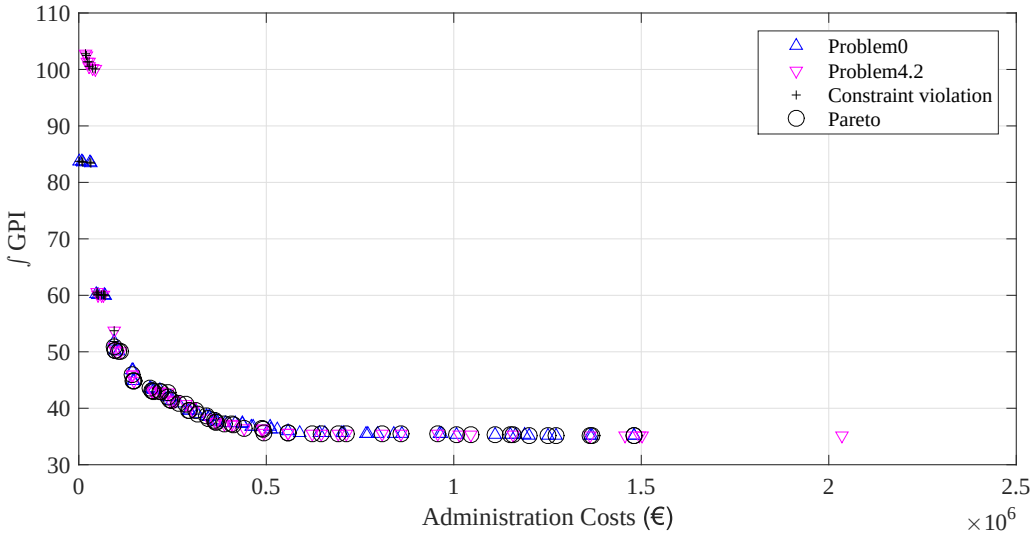


Figure 5.25: Results from MOGA for problem 0 and 4.2

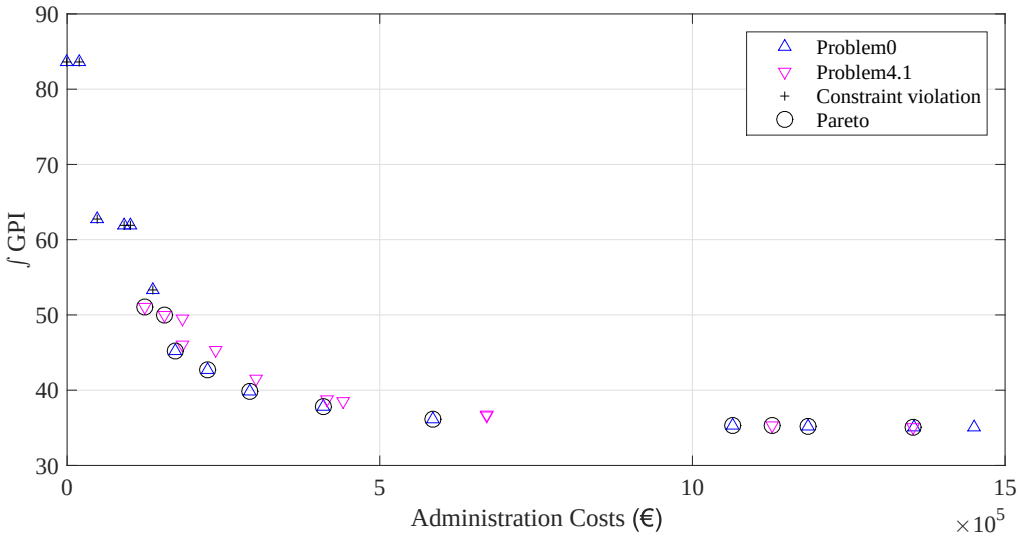


Figure 5.26: Results from TCGA for problem 0 and 4.1

Regarding the processing time, it was once again observed that MOGA is always faster than TCGA in providing solutions. Although there was not a rigorous analysis on this matter, the relative difference of processing time between MOGA and TCGA increases significantly with an increase in the number of variables.

5.5.3 Discussion and conclusions

In this subsection, some conclusions from the analysis of previous pictures and comments, and several other simulations, are depicted.

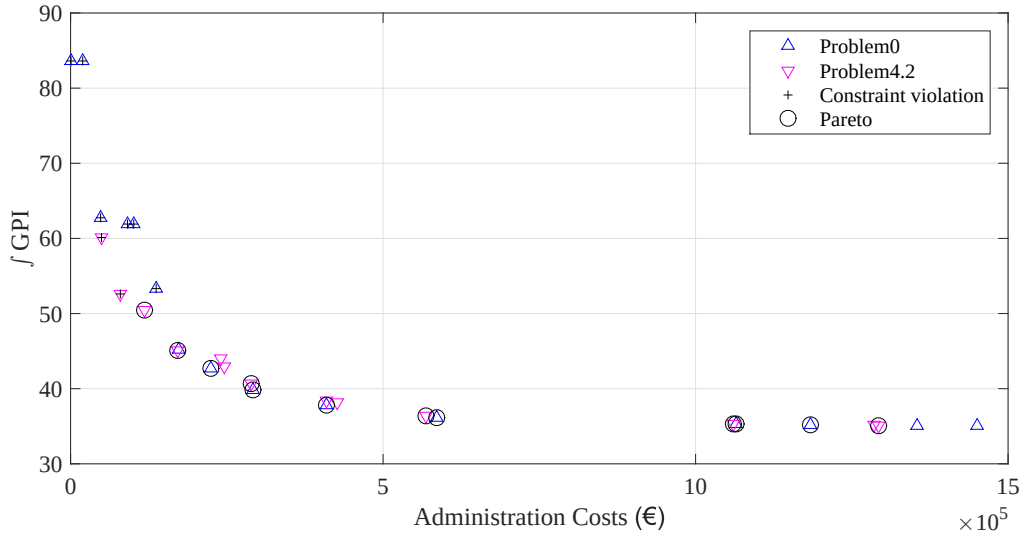


Figure 5.27: Results from TCGA for problem 0 and 4.2

For unconstrained problems, MOGA provided better results than TCGA. The same applies to problems with constraints directly limiting the objectives values. For more complex constraints applied before the optimization process, MOGA and TCGA efficiency varied according to the constraint handling method. For instance, when a constraint function was applied, such as the case of problem 4.1 and problem 4.2, TCGA provided better results, whereas when a penalty function method was used, MOGA results were the best ones. The differences in performance are more significant for a higher number of years under analysis.

Regarding the moment of constraint application, it was noticeable that, for MOGA, results obtained with the penalty function are very competitive with the feasible results obtained by the *a posteriori* constraint application. The imposition of a constraint function is clearly the less interesting option. On the other hand, TCGA results were similar for all the three constraint handling methods.

The worst results given by MOGA when a constraint function is imposed for complex constraints might occur due to the binary tournament selection performed by the NSGA-II implemented in MATLAB for multi-objective problems. In fact, when a feasible solution is compared to an infeasible one, it is assumed that the first dominates the second, regardless the overall amount of constraint violation. That can lead to the exclusion of solutions violating just one of the constraints by a small amount, which could be likely to generate offspring with potential optimal solutions. In contrast, the TCGA aims, at last, to optimize only one objective function so that the final feasible solutions are closer to the true Pareto frontier.

Despite the previous comments, the main purpose of this subsection was to select the best optimization approach to keep improving the optimization methodology for PMSs, rather than exploiting and modifying in detail the pre-implemented algorithms. By all the analysed results, the MOGA with a penalty function or with *a posteriori* application of constraints are the preferable approaches, because they are faster and provide a good diversity of solutions. For further optimization problems in this thesis, the *a posteriori* constraint handling technique was used because it is easier to implement in a diversity of problems and avoids the occurrence of possible errors caused by having to choose proper penalty parameters. Furthermore, the number and quality of feasible results given by both techniques are similar and it might be useful for a decision maker to see results of infeasible solutions as well.

5.6 Implementation of multi-objective genetic algorithm

5.6.1 Rehabilitation constraint

The problems to be later considered in this chapter differ from those shown in the previous section, because a rehabilitation constraint is included. Its purpose is to prevent the algorithm to suggest M&R plans with two consecutive interventions with significant improvements on the pavement. Specifically, it was defined that M&R with ID code from 3 to 10 (refer to Table 4.15), inclusive, could not take place in two consecutive years in the same pavement section. On the other hand, the occurrence of crack sealing, shot blasting and superficial treatments in consecutive years is allowed in the algorithm.

The rehabilitation constraint was added through a penalty function that penalizes the objectives fitness, as it proved to be effective after several trials in comparison with other alternatives.

5.6.2 Effects of considering user and CO2 emissions costs

The main goal of this subsection is to understand how the consideration of a third objective can influence the search of solutions. The objective function to be added is related to the use phase of the road, comprising user and environmental costs, named as society costs if considered together, as presented in Subsection 5.2.3. These depend on the evolution of PI_E, so it is relevant to analyse the importance of including it in the

search for optimal solutions by the optimization methodology. In fact, the pavement quality is related to PI_E, among others, but society costs as quantified in this thesis are only related to PI_E. The existence of M&R operations that improve only other PIs rather than the PI_E supports the possibility of considering society costs as a conflicting objective, because some M&R operations affect the pavement quality but not necessarily the pavement roughness (PI_E).

The results of optimizing the three objectives simultaneously are illustrated in Figure 5.28, considering the following inputs to define the problem:

- one pavement section of 1000 m length and 3.5 m wide;
- analysis period of 20 years;
- initial CS of all PIs = CS_2;
- discount rate = 2.5%;
- CO_2e price = 8 €/ton;
- yearly kESAL = 250;
- percentage of heavy vehicles = 5%
- Markov parameter = Time.

The 3D plot (Figure 5.28 (a)) includes the fitness for all objectives while parts (b), (c) and (d) represent the different pairs of conflicting objectives. It is observed that several Pareto solutions in the three-dimensional scatter would not be part of the Pareto frontier in the two-dimensional scatters. There are, however, some visible trends, such as the fact of having better quality (lower $\int GPI$) and lesser society costs for higher administration costs. It is interesting to notice that some solutions with very different costs for administration represent similar society costs. Regarding the confrontation of the latter costs with pavement quality (Figure 5.28 (d)), there is a high dispersion of points, but a correlation is noticed, matching the expectation of having less environmental impacts for better pavement quality. However, there are solutions with similar values of $\int GPI$ representing significant differences in society costs.

Figure 5.29 shows solutions found when optimizing administration costs and pavement quality alone (bi-objective), or these two objectives and the society costs (three-objective). Regardless the consideration of other objectives, solutions for the three-objective optimization are mostly dominated by solutions of the bi-objective optimization, which is expected because the algorithm was dedicated to that aim only. However,

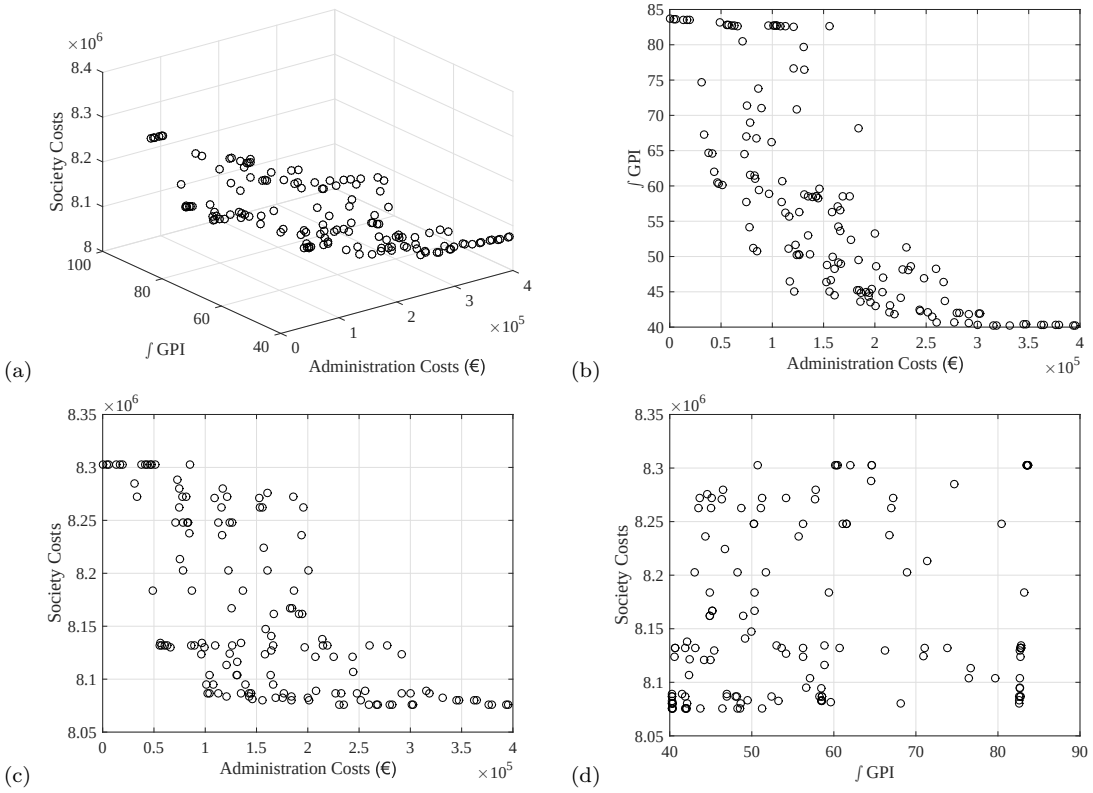


Figure 5.28: Results for the three objective problem

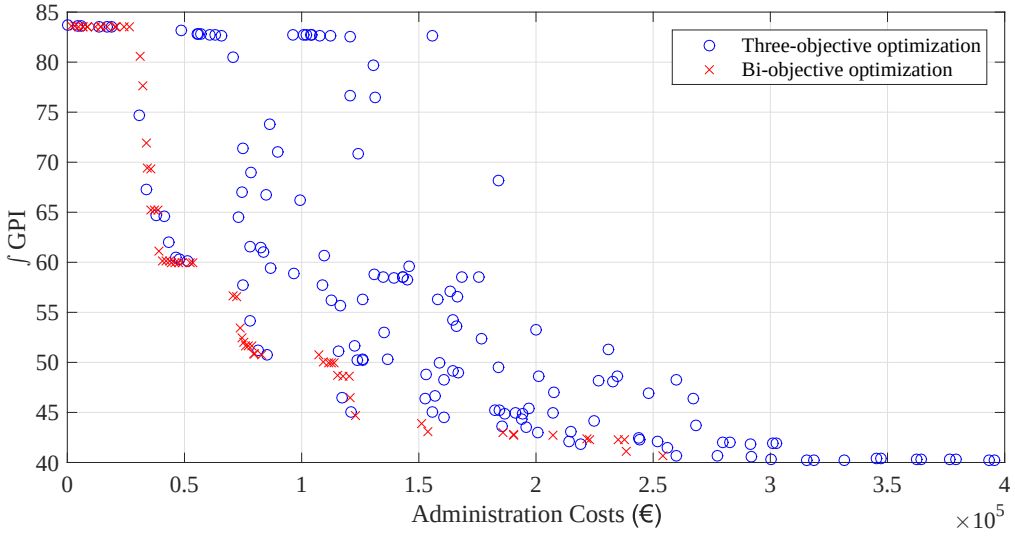


Figure 5.29: Results for two objectives *vs* three objectives problem

a significant increase of optimal solutions is noticed when the three objectives are considered, denoting the conflicting character between all of them.

User and environmental costs are related on the fuel consumption, thus depend on the traffic volume. If *Time* is the Markov parameter to define the pavement deteri-

oration, then society costs are proportional to the traffic volume. Nevertheless, the absolute amount of society cost does not influence the finding of optimal solutions, providing that this is considered as an independent objective. In other words, the minimization of society costs as a third objective results on the same optimal M&R plans regardless the amount of traffic. However, this statement is false if the deterioration process depends on the traffic, as it happens when the Markov parameter is *Traffic* or *Traffic/SN*. This not only influences the evolution of GPI, but also the evolution of PI_E and the consequent impacts on society costs. A demonstration of this fact is shown in Figures 5.30 and 5.31. Traffic 1 and 2 are defined by the number of kESAL passed each year in that section, as indicated in Table 5.2. These values are based on real data from two LTPP sections (1_4125 and 4_1003) that were part of historical data used to build the performance prediction models. If information about the annual average daily traffic (AADT) of all vehicles and all trucks is not available, a factor of 1146 is used to convert kESAL in the number of truck passed in the respective year, as this is the average value of all factors calculated with available information. Such assumption is used to simplify demonstration problems and does not interfere with their purpose. However, for more specific case studies, the real traffic distribution or a more specific correlation between kESAL and AADT is desirable.

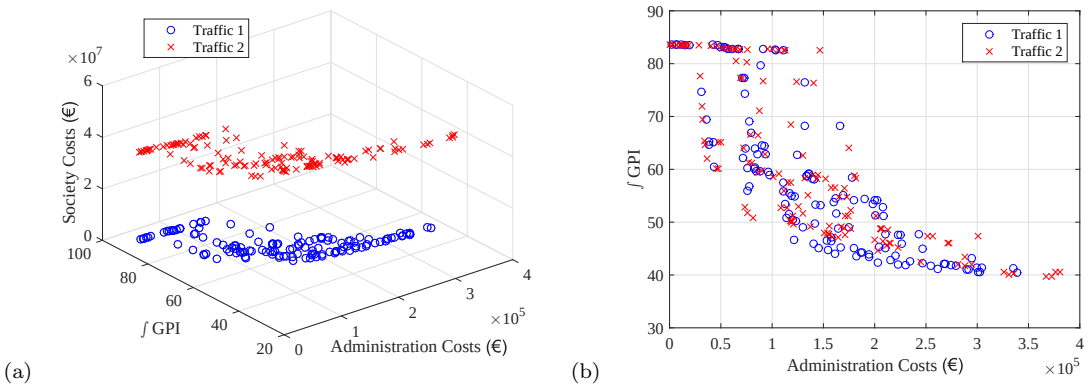


Figure 5.30: Results for three objective problem considering *Time* as Markov parameter: (a) three axis plot; (b) two axis plot

Figure 5.30 (b) shows similar solutions for sections with the same initial CS but different traffic volumes, meaning that similar M&R alternatives can be adopted for both. On the other hand, relevant differences of Pareto optimal solutions are evidenced in Figure 5.31 (b), when *Traffic* is used as the parameter to determine pavement deterioration. Obviously, both Figures 5.30 (a) and 5.31 (a) show a notorious gap in society costs for different traffic volumes.

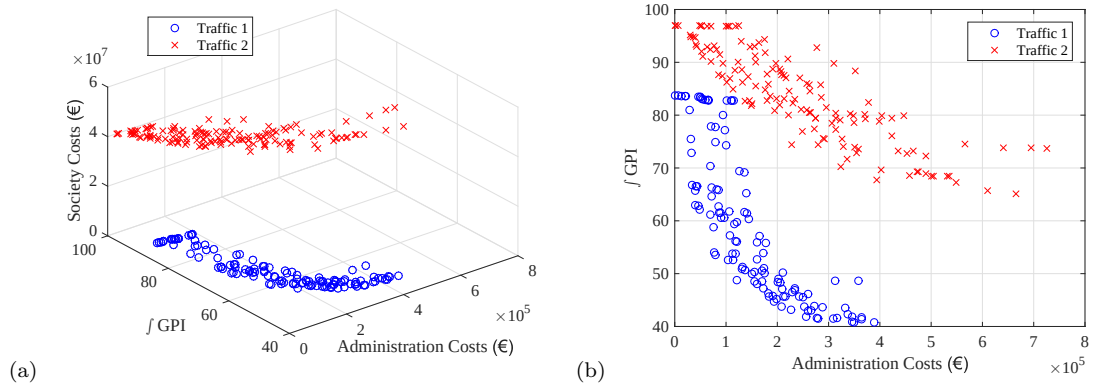


Figure 5.31: Results for three objective problem considering *Traffic* as Markov parameter: (a) three axis plot; (b) two axis plot

Table 5.2: Annual number of kESAL for Traffic 1 and Traffic 2

Year	1	2	3	4	5	6	7	8	9	10
Traffic 1	184	190	196	202	208	214	220	227	233	240
Traffic 2	1185	1250	900	960	1020	1080	1400	1300	1299	1386
Year	11	12	13	14	15	16	17	18	19	20
Traffic 1	248	255	263	271	279	287	296	305	314	323
Traffic 2	1530	1459	1387	1428	1241	1177	1294	1411	1528	1645

Conclusion

Figures above and respective comments demonstrated the importance of including a third objective related to user and environmental costs because these are conflicting with the pair of administration costs and pavement quality. It was concluded that for simultaneous optimizations of these objective functions, if *Time* is the only factor influencing pavement deterioration, then the distinction of traffic volumes is irrelevant because the search for optimal M&R plans does not depend on it.

The consideration of a third objective related to society costs can be made at the same level as other objective functions, as shown in Figure 5.28, or at different level as it will be further explained in Subsection 5.6.5.

5.6.3 Consideration of more than one pavement section

The optimization problems and results discussed until now regard only one pavement section. For a network level management, several sections must be considered in the same analysis. The division of a network into sections can be made regarding the factors influencing its deterioration and/or the importance of that road segment for

the society, for instance. In addition, for management purposes, a section might be defined according to the minimum length for which is reasonable to apply most of the M&R operations.

Considering the methodology developed in this thesis, pavement sections might differ by the initial condition state, traffic and structure (defined by the structural number), representing different deterioration curves and costs for society. Thus, the optimization methodology must be capable of considering different sections independently. Despite that, the road administration is the same and so are the financial constraints and objectives. Therefore, two approaches are proposed to solve a multi-section optimization problem:

- Approach 1: to minimize overall administration costs (C_A) and maximize the pavement quality for the network as a whole, i.e., to solve objective functions 5.22 and 5.23;
- Approach 2: to minimize overall administration costs and maximize the pavement quality of each section individually, i.e., to solve objective function 5.22 and objective function 5.24 for each section i.

$$f = min\ C_A = min \sum_{t=0}^{T} \frac{C_{A,t}}{(1+d)^t} \tag{5.22}$$

$$f = min \sum_{i=1}^{n} \int_0^t GPI_i \tag{5.23}$$

$$f_i = min \int_0^t GPI_i,\ i = 1, ..., n \tag{5.24}$$

where n is the number of pavement sections.

The consideration of several sections increases the number of decision variables in a proportion equal to the number of years per each additional section, i.e., $no.\ of\ variables = no.\ sections * no.\ years$. Consequently, the possible M&R alternative plans also increase significantly. Therefore, the necessity of using bigger population size for GA emerged in order to assure that solutions would not lose much of optimality. Some simulations were performed for a two section problem for a 20 years period, using population size of 200 (default), 400 and 800. Figures 5.32 and 5.33 illustrate the results for approach 1 and approach 2, respectively. As expected, the bigger the population is, the higher is the processing time for optimization and the number of solutions provided, as indicated in Table 5.3.

In approach 1, the fitness of solutions is similar regardless of the population size and, surprisingly, the MOGA with 200 individuals could find several solutions which

Table 5.3: Number of solutions and processing time for MOGA with different population sizes

Population size	Approach 1		Approach 2	
	No. of solutions	Processing time (minutes)	No. of solutions	Processing time (minutes)
200	90	92	127	89
400	159	185	230	197
800	233	354	402	565

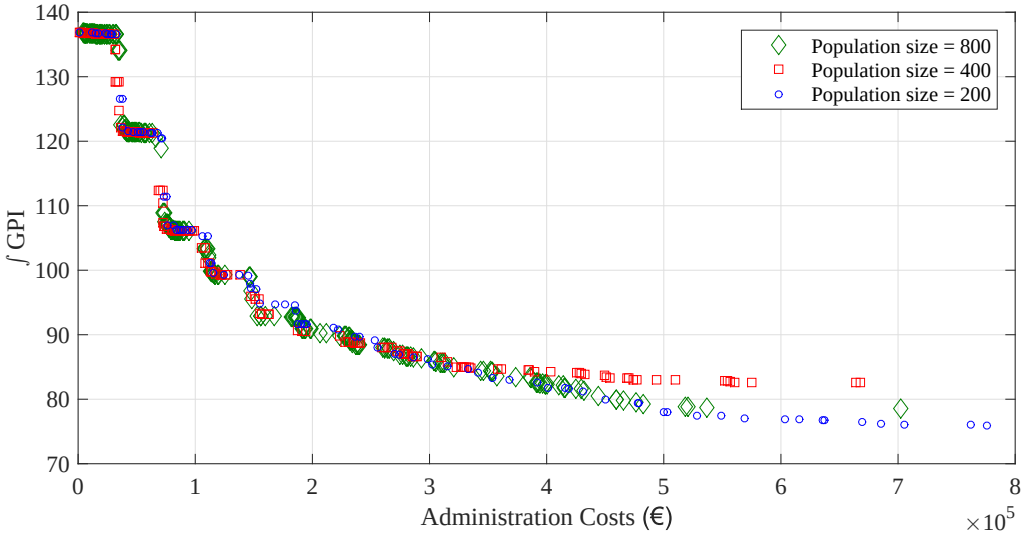


Figure 5.32: Approach 1 considering different population sizes.

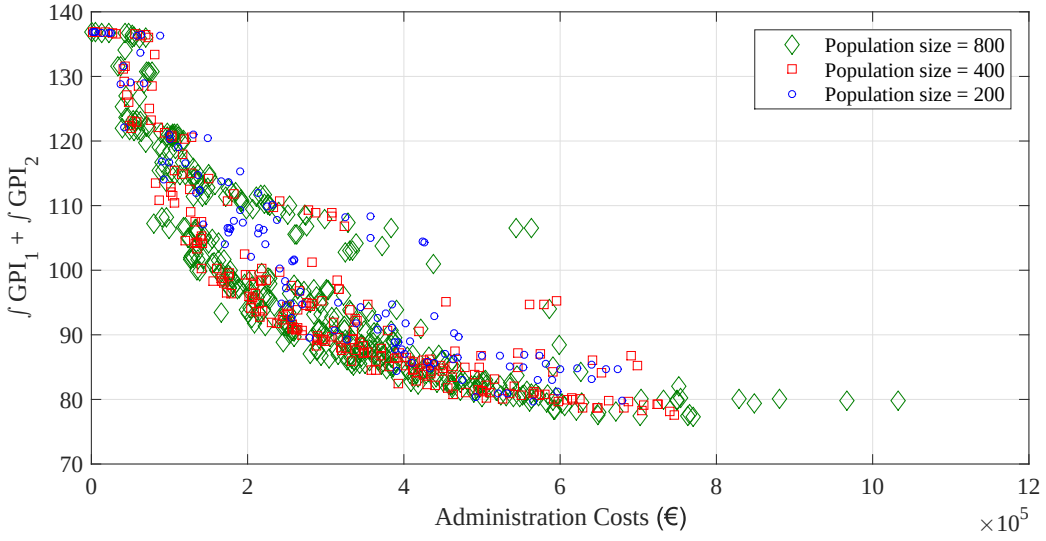


Figure 5.33: Approach 2 considering different population sizes.

are non-dominated when compared with those given by MOGA with 400 and 800 individuals. On the other hand, population size seems to have a positive influence in approach 2, since most of the non-dominated solutions are given when a population of 800 individuals is used. It must be noted that Figure 5.33 does not show Pareto frontiers because the optimization is actually done for three objective functions: administration costs, quality of section 1 and quality of section 2, so that a Pareto frontier would be only visible in a three dimensional scatter. A comparison of both approaches must then be made with regard to the quality of all network and to the quality for each section, as seen in Figures 5.34 and 5.35. Approach 1 is represented with results from MOGA of 200 individuals while results for approach 2 are from MOGA with 800 individuals.

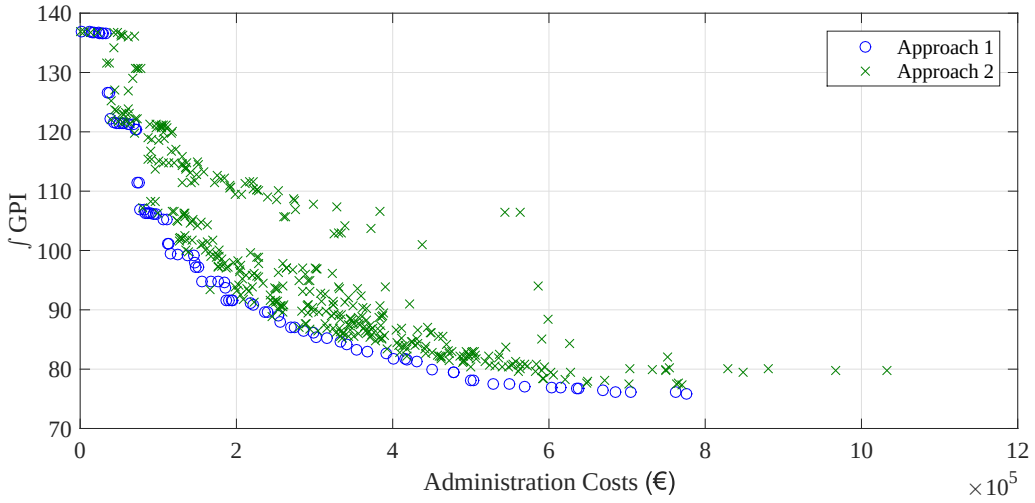


Figure 5.34: Comparison of approach 1 with 2 considering network as a whole

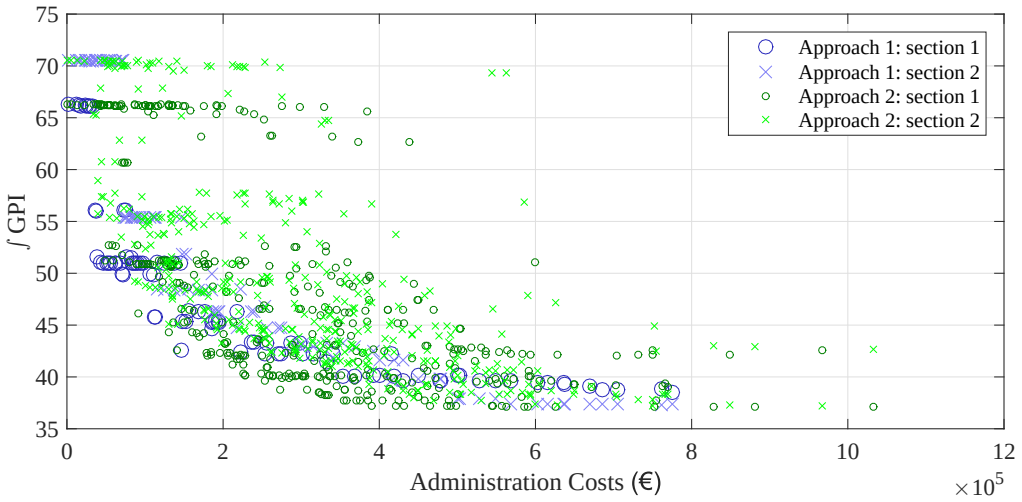


Figure 5.35: Comparison of approach 1 with 2 considering all sections individually

It is clearly depicted from Figure 5.34 that approach 1 has the best performance if the quality is quantified for the network, as a sum of each section $\int GPI$. In fact, the illustrated axes in the Figure are coincident with the objective functions that were optimized. From Figure 5.35 it is concluded that approach 2 provides solutions that result in higher differences between the quality of both sections, in opposition to approach 1. If section 1 is considered alone, solutions with the best quality are mostly provided by approach 2. However, those correspond to worst quality of section 2. This kind of situation might be acceptable for a PMS if two sections highly differ in their importance for the network or on the amount of traffic and have different quality demands. Normally it is desirable to have similar quality among the sections of a whole network, so in that situation approach 1 is preferable.

Conclusion

There are some drawbacks of considering all sections at the same optimization run due to the proportional increase of variables and, consequently, the considerable rise of computational cost/time. For dozens of sections, the population size would certainly need to be increased and results would potentially loose optimality. Looking for avoiding these concerns, a two-stage approach is proposed and assessed in the next subsection.

5.6.4 Two-stage multi-objective optimization approach

The optimization of preservation scheduling becomes significantly is more complex as the number of pavement sections in a road network increases. In fact, the capability of simultaneously optimizing large road networks is limited by the capacity of the existing optimization software and hardware to tackle extremely high computational demands. The optimization of a complex road network can be accomplished efficiently by decomposition, i.e., by dividing the optimization problem in more than one stage. In this subsection, a two-stage approach, partially developed in a journal paper (Denysiuk et al., 2017) is presented, in which the output of the first-stage serves as the input for the second-stage. It falls into a bottom-up methodology, as it progresses from a section to the whole system analysis.

The optimization of preservation schedules for each section constitutes the first-stage optimization task, so it is also referred as section-level optimization. Each obtained schedule must satisfy possible constraints imposed. The structure and interactions among various parts of the proposed methodology for the first stage are as previously presented in Figure 5.13, page 132. The outcome is a set of preservation schedules for a given pavement section that are optimal with respect to the performance

and preservation costs for administration. By applying a multi-objective optimization to each of the road pavement sections, a collection of sets is obtained that represents the optimal preservation plans for all the sections.

The sets obtained at the first-stage optimization are used as the input for preservation scheduling for the whole network, i.e., at second-stage optimization, or network-level optimization. Figure 5.36 shows the interactions among different parts of the developed methodology for the second stage. At this stage, preservation schedules for individual sections are combined through the optimization process considering network-level objectives and/or constraints. Each of the final solutions indicate a preservation schedule for each section.

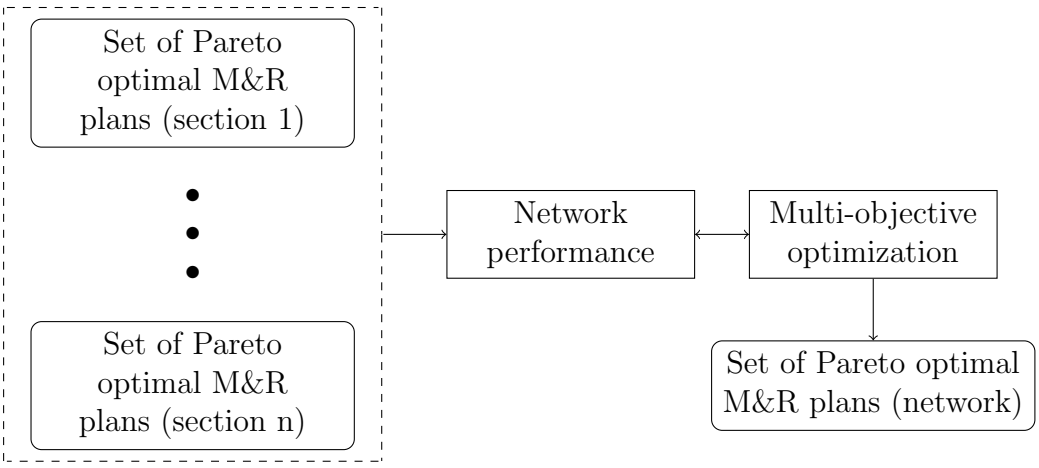


Figure 5.36: Flowchart of interactions among modules of second-stage optimization (adapted from Denysiuk et al. (2017))

In first-stage optimization, a solution is represented by a string of integers. Each integer indicates the M&R code (refer to Table 4.15), while the position in the string indicates the respective year to apply the M&R operation. The string length is equal to the number of years for the analysis period. For instance, a string [1 5 1 1 2 1 1 4 1 1] means that no action is taken in the first year, and M&R operation number 5 (milling ($\leq$ 5 cm) + tack coat + new surface course) is applied in the second year. Each string constitutes a line of a matrix comprising all Pareto solutions for that section, so that an index (the row number) is associated to a solution.

In the second-stage optimization, a solution for the network is represented by a string of integers with length equal to the number of sections encompassed. The position in the string corresponds to a specific pavement section in the network and each integer represents the index (row number) of the matrix with Pareto solutions for the respective section. As an example, the string [4 7 22 1 12 3 17] encodes that the forth solution of the Pareto set for section 1 must be used, while for section 2, it must be

the seventh solution of its corresponding Pareto set.

The pairs of conflicting objectives to be optimized at each stage can be defined by the decision maker, but goals and/or demands for each pavement section must be defined at the first-stage, while system-wide objectives are better addressed at the second-stage. In the problems to solve in this subsection, the first-stage optimization is intended to optimize the quality and administration costs for each pavement section. As for the second-stage, several pairs of objective functions are going to be used, in order to explore the capabilities of this approach, as indicated later on this section.

In the following examples used to demonstrate the applicability of the two-stage optimization, the Markov parameter in use is the *Time*.

First-stage optimization

The hypothetical network in consideration is divided in 10 sections of 1000m length and 3.5m width and they are distinguished by its initial condition state only, randomly defined, as indicated in Table 5.4. An optimization problem is solved for each section, according to the objective functions and constraints indicated in the group of equations 5.25 (Denysiuk et al., 2017), regardless of what is beyond and next to the pavement sections. The *a posteriori* handling technique is employed to control the constraints.

$$\begin{aligned} f_1 &= min \sum_{t=0}^{T} \frac{C_{A,t}}{(1+d)^t} \\ f_2 &= min \int_0^t GPI \\ PI_B &\leq 3 \\ PI_CR &\leq 3 \\ PI_E &\leq 4 \\ PI_F &\leq 4 \\ PI_R &\leq 4 \end{aligned} \tag{5.25}$$

Ten Pareto sets are then provided and represent the input for the second-stage optimization. For illustration purposes, Figure 5.37 shows the feasible Pareto solutions for section 1, 2 and 3. The differences on the initial condition clearly change the combination of administration costs and overall quality that can be obtained for each section. For instance, most of M&R alternative plans for section 1 are more expensive than for section 3 because the former is closer to overpass the constraints than the latter. More specifically, the fact of having PI_CR in CS_2 for section 1 is a significant difference

Table 5.4: Initial condition of pavement sections to be used in the examples of two-stage optimization approach

Pavement section	PI_B	PI_CR	PI_E	PI_F	PI_R
1	1	2	2	1	1
2	2	1	2	1	2
3	1	1	1	1	1
4	1	2	2	3	1
5	2	2	2	2	2
6	2	2	1	2	1
7	1	1	1	3	1
8	2	3	3	2	2
9	2	3	2	3	2
10	1	2	1	2	1

to define feasible M&R plans, as this PI has fast deterioration. Ultimately, some trend of having closer values of $\int GPI$ among the sections as the administration costs increase is noticed, which is plausible due to the several pavement quality improvements that take place in all sections.

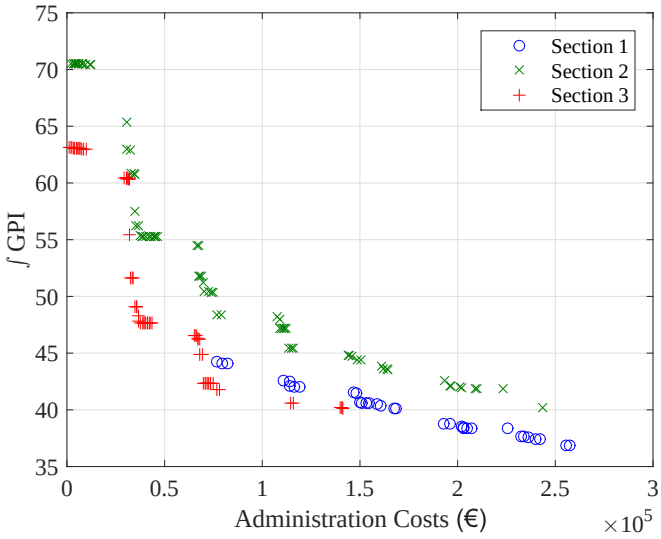


Figure 5.37: Pareto frontiers for section 1, 2 and 3

Second-stage objectives: pavement quality and total administration costs

The objective functions considered in this case are similar to those optimized at section-level, but with regard to the whole network, as indicated by the pair of equations

in 5.26:

$$f_1 = min \sum_{i=1}^{s} C_{A,i}$$
$$f_2 = min \sum_{i=1}^{s} \int_{t=0}^{T} GPI_i \tag{5.26}$$

where $C_{A,i}$ is the total cost for administration allocated to section i for the analysis period T and s is the number of sections. These are, in fact, coincident with the objectives considered in Subsection 5.6.3, then defined by Equations 5.22 and 5.23.

Figure 5.38 depicts the Pareto optimal solutions obtained by the two-stage optimization approach for this particular case. The cheapest solution (solution A) to maintain

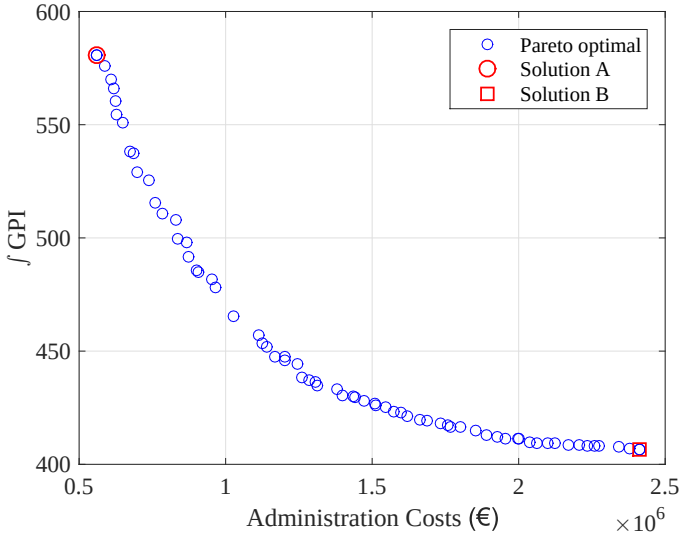


Figure 5.38: Pareto optimal solutions for the network obtained by the two-stage approach considering pavement quality and administration costs as objectives

the network within acceptable levels of pavement performance costs 558 735 € to the administration (net present value) and corresponds to a global performance ($\int GPI$) of 581, while the solution maximizing the pavement performance correspond to a $\int GPI$ of 406 and costs 2 410 979 € (solution B). With regard to the first-stage Pareto solutions presented for the first three sections in Figure 5.37, solution A selected the 1st section-level solution for sections 1, 2 and 3, while solution B selected the 33th, the 51th and the 64th for sections 1, 2 and 3 respectively. Note that the numeration of section-level solutions is ordered from the left to the right, i.e., from the less to the most expensive.

A comparison of results obtained from the two-stage approach with the simultaneously optimization (single-stage approach) of all the network as presented in Subsection 5.6.3 is illustrated in Figure 5.39, regardless the imposition of constraints. The

number of variables to be considered at the same time for the single-stage approach was equal to 200 ($20 years * 10 sections$). Thus, a population of 2000 was chosen to run the GA. As for the two-stage approach, default GA options as indicated in subsection 5.5.1, page 133, were used for the first and the second-stage optimization. It is observed that the majority of non-dominated solutions are provided by the two-stage approach, namely the more expensive M&R plans that result in lower quality if a single-stage approach is used. In fact, the dominance of single-stage solutions is only slightly noticed in the upper-left side of the Pareto front, where most of the solutions are likely to be incompatible with *a posteriori* constraints. The processing times were 49.5 hours and 11.9 hours for the single-stage and two-stage approach, respectively. In case of networks with more sections to be considered, the former approach efficiency and processing time highly depends on the population size to be chosen, whereas the processing time of the latter approach is proportional to the number of sections and its efficiency is not compromised, since optimal results are calculated per section as well. In conclusion, the two-stage approach is the best choice for optimization when several sections are considered.

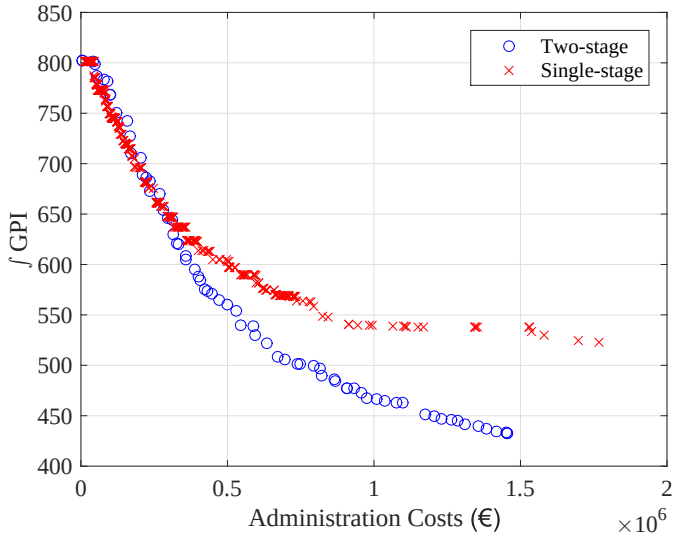


Figure 5.39: Pareto optimal solutions for the network obtained by single-stage and two-stage approaches, considering administration costs and global performance as objectives

Second-stage objectives: balanced administration costs over the analysis period

Financial constraints for road administrations might refer to larger or shorter time spans. Furthermore, it is reasonable for administrations to have balanced expenses

along the years, i.e., to have a distribution of yearly expenses as equal as possible. Therefore, minimizing the variation of administration costs and its total can be a pair of functions to consider at the second-stage optimization, formally defined as follows:

$$\begin{aligned} f_1 &= min \sum_{i=1}^{s} C_{A,i} \\ f_2 &= min \sqrt{\frac{1}{T}\sum_{t=1}^{T}(C_{A,t} - \overline{C_A})^2} \end{aligned} \tag{5.27}$$

where $\overline{C_A}$ is the average of administration costs over the analysis period T, so that f_2 corresponds to minimize the standard deviation of administration costs along T.

Results are shown in Figure 5.40, evidencing that the two objectives are conflicting. A reduction in variation of annual costs results in more expensive M&R strategies, so that a trade-off should be accepted regarding the financing model of the administration. Three solutions are highlighted from the Pareto frontier, corresponding to extreme solutions (A and B) and an intermediate solution (C) manually chosen, due to the fact that the next Pareto solution would represent much higher cumulative costs for just a slight decrease in the annual variation of costs.

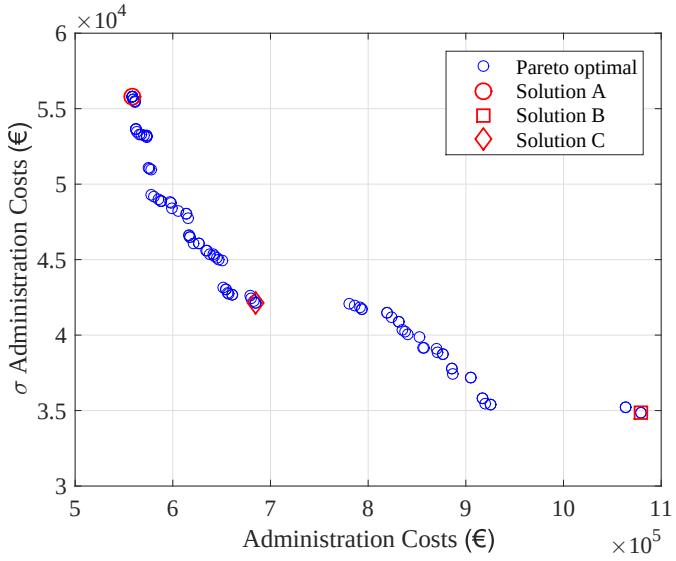


Figure 5.40: Pareto optimal solutions for the network obtained by the second-stage optimization considering variation of administration annual costs and total administration and its total as objectives

Figure 5.41 indicate the distribution of annual costs to be spent in the network preservation. It is clearly observed the differences in annual spendings for solution A. They diminish for solutions C and B, although the cumulative costs increase. The

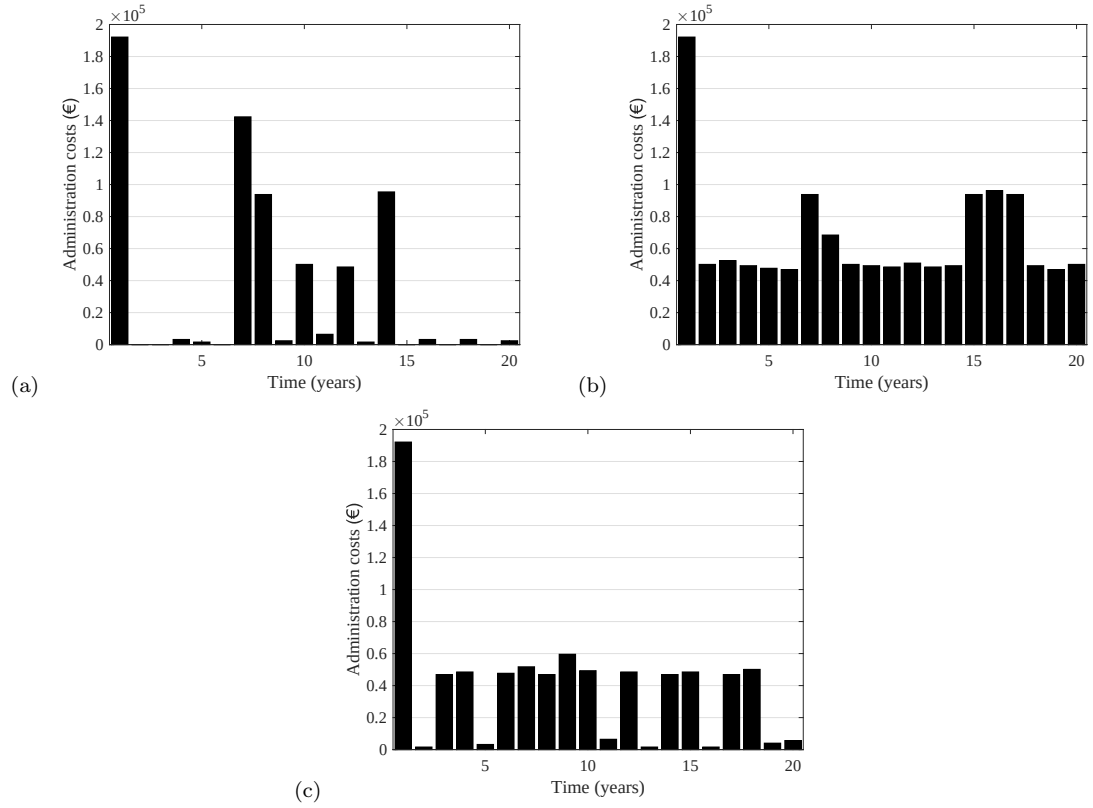


Figure 5.41: Annual costs for solutions highlighted in Figure 5.40: (a) solution A; (b) solution B; (c) solution C

spending in the first year is the same for all M&R strategies, because the imposition of constraints demand the occurrence of M&R operations in some sections in order to respect quality demands in the next years.

Several solutions suggest preservation strategies with significant M&R operations occurring every year in the network. Even though the occurrence of operations in consecutive years is constrained at the section-level, such imposition is not made at the network-level. However, it might be of interest for road administrations to avoid mobilizing maintenance equipment and teams every year for different sections, namely if these are close to each other. Furthermore, the traffic disruption due to M&R works are not desirable to happen so often in nearby locations to avoid increasing user costs and eventual penalties that administrations might suffer because of that. In fact, the rehabilitation constraint was not included at the second-stage optimization because a preservation scheduling problem might consider several hundreds of pavement sections which are actually far from each other and might have other seasonal restrictions that should be addressed at a project-level analysis. Nevertheless, a suggestion to avoid having M&R works every year fo nearby sections is addressed in the hypothetical example of next subsection (5.6.5).

Second-stage objectives: balanced performance levels over the network for each year

Besides the importance of having pavement sections with good quality during the analysis period, it is additionally desirable to maintain a network with similar levels of performance along all sections in the same time frame. This can be achieved by minimizing the standard deviation of sections' GPI in each year. Ultimately, the variation over the analysis period can be determined by its average value, as formally indicated in the group of Equations 5.28,

$$\begin{aligned} f_1 &= min \sum_{i=1}^{s} C_{A,i} \\ f_2 &= min \frac{1}{T} \sum_{t=1}^{T} \sigma_t^{GPI} \end{aligned} \tag{5.28}$$

where σ_t^{GPI} is the standard deviation of the GPIs of pavement sections for year t, and is calculated by Equation 5.29,

$$\sigma_t^{GPI} = \sqrt{\frac{1}{s} \sum_{i=1}^{s} (GPI_t^i - \overline{GPI_t})^2} \tag{5.29}$$

where s is the number of sections, GPI_t^i is the global performance indicator value of the i^{th} section in year t and $\overline{GPI_t}$ is the mean of GPI values of all sections in the t^{th} year. Pareto optimal solutions for the problem defined by the Equations above are shown in Figure 5.42.

As they proved to be conflicting objectives, the election of a solution demands the trade-off among them, adjusting preferences to the uniformity of pavement performance and to total administration costs. Solutions representing extreme preferences are highlighted as solution A and B. The former results in more variance performance among sections and worst quality (i.e., higher GPI values), when compared to solution B, as observed in Figure 5.43 (a) and (b). An intermediate solution (C) is chosen for a middle value of the average σGPI_t. It is noticed that slighter variations of sections quality happen for lower GPIs which demand higher costs for administration. Indeed, to maintain similar performance among all the sections, at first, those with the worst condition would be submitted to significant preservation actions to reduce their GPI and, afterwards, such scenario would require frequent M&R operations for the whole network. From the road user perspective, an equality of quality among nearby sections in the same network is relevant in defining driver's expectations regarding comfort and

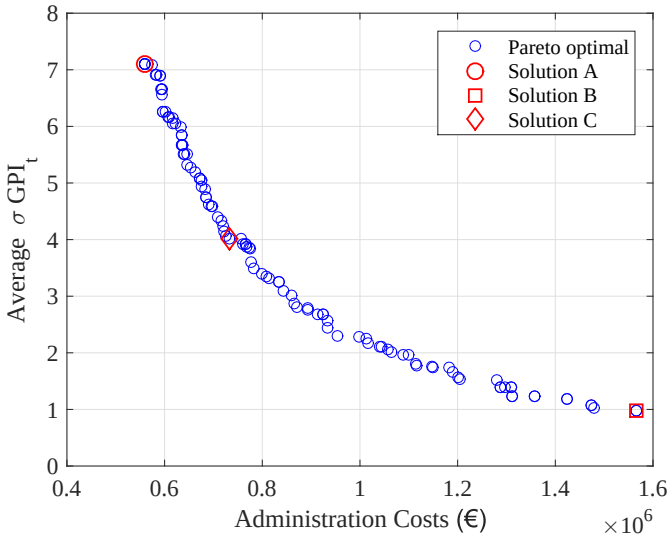


Figure 5.42: Pareto optimal solutions for the network obtained by the second-stage optimization considering variation of GPI and total administration costs

safety conditions. The consequences of defrauding drivers expectations in terms of pavement quality are hard, if not impossible, to quantify, but they certainly play an important role in matters of road safety, namely in the presence of adverse conditions such as rain or snow.

Conclusions

Besides the aforementioned examples, a variety of different pairs of objectives can be defined, either at the first or at the second-stage level. Although changing objectives at the first-stage might require longer computational effort that can take several days if many sections are considered, once these are solved, it is easy and fast to test different objectives for the second-stage optimization, so that a decision maker can balance several goals for the network, administration and other stakeholders of road pavements, such as car drivers, for instance. A case study with several stakeholders is demonstrated in the next subsection (5.6.5).

Experimental results as the one illustrated in Figure 5.39 suggest than preservation strategies obtained by the two-stage approach result in solutions closer to the real optimal than those given by the single-stage approach.

To summarize, the two-stage approach appears to be useful to define preservation strategies according to a variety of criteria by coordinating preferences among objectives at different levels of optimization.

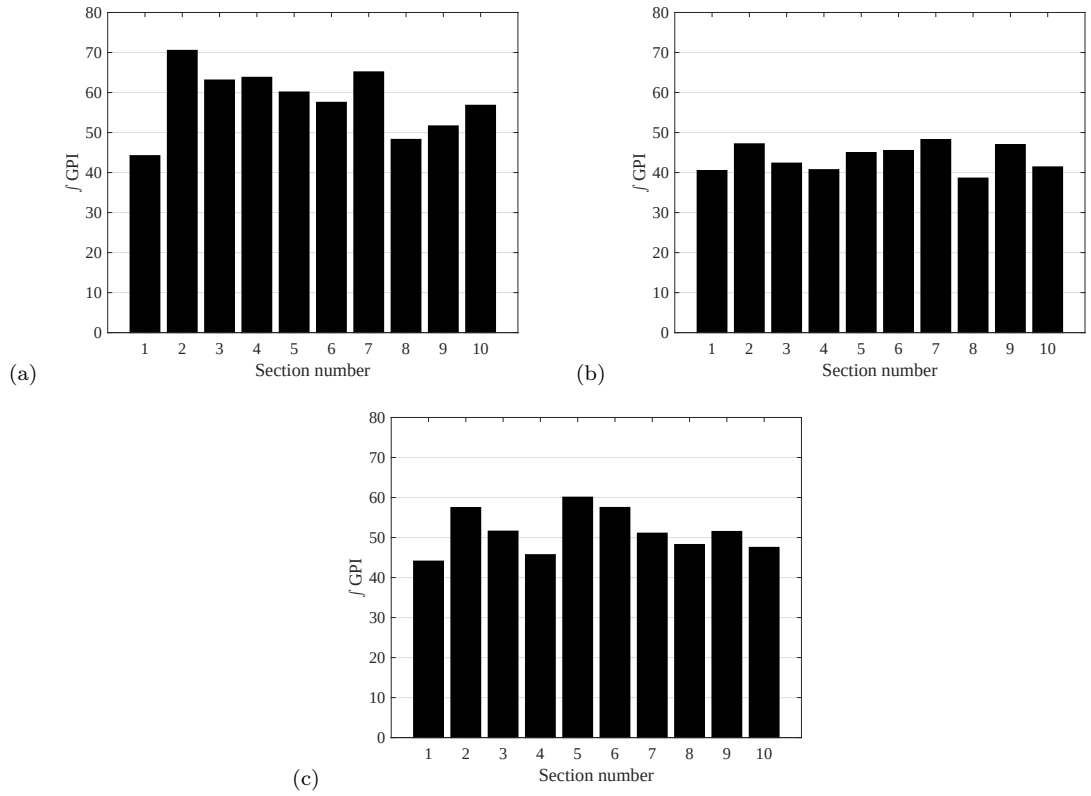


Figure 5.43: $\int GPI$ for the analysis period for each pavement section, regarding the solutions highlighted in Figure 5.42: (a) solution A; (b) solution B; (c) solution C

5.6.5 Coordination of society and agency costs

In the previous subsection, different pairs of objective functions were considered, but all related to administration costs and pavement quality, which are the most common concerns of road administrations and, thus, those which actually influence decision makers. In Subsection 5.6.2, the influence that user and environmental costs could have in decision making was demonstrated, however when these are considered, the optimal solutions are often unpractical to be accepted by road administrations, given the dominating share of user costs in the life-cycle costs (Moreira et al., 2017a,b).

The two-stage approach is an interesting approach to work around this issue, as it allows the prioritization of objectives and constraints. In fact, if user and/or environmental costs are considered only at the second-stage, it is assured that all the resulting solutions comply with optimal trade-off between first-level objectives and respect imposed constraints, such as pavement section quality and possible maximum budgets to be allocated for each section.

The consideration of user and/or environmental costs alone or summed up as society costs depends on the financial framework of a specific community or nation and

on the business model of road administrations and its interaction with governments. Nevertheless, expenditures on fuel affect almost all the population of economically developed countries, and carbon taxes or fees are ultimately reflecting environmental consequences that affects everyone. For these reasons, the M&R optimization problems to address in the present subsection consider society costs as an objective function, although the developed methodology is capable of considering user or environmental costs individually.

Case study

The present case study intends to demonstrate the applicability of the two-stage approach in considering society costs in a practical way, and consists in the same hypothetical road network mentioned in the previous subsection, with ten pavement sections of a kilometer length and initial condition states as indicated in Table 5.4, page 155. Objectives and constraints at the first-stage optimization are also the same, indicated below in the group of equations 5.30. The Markov parameter in use is *Time*.

$$\begin{aligned} f_1 &= min \sum_{t=0}^{T} \frac{C_{A,t}}{(1+d)^t} \\ f_2 &= min \int_0^t GPI \\ PI_B &\leq 3 \\ PI_CR &\leq 3 \\ PI_E &\leq 4 \\ PI_F &\leq 4 \\ PI_R &\leq 4 \end{aligned} \tag{5.30}$$

As for the second-stage optimization, the conflicting objectives to be minimized are administration costs (C_A) and society costs (C_S), as defined in 5.31.

$$\begin{aligned} f_1 &= min \sum_{i=1}^{s} C_{A,i} \\ f_2 &= min \sum_{i=1}^{s} C_{S,i} \end{aligned} \tag{5.31}$$

Traffic data of section 26_1013 of the LTPP database was used as the traffic for all the sections. This was a random choice providing that the traffic volumes would not be exaggeratedly low nor high in comparison with the majority of sections. Table 5.5

summarizes the yearly traffic in terms of kESAL and average annual daily traffic AADT of trucks and all vehicles.

Table 5.5: Characterization of traffic for section 26_1013

Year	1	2	3*	4*	5*	6*	7*	8*	9*	10
kESAL	254	261	269	277	285	294	303	312	321	330
AADT trucks	693	714	735	757	780	804	828	853	878	904
AADT all vehicles	6795	6999	7209	7425	7648	7877	8114	8357	8608	8866
Year	11	12	13*	14*	15*	16*	17*	18*	19*	20*
kESAL	340	350	361	371	382	394	406	418	430	443
AADT trucks	931	959	988	1017	1048	1079	1112	1145	1179	1215
AADT all vehicles	9132	9406	9688	9979	10278	10587	10904	11231	11568	11915

* Values for these years were estimated considering an yearly traffic increase of 3%.

For illustration purposes, the feasible Pareto optimal solutions at a section-level for some pavement sections are shown in Figure 5.44. It is observed that there are less feasible solutions for section 6, while for sections 4 and 5, the region of higher administration costs is also populated with some solutions.

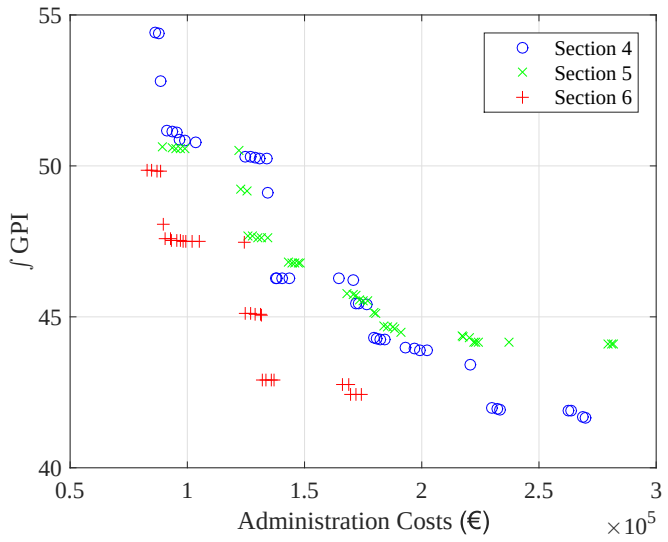


Figure 5.44: Feasible Pareto optimal solutions for section 4, 5 and 6

Regarding the second-stage optimization considering administration and society cost as the conflicting objectives, the Pareto optimal results are illustrated in Figure 5.45, where a true Pareto frontier is only seen in part (c) of the figure, with axis representing the objectives for which the solutions were optimized. As expected, the higher magnitude of society costs and the fact that its reduction demand more costs for administration can be noticed.

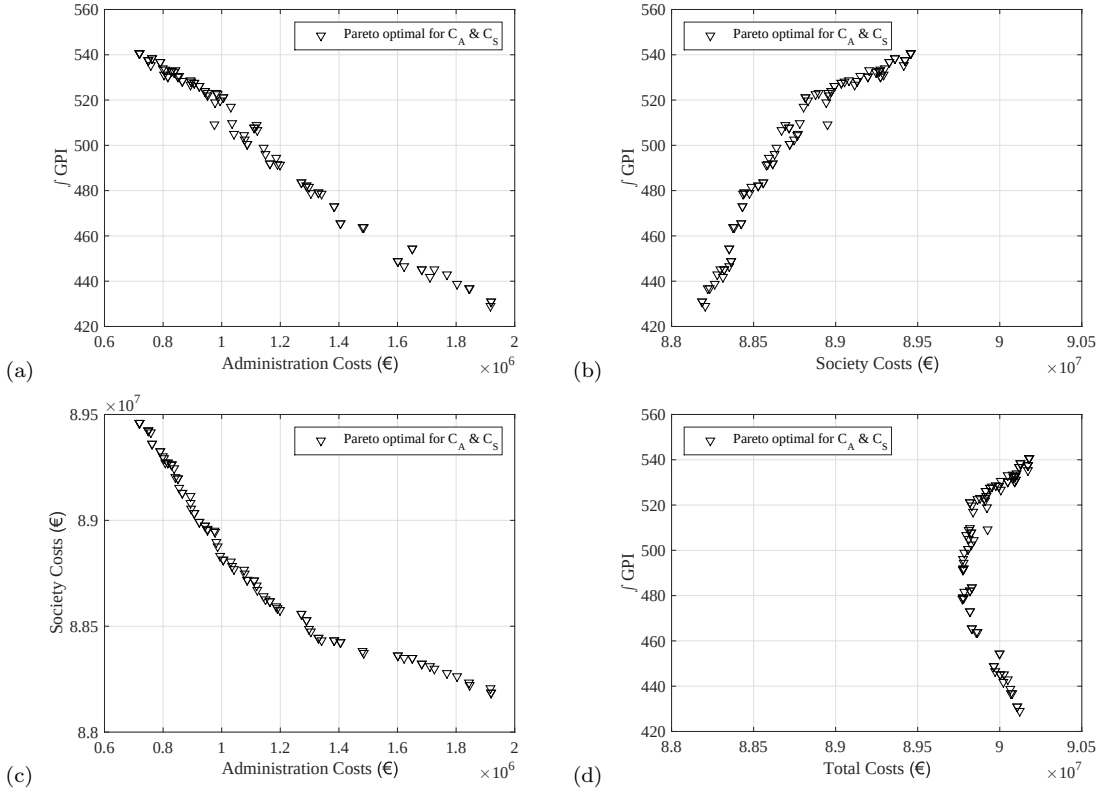


Figure 5.45: Pareto optimal solutions for the network obtained by the second-stage optimization considering C_A and C_S: (a) C_A and $\int GPI$ axis; (b) C_S and $\int GPI$ axis; (c) C_A and C_S axis; (d) T_C and $\int GPI$ axis

In Figures 5.45 (a) and (b), the expected trend of having higher C_A and lower C_S for lower $\int GPI$ (better pavement quality) is observed. It is worth noting, however, that similar C_A can correspond to different pavement quality and, in its turn, similar $\int GPI$ can result in a variety of C_S. Finally, part (d) of the figure represents the trade-off between pavement quality and total costs (C_T), which are the sum of society with administration costs, as formally indicated in Equation 5.32.

$$C_T = C_A + C_S \tag{5.32}$$

In this case, a curvature is noticed, meaning that C_T decreases with $\int GPI$ until a certain point where the improvement of pavement quality (reduction of $\int GPI$) actually results in increasing C_T. Such variance is better seen and detailed in Figure 5.46, where the solution with lower quality and administration costs is highlighted as the base set.

Starting from the base set to the following ones with lower $\int GPI$, the decrease of C_T is explained by the fact that C_S reduction is higher than C_A increase. In opposition, for better quality levels, the addition of C_A overpasses the reduction of C_S, so that C_T

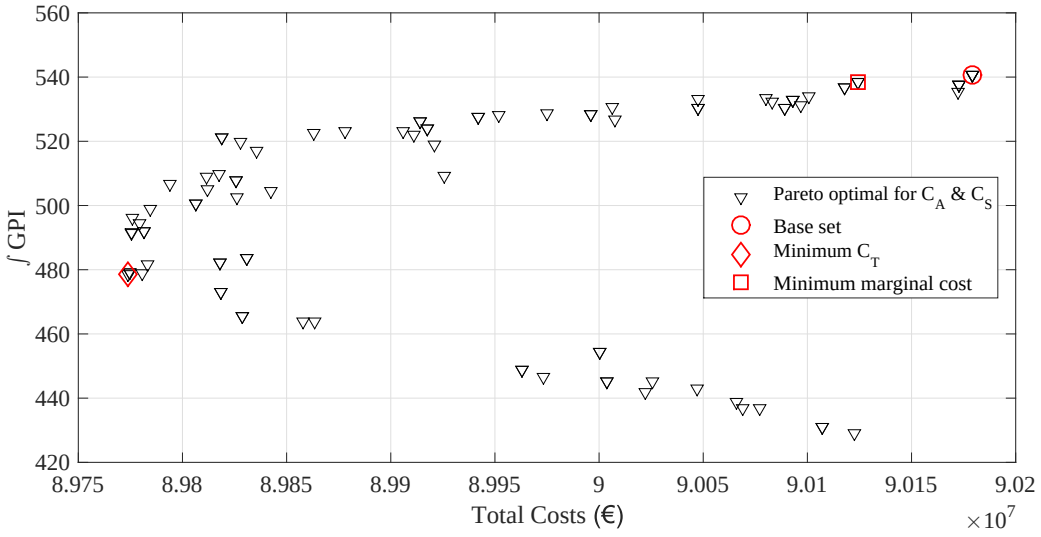


Figure 5.46: Pareto optimal solutions for the network obtained by the second-stage optimization considering C_A and C_S, plotted in T_C and $\int GPI$ axis

increase. Sets with similar C_T for different $\int GPI$ occur when the increase of C_A are about the same amount as the decrease of C_S. A graphical representation regarding this analysis is shown in Figure 5.47. For graphical and interpretation convenience, the differences of C_S are represented with its inverse values.

The lines illustrated in Figure 5.47 represent the difference between C_A, C_S and C_T of each set and the base set (set ID 1) values. This analysis is useful to understand the impact of choosing some set rather than the cheapest one for the highway administration. For the present case, all sets (from set 2 to 66) correspond to M&R strategies for which the increase of C_A is lower than the decrease of C_S. The maximum difference happens for set 50, where the reduction of C_T is maximum and its real value is the minimum. Other cases could provide optimal scenarios in which C_T of some sets could be higher than those of the base set.

Depending on the administration fund allocation system and on the existent mechanism of funding M&R costs, some scenarios can be pointed out from this case study:

- From a global perspective where all the costs are considered, any set within the administration budget and within the sets where the reduction of C_S is higher than the increase of C_A would be an acceptable option. The best option would be set 50, since it is the one that maximizes the difference between the decrease in C_S and the increase in C_A. Consequently, the decrease in C_T is also maximum. It is the most cost-effective option.

- For very limited budget, a good investment analysis is related to the marginal

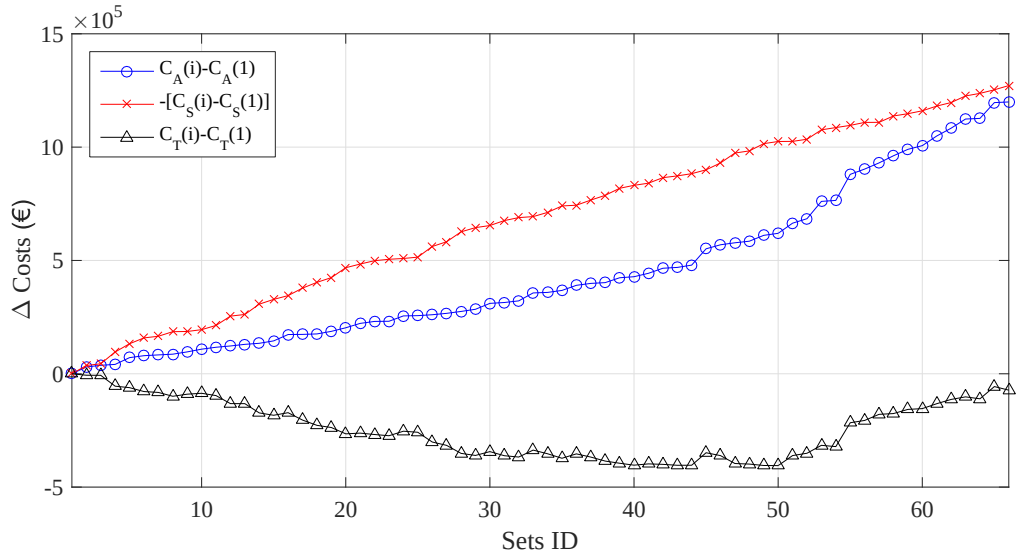


Figure 5.47: Variation of costs from base set

cost, so that the administration could look for a set that maximizes the benefit of an extra unitary investment in terms of C_S. For instance, the C_S reduction by choosing set number 4 instead of the base set, is 2.3 times higher than the increased amount of C_A. This is the set that minimizes the marginal cost, as it is observed in the graph of Figure 5.48.

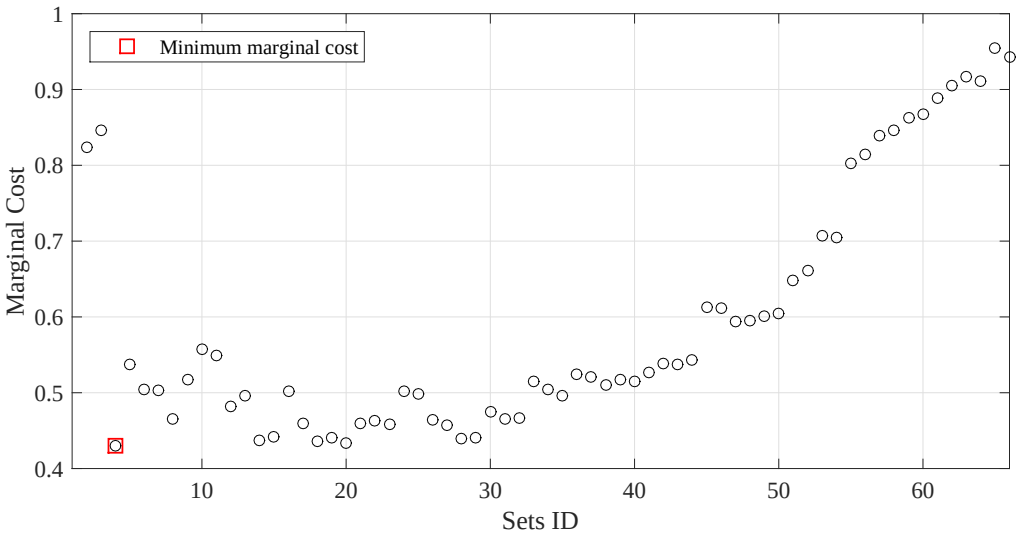


Figure 5.48: Marginal cost in terms of benefit for society costs

The exact values of costs and quality for the highlighted sets are indicated in Table 5.6. It is important to note that, providing the pavement section level Pareto-optimal solutions, different objective functions for the network level optimization could lead to

Table 5.6: Costs and $\int GPI$ values for the highlighted sets on Figure 5.46

	C_A (€)	C_S (€)	C_T (€)	$\int GPI$
Base set	720 162	89 459 037	90 179 199	540.7
Minimum CT	1 339 788	88 434 197	89 773 986	478.7
Minimum marginal cost	761 524	89 362 938	90 124 462	538.3

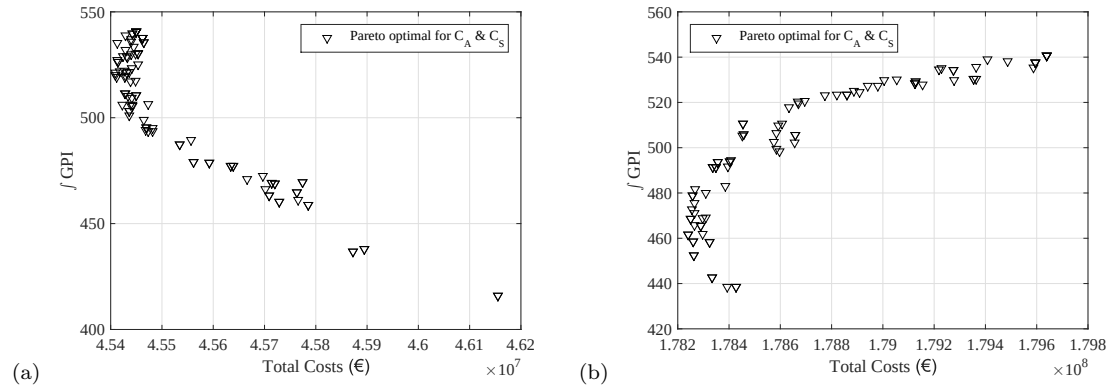


Figure 5.49: Pareto optimal solutions for the network obtained by the second-stage optimization considering C_A and C_S, plotted in C_T *vs* $\int GPI$ axis: (a) lower traffic volume; (b) higher traffic volume

even lower C_T. However, such optimization would not always guarantee a compromised balance of C_A and C_S. In fact, the minimization of total costs as a single-objective problem was experimented and resulted in a minimum of 89 748 686 €, corresponding to 1 172 571 €and 88 576 115 €for C_A and C_S respectively, with a pavement quality of 497.9 measured by the $\int GPI$. For the presented case, this solution can be part of the Pareto frontier shown in Figure 5.45 (c), so that it could consist in a potential choice for a decision maker.

In fact, the importance of administration and society costs in the decision making highly depends on the traffic affecting user costs and CO_2e emissions. The more the traffic is, the higher is the magnitude of society costs and thus its potential influence for the decision making process. Figures 5.49 (a) and (b) illustrate Pareto optimal results for different traffic levels, regarding administration and society costs, but plotted in C_T *vs* $\int GPI$ axis. Parts (a) and (b) correspond to lower and higher traffic volumes, respectively, when compared to the example of Table 5.5. It is observed for the lower traffic that a quality improvement increases C_T, because the costs for administration are more significant than the reduction of society costs, whereas for the higher traffic (Figure 5.49 (b)), society costs are much more significant, causing a reduction of C_T if pavement quality is improved.

Returning to the presented case study, the following paragraphs describe in more detail the preservation strategy defined by the solution of the minimum marginal cost, which could be an interesting choice for a decision maker to analyse more carefully. This solution consists in the network-level decision vector [1 1 1 1 1 1 1 4 1 2], meaning that all pavement sections would receive the M&R plan as defined in the 1st solution of their feasible set, except for section 8 and 10 that would be affected by the 4th and 2nd solution of the respective feasible set. For sections 4, 5 and 6, the elected solutions correspond to the most left solution illustrated in Figure 5.44, page 164. The M&R operations to be carried out in each section and year are indicated in Table 5.7, together with the quantification of costs and quality. The evolution of the pavement performance for section 5 is illustrated in Figure 5.50.

Table 5.7: M&R plan for the solution with minimum marginal cost

Year	Sections									
	1	2	3	4	5	6	7	8	9	10
0	1	1	1	1	1	1	1	4	4	1
1	2	1	1	1	1	1	1	1	1	1
2	1	2	1	1	1	1	1	1	2	1
3	2	1	1	1	1	1	1	1	1	1
4	1	2	1	1	4	1	1	2	2	1
5	1	1	1	1	1	1	1	1	1	1
6	1	1	1	4	1	4	1	1	2	4
7	4	1	1	1	1	1	1	4	1	1
8	1	1	1	1	1	1	1	1	2	1
9	2	1	1	1	1	1	1	1	2	1
10	1	1	1	2	1	1	4	1	1	1
11	1	1	1	1	4	1	1	3	4	1
12	1	1	1	1	1	1	1	1	1	1
13	4	1	1	4	1	1	1	4	2	1
14	1	1	2	1	1	1	1	1	1	4
15	1	1	1	1	1	1	1	1	2	1
16	1	1	1	1	1	4	1	1	1	1
17	1	1	1	1	1	1	1	1	2	1
18	2	2	1	1	1	2	1	1	2	1
19	1	1	1	1	1	1	1	2	1	1
$\int GPI$	44.2	70.3	63.1	54.4	50.6	49.9	63.8	43.0	50.6	48.3
C_A (€ x 10^3)	88.7	3.1	1.1	86.3	89.3	82.8	41.8	179.9	104.4	84.1
C_S (€ x 10^3)	8989	9033	8848	8989	9033	8848	8848	8893	9033	8848
C_T (€ x 10^3)	9078	9036	8849	9075	9123	8931	8890	9073	9138	8932

According to the M&R codes displayed on Table 5.7, there are several moments with application of crack sealing, in order to retard the increasing of PI_CR which is normally fast. In the first year, only sections 8 and 9 are submitted to a major M&R operation, an overlay on the surface course, explained by the fact of having some PIs achieving the imposed quality constraints. For the solution in analysis, this operation comprises the majority of the remaining operations for the network, besides crack sealing. The

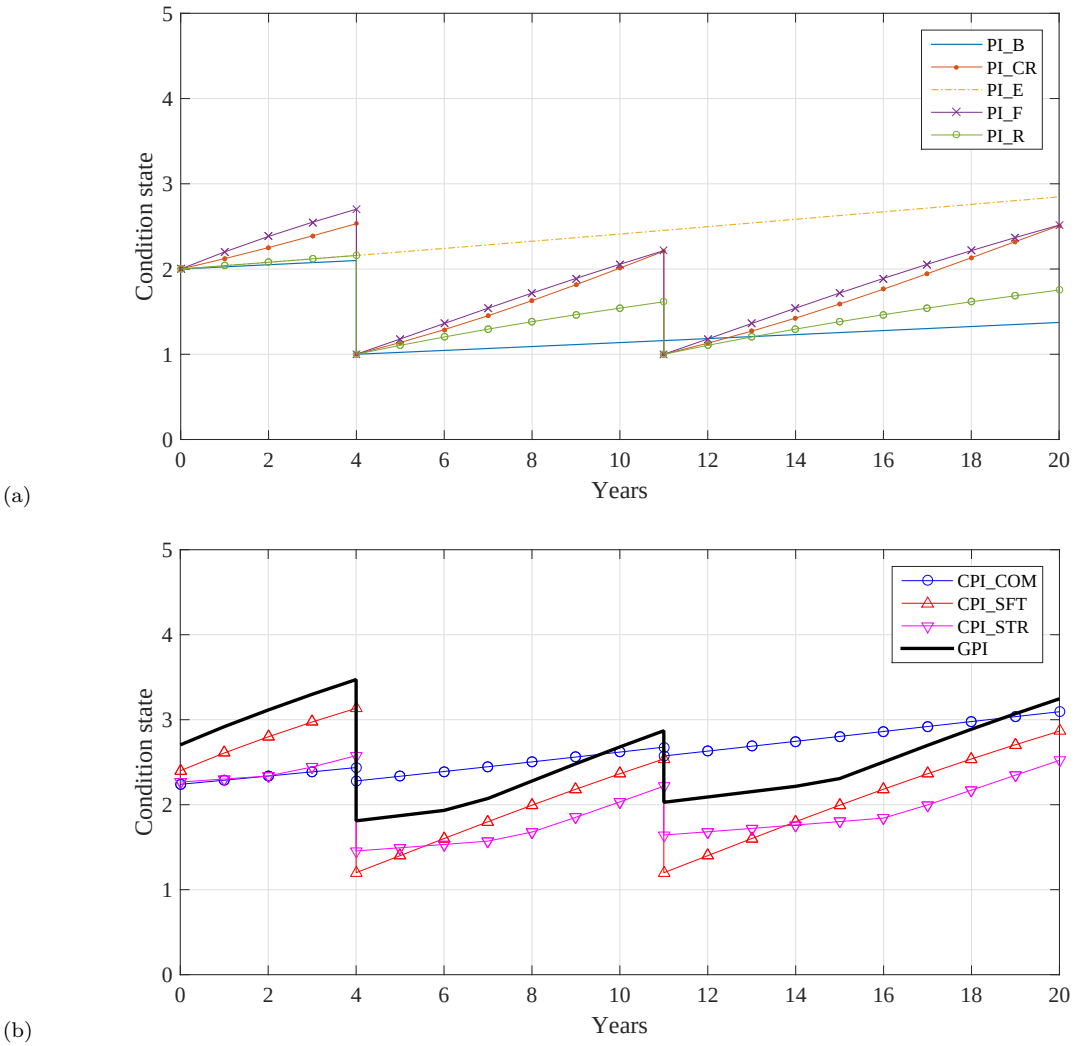


Figure 5.50: Evolution of pavement performance for section 5 subjected to the M&R strategy defined in Table 5.7: (a) PIs; (b) CPIs and GPI

exact layer types and respective thickness are defined at a project-level analysis, thus the associated costs might vary from those predicted at a network-level analysis. This uncertainty is addressed later in Subsection 5.6.6. The frequency of M&R is relatively low for several sections, namely those which have a very good condition at the beginning of the analysis period. In fact, the contemplated solution does not provide the best possible quality for the network as it could be noticed in Figure 5.46.

It is observed in Figure 5.50 (a) that all the PIs are below the maximum limits during the whole analysis period, being the year 4 and 20 the moments when the constraint for PI_CR is more close to be reached. A slow deterioration of bearing capacity and longitudinal roughness is noticed. Part (b) of the figure shows the evolution of combined and global indicators. A faster growing of CPI_SFT is generally noticed, which is

compatible with a fast reduction of friction as modelled by the Markov models, however it keeps always good or reasonable levels. The GPI is mostly between CS_2 and CS_3, achieving the worst value at the year 4. The illustrated graphs represent the most likely CS for each PI in each year. The uncertainty about it can be assessed using Monte Carlo simulations, which is addressed in Subsection 5.6.6.

For each pavement section, there are no consecutive years with major M&R operations, i.e., M&R with ID between 3 and 10, as imposed by the rehabilitation constraint presented in Subsection 5.6.1. However, there are consecutive years with major M&R operations within the network, in different sections. This fact can be undesirable because it might increase logistic and mobilization costs for road administrations, as well as disrupt the normal traffic flow more often in the same network. Besides causing inconveniences for users, thus increasing society costs, administrations might as well incur in additional costs as a consequence of disrupting normal traffic flow conditions.

A final analysis with possible modifications to the elected preservation plan for the network should then be performed. There are several aspects to account for herein, such as the administration business model, available self-resources of administration and dependence on subcontractors. Nevertheless, it is plausible to assume that neighbour pavement sections or those belonging to the same sub-network (or whichever is a smaller division of a specific road network) should not be subjected to major M&R operations in consecutive years. Hence, the dates of some operations should be modified in order to be compatible with all sections of the sub-network, providing that constraints are still respected.

Supposing the 10 sections of the case study are part of the same sub-network, Table 5.8 shows the modifications made to the original preservation plan in order to avoid the occurrence of major M&R operations in consecutive years. Two lines are used to indicate the M&R plan for each section. The first line is the original plan, while the second is the modified plan. M&R operations that were moved for a different year are highlighted on bold. For pavement sections 1, 5, 9 and 10, M&R 4 was anticipated one year, while for section 8, there was an anticipation of M&Rs 4 and 3. These are the most intuitive changes to do in order to respect the constraints, although other modifications could be preferred. A new verification of PIs evolution was performed in order to assure that all constraints are still respected. That proved to be true in the present case study. If that is not the case, then the modifications should be avoided and/or another potential solution should be analysed. The influence of modifying the M&R plan for the network is quantified in Table 5.9 and illustrated in Figure 5.51, where the average GPI for the network is plotted for both preservation plans. The modifications on the M&R strategy caused an anticipation in the improvement of PI_E,

Table 5.8: Modified M&R schedule for the solution with minimum marginal cost

Section	Year																			
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	2	1	2	1	1	1	**4**	1	2	1	1	1	4	1	1	1	1	2	1
1*	1	2	1	2	1	1	**4**	1	1	2	1	1	1	4	1	1	1	1	2	1
2	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
2	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1
4	1	1	1	1	1	1	4	1	1	1	2	1	1	4	1	1	1	1	1	1
4	1	1	1	1	1	1	4	1	1	1	2	1	1	4	1	1	1	1	1	1
5	1	1	1	1	4	1	1	1	1	1	1	**4**	1	1	1	1	1	1	1	1
5*	1	1	1	1	4	1	1	1	1	1	**4**	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1	4	1	2	1
6	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1	4	1	2	1
7	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1
8	4	1	1	1	2	1	1	**4**	1	1	1	**3**	1	4	1	1	1	1	1	2
8*	4	1	1	1	2	1	**4**	1	1	1	**3**	1	1	4	1	1	1	1	1	2
9	4	1	2	1	2	1	2	1	2	2	1	**4**	1	2	1	2	1	2	2	1
9*	4	1	2	1	2	1	2	1	2	2	**4**	1	1	2	1	2	1	2	2	1
10	1	1	1	1	1	1	4	1	1	1	1	1	1	1	**4**	1	1	1	1	1
10*	1	1	1	1	1	1	4	1	1	1	1	1	1	**4**	1	1	1	1	1	1

* Modified M&R plans.

Table 5.9: Comparison between original and modified preservation plan for the minimum marginal cost solution

	C_A (€)	C_S (€)	C_T (€)	$\int GPI$
Original plan	761 524	89 362 938	90 124 462	538.3
Modified plan	769 787	89 353 354	90 123 142	537.8

which decreased the rolling resistance and, consequently, fuel consumption. Therefore, society costs, as defined in this thesis, decreased from the original to the modified M&R plan. The difference in administration costs is caused by the fact of considering the discount rate which makes the same operation to represent lower NPV if applied later in time. In terms of quality, the sum of $\int GPI$ of all sections changed slightly, as it can be observed on the graph of average GPI (5.51).

As conclusion, the modified plan for the solution that minimizes the marginal cost seems to be a promising option for a decision maker to choose, but always bearing in mind the prediction uncertainty and optimization stochasticity. The next subsection presents a probabilistic and uncertainty analysis.

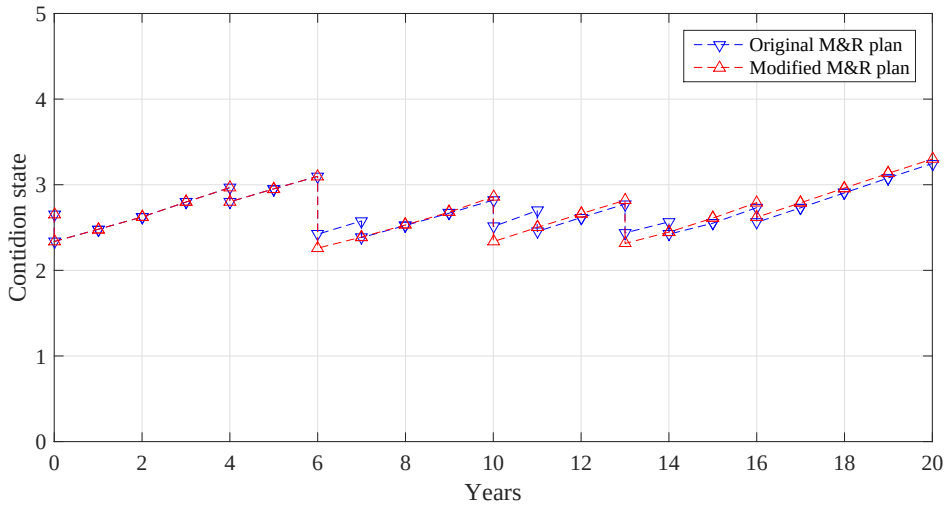


Figure 5.51: Evolution of network average GPI for the original and modified M&R plans

5.6.6 Probabilistic and uncertainty analysis

Having selected and redefined a preservation plan at the network level that is a potential final choice for a decision maker, it is important to assess the uncertainty of the predicted results, both in terms of pavement performance and administration costs. User and environmental costs are, by their nature, much more uncertain and harder to quantify and control. Furthermore, they are not part of constraints so the assessment of their uncertainty is not a priority for defining pavement preservation strategies. It is important to note, however, that a reasonable change on the price of fuel or CO_2e emissions could lead to significant changes at the second-level optimization.

Regarding pavement performance, the uncertainty on its quantification comes primarily from the prediction models, for their dependence on many factors that are unpredictable themselves. Additionally, there is no prediction model accounting for all the influential factors on pavement deterioration and the stochasticity is always present in the phenomenons that lead to deterioration. Therefore, probabilistic models were adopted in this thesis. Indeed, the pavement performance uncertainty is based on those probabilities.

As explained in Section 4.5, Monte Carlo simulations are used to impose stochasticity in the evolution of PIs. By generating hundreds or thousands of results for a specific plan of M&R operations to be applied in a pavement section, the chances of achieving different CSs can be determined. Consequently, the probability of failure, i.e., of violating constraints, can be calculated. As an example, for pavement section 5, Figure 5.52 illustrates the probability of PI_F being in each CS for each year during

the analysis period.

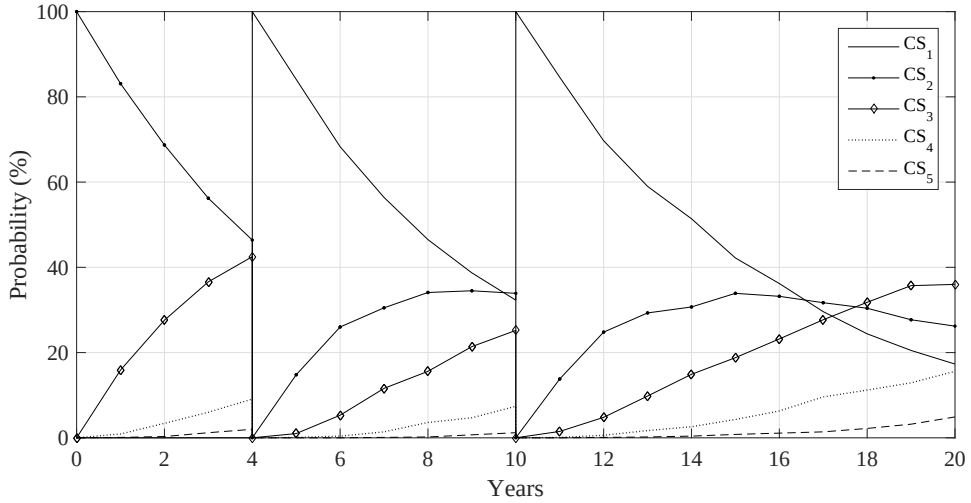


Figure 5.52: Probability of pavement section 5 being in a specific CS for PI_F along the analysis period

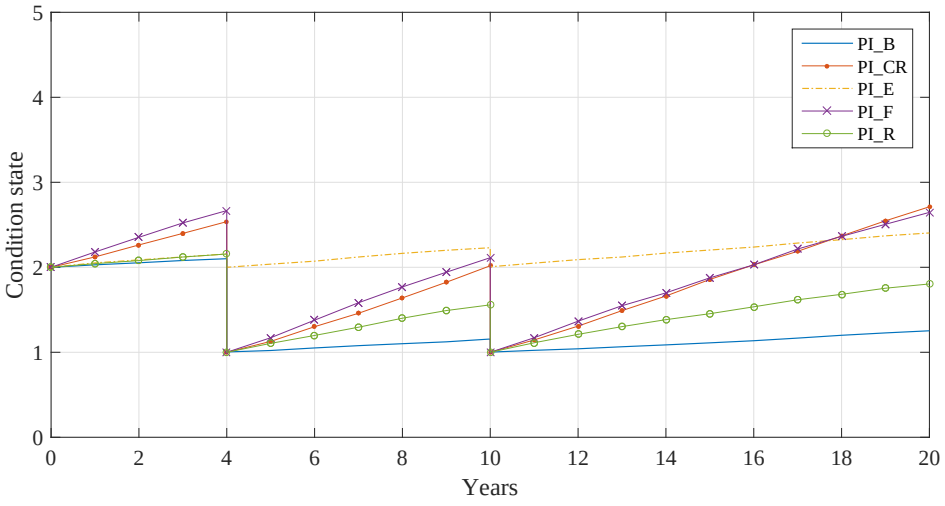
Initially, PI_F is on CS_2 and the probabilities of being in worst condition states increase until year 4, when a M&R is applied, taking PI_F to CS_1. The probability of remaining in the best CS decreases until the year 10, when the chance of finding the pavement section in condition state 1, 2 or 3 is quite similar. The chances of achieving CS_5 are very remote during the whole analysis period, meaning that the optimization algorithm kept low chances of violating the constraint defined for the friction indicator in pavement section 5.

Table 5.10 quantifies the constraints violation probabilities for the same pavement section with regard to all PIs, evidencing higher risk of failing with the required levels of cracking, namely in the year 4, 10 and the last of the analysis period, with 12%, 12% and 30% probability of failure, respectively. Not only PI_CR is an indicator with fast deterioration but also the one with stricter constraints. As for other PIs, the chance of failure is very remote.

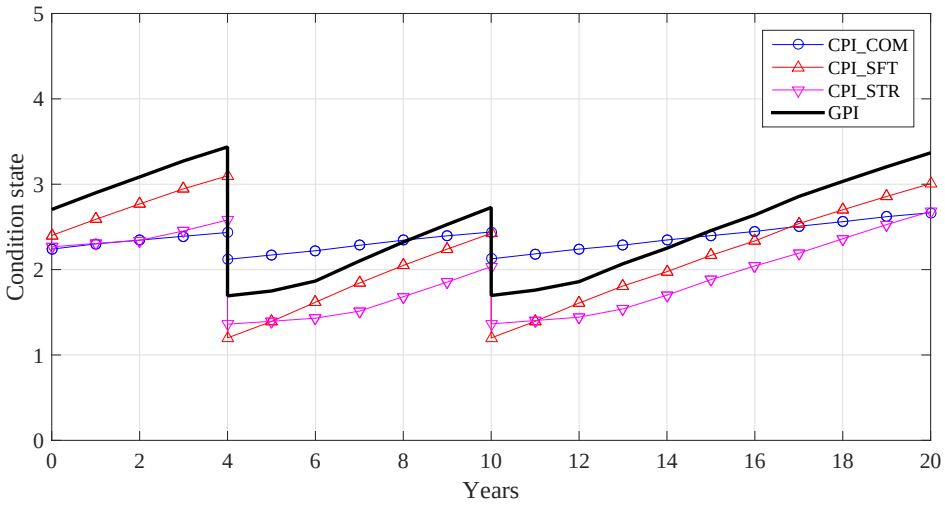
Table 5.10: Constraints violation probabilities (%) for section 5, for each PIs and year

PI	Years																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PI_B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PI_CR	0	1	4	8	12	0	1	3	6	8	12	0	1	3	6	10	13	17	22	26	30
PI_E	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	2
PI_F	0	0	0	1	2	0	0	0	0	1	1	0	0	0	0	1	1	1	2	3	5
PI_R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The evolutions in time of PIs, CPIs and GPI for section 5 are represented in Figure 5.53. These were obtained by the average results of 1000 Monte Carlo simulations.



(a)



(b)

Figure 5.53: Evolution of pavement performance for section 5 subjected to the M&R strategy defined in Table 5.8 (average of 1000 Monte Carlo simulations): (a) PIs; (b) CPIs and GPI

The graphs are similar to those obtained by the deterministic approach, previously illustrated in Figure 5.50, page 170. As expected, PIs and CPIs now reduce their values on year 10 instead of 11. A curious difference relies on the reduction of PI_E verified at the year 4 and 10, which was not previously noticed. The M&R 4 affects PI_E only for sections in the CS_3 or more. In 1000 simulations, several achieved such CS so that a reduction to CS_1 was imposed, while for the deterministic approach, PI_E was in CS_1 and CS_2 for which M&R 4 produces no effect. In general, the differences on the evolution of individual and combined performance indicators given by both approaches are not significant, regardless the fact of changing the application year of

a M&R operation.

In order to have an overview of constraint compliance for the whole network, a quantification of failure probabilities for all performance indicators and sections along the time is represented in Figure 5.54. For bearing capacity, longitudinal evenness and rutting, probabilities of violating constraints are low during all period. Cracking is the indicator with higher risk of failing, achieving values between 25 and 40% for five sections during the analysis period, but mostly at its end, due to the lack of M&R operations in the last few years of the time horizon. In fact, the positive contribution

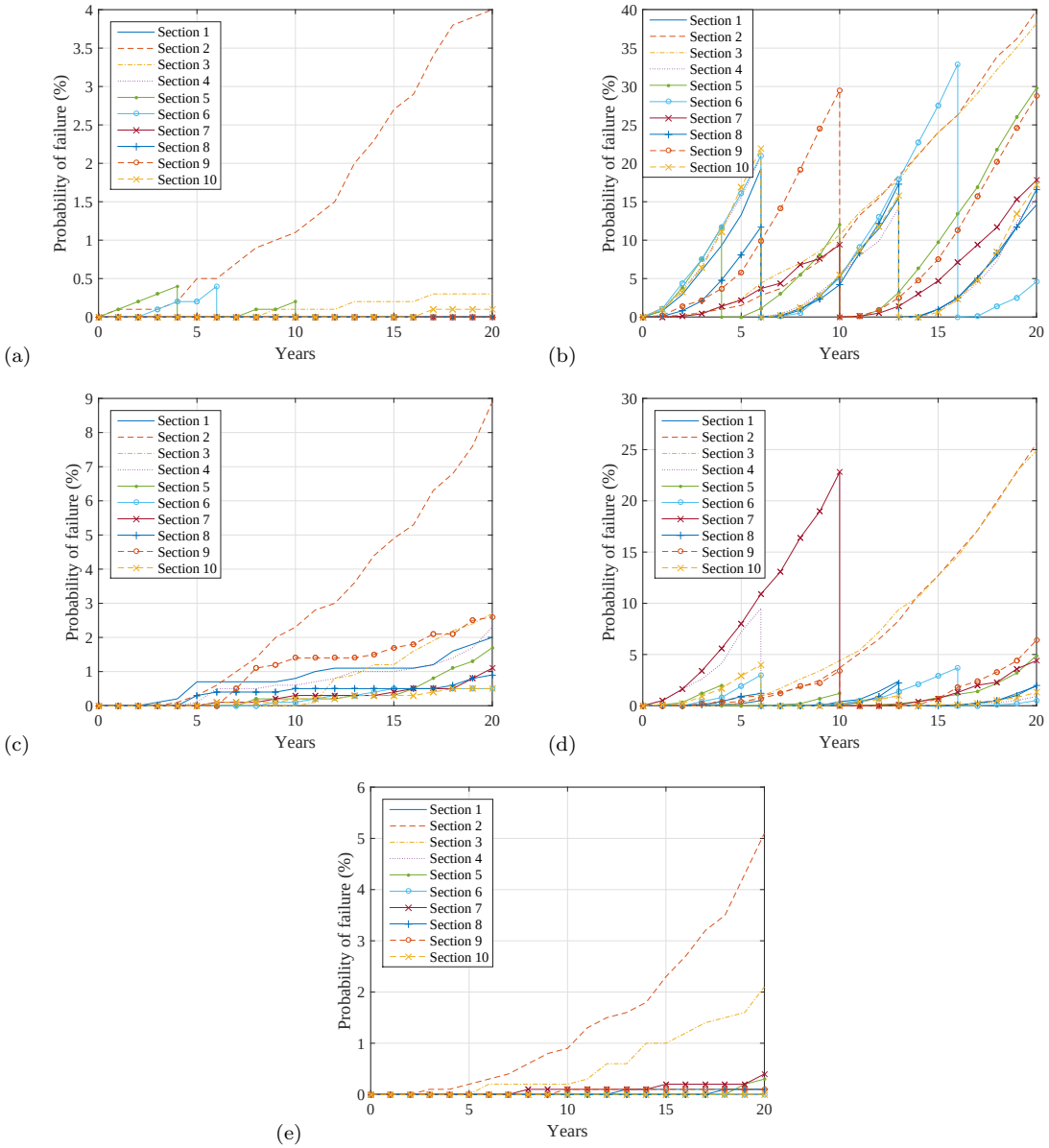


Figure 5.54: Constraints violation probabilities: (a) PI_B, (b) PI_CR, (c) PI_E, (d) PI_F, (e) PI_R

for pavement quality for the overall period of analysis is lower as the time becomes closer to the last year, so that M&R operations become less cost-effective.

Regarding the friction indicator, besides the higher risk of failure at the end of the analysis period, Figure 5.54 (d) evidences a peak at year 10 for section 7, representing around 23% chances of overpassing CS_4. In fact, the initial condition of this section is very good for all PIs, except for friction, which is in CS_3 at the beginning of the analysis period. For some decision makers, that percentage of failure for PI_F might be too high, as this indicator might compromise road safety. In such scenario, the application of specific M&R operations to increase friction in section 7, such as surface shot blasting, could be an option to reduce the risk of failure.

As mentioned before in Section 4.6, the considered M&R operations in this thesis result from an extensive list, where several other operations differ only by the new or replaced layer thickness and material to be used, thus differing in the unit cost but not in the effects on PIs. A minimum and maximum cost for administration should then be defined at a network-level to account for uncertainties that can only be resolved at project-level analysis. Considering the variation indicated in Table 4.15, page 110, the minimum and maximum expected administration costs for each section, converted to the NPV, would be as indicated in Table 5.11. Differences between the minimum and maximum expected cost are more significant for sections with higher number and more expensive M&R operations. The total administration costs variation can represent a reduction of 12% and an increase of 10% approximately.

Table 5.11: Minimum and maximum expected discounted costs for administration per pavement section

Section	1	2	3	4	5	6	7	8	9	10	Total
Minimum cost (€)	78987	4822	1087	75664	79127	72527	36638	162678	93085	74464	679080
average cost (€)	89791	5083	1146	86287	90347	82768	41833	182064	105447	85022	769787
Maximum cost (€)	98927	5344	1204	95243	99795	91395	46208	198733	115939	93913	846702

5.7 Conclusions

In this chapter, features of the optimization methodology and its implementation were presented, supported by examples and an hypothetical case study.

Pavement quality is measured by the integral of the GPI graph, administration costs refer to costs of maintenance and rehabilitation operations only, and society costs are

the sum of user and environmental costs. The former depend on the money spent by users in fuel, while the latter is related to the price of CO_2e emissions. Ultimately, both are dependent on the fuel consumption which is considered to be directly influenced only by the pavement roughness quantified by the parameter IRI. Pavement quality, administration costs and society costs comprise conflicting objective functions and can also be used as constraints, except for the society costs.

Sections 5.3 and 5.4 served to present and briefly explain multi-objective and genetic algorithms concepts. The Tchebycheff method, also known as min-max method, was introduced in more detail as it is a promising scalarization method to solve multi-objective problems, together with another single-objective optimization algorithm. Fundamentals of the non-dominated sorting genetic algorithm-II (NSGA-II) were presented, since it is a promising genetic algorithm for multi-objective problems, because of its elitism and diversity preservation capabilities.

The performance of Tchebycheff method + GA (TCGA) and of the multi-objective GA (MOGA) in terms of results optimality and running time was compared. At the same time, some constraint handling methods - constraint function, penalty function and *a posteriori* - were tested in a variety of problems differing in their constraints. These were presented in Section 5.5. The general conclusion was that MOGA is significantly faster than TCGA and provides much more diverse Pareto optimal solutions. The *a posteriori* application of constraints was preferable because it is easier to use in a wide range of problems and avoids potential errors caused by the definition of penalty parameters for the penalty function. The use of a constraint function proved to be effective for the TCGA only. In conclusion, the MOGA with constraints *a posteriori* was elected as the approach to use in the optimization methodology.

The methodology includes a rehabilitation constraint that forbid it to suggest the application of major M&R operations in two consecutive years for the same pavement section. At the network-level, a preservation plan that suggest major M&R operations in two consecutive years in adjacent sections might be later modified by a decision maker to fit eventual administration logistic requirements.

The influence of considering society costs as a third objective was shown in Subsection 5.6.2, as the optimization of three conflicting objectives resulted in much more Pareto optimal solutions than those obtained from the two-objective optimization. If the pavement performance prediction does not depend on traffic, the optimized M&R strategies are similar for a similar pavement section with different traffic volumes, even though the absolute value of society costs are different.

Subsection 5.6.3 addressed the problem of considering more than one pavement section, thus turning the problem in a more realistic one regarding pavement manage-

ment at a network-level. Two solving approaches were tested: (1) the consideration of administration costs and pavement performance for the whole network as objective functions and (2) the consideration of administration costs for the network and pavement performance for each section. Results showed the second approach was preferable because not only it provided solutions with better network performance but also with a better balance among the quality of each pavement section. In addition, by having an objective function for each section would demand much higher computational effort to have the same assurance of obtaining near optimal solutions. Nevertheless, for networks with dozens or hundreds of pavement sections, finding optimal solutions with approach 1 is still a complex and computationally heavy problem to be optimally solved.

A two-stage optimization approach was then presented in order to deal with the drawbacks of optimizing all the network at once in a single-stage optimization. This consists in decomposing the problem in two optimization levels. At the first-level, a set of M&R schedules for each pavement section is determined. A solution at the second-level corresponds then to one M&R plan for each section that was part of the optimal set. The benefits of the two-stage approach was demonstrated by comparing its Pareto solutions with the Pareto frontier of the single-stage optimization.

In line with the two-stage optimization, an approach to include user and environmental costs (society costs) in the optimization methodology was presented and applied in an hypothetical case study, in Subsection 5.6.5. The main goal was to include society costs, often disregarded in PMSs, in the decision making process, considering them at a second-level of optimization. By providing that pavement performance quality was assured at a section-level, the proposed approach allows to balance administration with society costs. The offset between the increase of administration costs and the consequent decrease of society costs was used as a key aspect for decision making at a network-level. The influence of traffic volume in the decision making was demonstrated. In reality, the coordination of these costs might depend on the funding system of administrations, users obligations and contracts with governments.

Finally, in the last subsection (5.6.6), an uncertainty analysis was performed, as the problems and the optimization methods being used are stochastic. The uncertainty about the pavement quality is estimated through the application of Monte Carlo simulations to compute the evolution of pavement performance for a given M&R plan. This allows to indicate the number of simulations that a pavement section is in a certain condition state at a specific date and, consequently, to quantify the probability of failing with respecting an imposed constraint. Furthermore, a variation on the administration costs was also considered, as several M&R operations can only be exactly defined in

terms of layer types and thickness at a project-level analysis.

Summarizing, this chapter described and justified the steps taken in the development and refinement of the optimization methodology.

Chapter 6

Application to real problems

6.1 Introduction

The purpose of this chapter is to demonstrate the applicability and practicality of the developed optimization methodology outcomes, based in two main tasks. The first is to compare the evolution of pavement performance predicted by the methodology with available historical data, considering the M&R strategies that were actually verified. This allows assessing the reliability of the developed prediction models and adopted M&R effects on pavement performance. The second task consists in analysing and, if possible, comparing the optimal M&R strategies suggested by the methodology with the real one, in terms of the adopted objective function values, of similarities in costs for administration and in terms of similarities regarding the type and the moment of application of M&R operations.

Two significantly different scenarios are selected as case studies to apply the methodology.

The first case study, presented in Section 6.2, relies on historical data from the LTPP database. This covers a long period in time, with more than 20 years for some pavement sections. Historical data are available for sections of 152 m length of one lane, spread around USA and Canada. Within the same region or administrative state, the pavement sections are also disperse, meaning that there is not a long extension of road with continuous available data for adjacent pavement sections.

The second case study, presented in Section 6.3, consists in applying the developed methodology in a Portuguese context. Due to the close link between this thesis and the project SustIMS, as mentioned in Chapter 1, some data of the road administration ASCENDI was used for this purpose. Furthermore, a closer contact with ASCENDI engineers was also possible, who provided necessary data inputs and opinions and

validated conceptual ideas towards the application of the methodology. Historical information about this second case study covers a shorter period of time than the LTPP case. However, the amount of available data for a short period is extremely large, as pavement distress data are available for each 100 m length of each lane of the whole network.

The difference in the type and quantity of available data among the case studies allows and demands the use of different approaches in the application of the optimization methodology. For the LTPP case study, a variety of pavement sections is first analysed individually and then considered together for a optimization for the group of sections as a network. For the ASCENDI case study, by having distress data for several adjacent sections within the same road segment, the pavement condition for each performance indicator can be indicated in terms of relative areas in a specific condition state. This is coherent with the nature of Markov prediction models as further explained in Subsection 6.3.3.

Ultimately, the intention is to assess the positive and useful aspects of the methodology, to make slight modifications in order to adapt it to current maintenance and rehabilitation programming practices and to identify problems and gaps that should be further improved and/or added towards an effective implementation of an optimization methodology in the decision making process of road pavement administrations.

6.2 Case study with the LTPP database

6.2.1 Selection of pavement sections

In order to make the comparison between LTPP historical records of pavement performance and M&R programs as more reliable as possible, pavement sections with more available data and higher time span between the first and last records are preferred. Furthermore, the more preferred sections exist within the same administrative state, the better, as they are more likely to be ruled by similar preservation policies and practices, and are probably managed by the same entity, as each American State has its own Department of Transportation.

The maximum time span with historical data found in LTPP was of 24 years for some pavement sections, thus a period of 20 years was assumed as reasonable for application purposes. Nevertheless, some sections within the same administrative state with less historical data, but above 15 years for some performance indicators, were also selected as promising ones to test the methodology.

In a first approach to select the sections for the case study, eight groups were highlighted: 14 sections from the State of Arizona, 5 from Florida, 4 from Indiana, 5 from New Jersey, 3 from Oklahoma, 24 from Texas, 6 from Washington and 4 from Manitoba, Canada. Preference was given for the States of Arizona and Texas, because they comprise higher number of selected pavement sections. Friction data are quite scarce for both, specially for Arizona, where there are no sections with friction data beyond the first four years. For this reason, more attention was given to the State of Texas, even though the methodology was also tested for Arizona's sections. In addition, for reading and textual convenience, only analysis and results of sections of Texas are presented in this document.

A map indicating the location of the selected pavement sections of Texas is shown in Figure 6.1, where the red flags refer to those that are actually further taken in consideration as later explained in subsection6.2.3. The remaining ones are signalized with a grey pin.

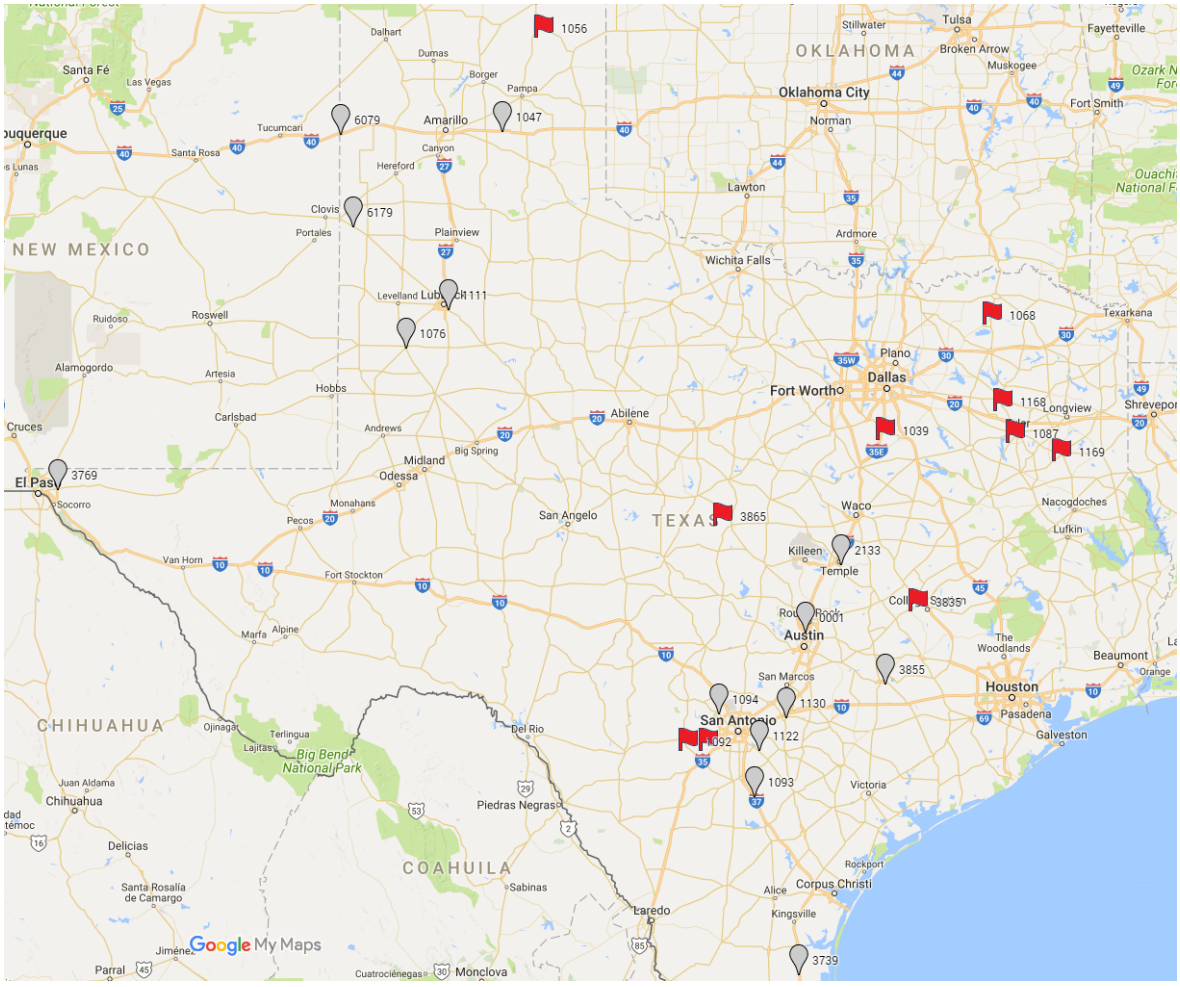


Figure 6.1: Location of the selected pavement sections of Texas (base map retrieved from google maps)

6.2.2 Definition of maintenance and rehabilitation operations effects and costs

Ideally, for each application of the optimization methodology, there must be a calibration of the prediction models and M&R effects and costs in order to represent specific scenarios as much as possible.

As the prediction models of this thesis were developed under LTPP data, it is assumed that they represent well the real evolution of pavement performance for Texas sections.

Additionally, the list of M&R operations previously considered (Table 4.15) is adapted in order to include those typically observed in the LTPP database, more specifically in that State, which are those with M&R code 1, 12, 19, 21, 22, 23, 25, 27, 28, 31, 33, 34, 36 and 51, defined in Table 6.1. Some are similar among each other, and its selection often relies on project-level analysis, so they were grouped in wider, but fewer M&R types to be considered on the methodology, as indicated in Table 6.2. In addition, LTPP M&R operations with code 21, 22, 23, 25 and 27 are not considered as useful operations, because they are used for routine maintenance purposes to repair localized surface defects that are not taken into account in the methodology.

Table 6.1: Influential M&R operations

LTPP M&R code	Description
1	Crack Sealing
12	Grinding Surface
19	AC Overlay
21	Mechanical Premix Patch
22	Manual Premix Spot Patch
23	Machine Premix Patch
25	Patch Pot Holes: Hand Spread, Compacted With Truck
27	Strip Patching
28	Surface Treatment, Single Layer
31	Aggregate Seal Coat
33	Slurry Seal Coat
34	Fog Seal Coat
36	Tack Coat
51	Mill Off AC and Overlay With AC

The definition of the M&R operations effects of the new list are mostly based on the previously defined effects (Appendix A), but complemented with detailed analysis on the influence they produce in historical data of pavement performance. In fact,

Table 6.2: M&R operations considered for the case study of LTPP database

LTPP M&R code	M&R ID for the case study and description	Cost (€/m²) min.	mean	max.
not applicable	1 - Do nothing		0.0	
1	2 - Crack sealing	3.51	3.70	3.89
12	3 - Surface shot blasting	2.56	2.70	2.84
19	4 - AC overlay	13.40	15.30	16.90
28, 31, 33, 34, 36	5 - Surface treatment	5.32	5.60	5.88
51	6 - Mill off and overlay with AC	19.10	21.00	22.30

initially, there was an attempt to define M&R effects based only on LTPP data for all pavement sections, but these revealed a significant and inconclusive variety of effects for the same operation in pavement sections with the same condition state. The main difference on the new effects consists on having defined improvements for the rutting and longitudinal evenness indicators when these are in the worst condition state, since identical situations were verified in LTPP data. As an example, Table 6.3 indicates the effects defined for the new M&R ID 6 (Mill off and overlay with AC), which can be compared with those previously defined in Table 4.16. Other operations effects can be viewed in Appendix B.

Table 6.3: Effects of the new M&R ID 6 on all PIs

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
PI	Reduction of CS					Change of deterioration rate (%)					Years with changed deterioration rate				
PI_B	–	1	2	3	–	–	0	0	0	0	–	–	–	–	–
PI_CR	–	1	2	3	4	–	40	50	60	80	–	per.	per.	per.	per.
PI_E	–	1	2	3	3	–	0	0	0	0	–	–	–	–	–
PI_F	–	1	2	3	4	–	0	0	0	0	–	–	–	–	–
PI_R	–	1	2	3	3	–	0	0	0	0	–	–	–	–	–

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Regarding the administration costs for each M&R operation, its definition for this case study could not be based on LTPP data because of the very low correlation between the total expenditure and the quantity of work or repaired thickness registered for various operations. As an example, Figures 6.2 a) and b) plot values of thickness (inches) *versus* costs (thousands of USD) for all records of the rehabilitation 19 (AC overlay) and 51 (mill off AC and overlay with AC), two frequently occurred opera-

tions. Therefore, the costs adopted for this case study are those previously indicated in Table 4.15.

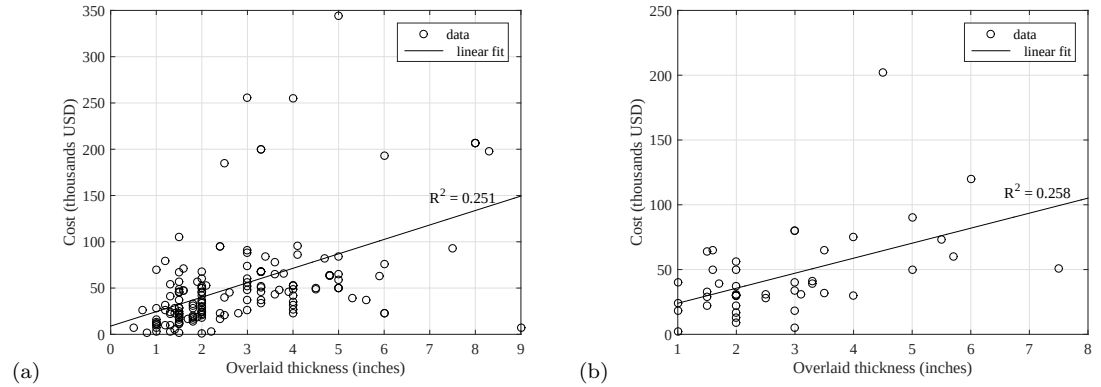


Figure 6.2: LTPP reported costs and thickness for (a) AC overlay and (b) mill off AC and overlay with AC

6.2.3 Historical data *vs* predicted results

Having defined the correspondence between LTPP M&R operations with those to be used in the methodology, as well as its effects, a comparison between real data and predicted values was performed in order to assess the reliability of prediction and preservation models.

Most of the available data for the considered pavement sections started being collected on the year 1990, though the first data for some sections are from one or two years earlier or later. For this reason, the year 1990 was defined as the year 0 of a planning period, which comprises the number of years between the first and last moment with available data for each section. When unknown, the initial (for year 1990) condition state (CS) of performance indicators (PIs) are estimated based on the closest available record in time. Predictions of the pavement performance based on the real M&R strategy is then performed and compared with historical data, as exemplified in Table 6.4 for section 48_1068 (Texas), using the Markov parameter *Time* for the prediction models.

In the row "Year" of that Table, letter *b* stands for *before* and letter *a* stands for *after* the occurrence of a possible M&R operation in that year. For instance, in the year 10, CSs before and after a pavement overlay operation are indicated in the column 10b and 10a, respectively. In this pavement section, all PIs are in the best condition state at the beginning of the planning period. The low deterioration of bearing capacity is verified for real and predicted data. As for cracking, the model predicts slightly slower

Table 6.4: Comparison of real with predicted condition states for all individual PIs for section 48_1068

Year	0b	0a	1b	1a	2b	2a	3b	3a	4b	4a	5b	5a	6b	6a	7b	7a
M&R LTPP						34		36								
M&R methodology		1		1		5		5		1		1		1		1
PI_B real	1							1	1		1		1		1	
PI_B predicted	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PI_CR real	1		1				1				2				3	
PI_CR predicted	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2
PI_E real	1		1				1	1	1		1				2	
PI_E predicted	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PI_F real	1				1		1				1		3		3	
PI_F predicted	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2
PI_R real	1		1		1		1				2				2	
PI_R predicted	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2

Year	8b	8a	9b	9a	10b	10a	11b	11a	12b	12a	13b	13a	14b	14a	15b	
M&R LTPP				31		19								34		
M&R methodology		1		5		4		1		1		1		5		
PI_B real							1				1					
PI_B predicted	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
PI_CR real			2	1			1				1				1	
PI_CR predicted	2	2	2	1	1	1	1	1	1	1	2	2	2	1	1	
PI_E real				2	2	1					1				1	
PI_E predicted	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	
PI_F real																
PI_F predicted	2	2	3	3	3	1	1	1	1	1	2	2	2	2	2	
PI_R real			2	2			1		1		1				1	
PI_R predicted	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	

deterioration until the year 9, but faster afterwards. PI_E achieved the real CS_2 at year 7, while the model predicted it to happen just on the year 9, which represents just a little deviation from reality. Similar fact is verified for PI_R, for the model predicted its deterioration for CS_2 a year after than what actually happened. Friction data are only available until half of the analysis period, so it is impossible to compare the predicted values for the remaining years. A transition from CS_1 to CS_3 is observed, which is something that the model does not predict. Overall, considering all PIs, the prediction and preservation model correctly predict 79% of the observed CSs for section 48_1068.

Table 6.5 indicate the initial CSs and percentage of correct predictions for all pavement sections considered in this case study, as well as the range of years with available historical data. Note that from all 24 sections previously identified, only 10 are finally considered, because there was a big lack of friction data for some of the other 14 sections, while others were reported to have the PI_F in the worst CS since early years. Although this fact is partially explained by the adopted transfer function to determine the CS for PI_F, it was decided to ignore those 14 sections in order to avoid bias in the optimization process to be presented in Subsection 6.2.4.

Table 6.5: Initial condition state and percentage of correct predictions for the considered pavement sections of Texas (state code 48)

Section	Initial PI_B	Initial PI_CR	Initial PI_E	Initial PI_F	Initial PI_R	Correct predictions (%)	Analysis period (years)
1039	1	4	1	1	2	61	18
1056	3	2	2	2	2	50	21
1068	1	1	1	1	1	79	16
1087	1	1	1	1	2	56	23
1092	1	2	1	3	2	69	22
1096	1	1	2	3	2	76	21
1168	3	1	1	1	1	45	16
1169	2	1	2	1	2	71	16
3835	1	1	2	3	1	69	21
3865	2	1	2	1	2	64	23

The percentage of correct predictions vary from 45% to 79%. While some performance indicators in some sections actually deteriorate faster than what is predicted, in some others the opposite case is verified, so there is no clear trend about the relative differences between the predicted and historical data, confirming that the prediction model is not biased.

In order to obtain the historical value of the objective function related to quality, $\int GPI$, CPIs and GPI must be known for as many years as possible. Therefore, for each pavement section, if there is a record regarding the condition state of one or more performance indicators (PIs) at a certain year, then all the other PIs should be known for that same year. Unknown values are estimated through comparison with previous and further CSs taking the existence of M&R operations into account. If a missing value is not bounded by previous and further records, the developed prediction model is used to determine the CS of the PI in that year. In such cases, the prediction starts from the most recent available data. For illustration purposes, Table 6.6 indicates the observed (on bold) and estimated CS for section 48_1068.

The estimated values that complement sequences of observed values are referred as real values hereinafter and should not be confused with predicted values by the prediction and preservation model used in the optimization methodology. The PIs evolution as indicated in Table 6.6, and the respective CPIs and GPI for section 48_1068 are graphically represented in Figure 6.3.

Predicted values for PIs are given in their decimal form (blue diamonds), as calculated by the prediction models, but also in the integer form (black crosses) by normal rounding, so a more direct comparison with real values can be made. CPIs and GPI are not directly measured and determined indicators, hence, they are simply calculated by combining individual PIs so they are not necessarily integers. Generally, the predictions (blue diamonds) lie in between the lower and subsequent upper real CSs,

Table 6.6: Observed and estimated (real) condition states for all individual PIs for section 48_1068

Year	0b	0a	1b	1a	2b	2a	3b	3a	4b	4a	5b	5a	6b	6a	7b	7a
M&R LTPP						34		36								
M&R methodology		1		1		5		5		1		1		1		1
PI_B real	**1**	1	1	1	1	1	1	**1**	**1**	1	**1**	1	**1**	1	**1**	1
PI_CR real	**1**	1	**1**	1	1	1	**1**	1	1	1	**2**	2	2	2	**3**	3
PI_E real	**1**	1	**1**	1	1	1	**1**	**1**	**1**	1	**1**	1	1	1	**2**	2
PI_F real	**1**	1	1	1	**1**	1	**1**	1	1	1	**1**	1	**3**	3	**3**	3
PI_R real	**1**	1	**1**	1	**1**	1	**1**	1	1	1	**2**	2	2	2	**2**	2

Year	8b	8a	9b	9a	10b	10a	11b	11a	12b	12a	13b	13a	14b	14a	15b
M&R LTPP				31		19								34	
M&R methodology		1		5		4		1		1		1		5	
PI_B real			1	1	1	1	**1**	1	1	1	**1**	1			1
PI_CR real			**2**	**1**	1	1	**1**	1	1	1	**1**	1			**1**
PI_E real			2	**2**	**2**	**1**	1	1	1	1	**1**	1			**1**
PI_F real			3	3	3	1	1	1	1	1	2	2			1
PI_R real			**2**	**2**	2	1	**1**	1	**1**	1	**1**	1			**1**

denoting the continuous pavement deterioration.

Comparing the black crosses with the red circles for CPIs, it is noticed that the model slightly delayed the deterioration of the comfort indicator. The evolution of safety indicator was at first over predicted until the year 5 when it became under predicted, which is explained by the real deterioration of PI_E by two CSs from year 5 to 6. Regarding the structural indicator, it matters to note the unexpected transition from CS_2 to CS_3 and CS_2 again without any M&R operation. This goes in line with the fact of having PI_CR as the most influential indicator for CPI_STR, because the PI_B is in CS_1 during the whole period.

Finally, Figure 6.3 (i) shows the evolution of the GPI. Bearing in mind that the objective function related to quality is equal to the area below the GPI line, in this section, one can expect the $\int GPI$ to be similar for both the predicted and the real curves, even though they are not coincident. In fact, what is initially over predicted, as a consequence of a continuous deterioration curve, it is after compensated with lower prediction. The predicted (blue diamonds) and real $\int GPI$ equal 32.95 and 34.38, respectively, meeting the expectations of having similar predicted and real global quality indicator. An overview of predicted and real quality ($\int GPI$) that result from the actual implemented M&R strategy is illustrated in Figure 6.4 for all considered sections.

The quality value cannot be compared among sections, because they are determined for different periods according to available historical data for each section. It is observed that from the 10 sections, 7 are predicted to have better quality than what actually happens, while the opposite scenario is verified for the other 3. This fact supports the

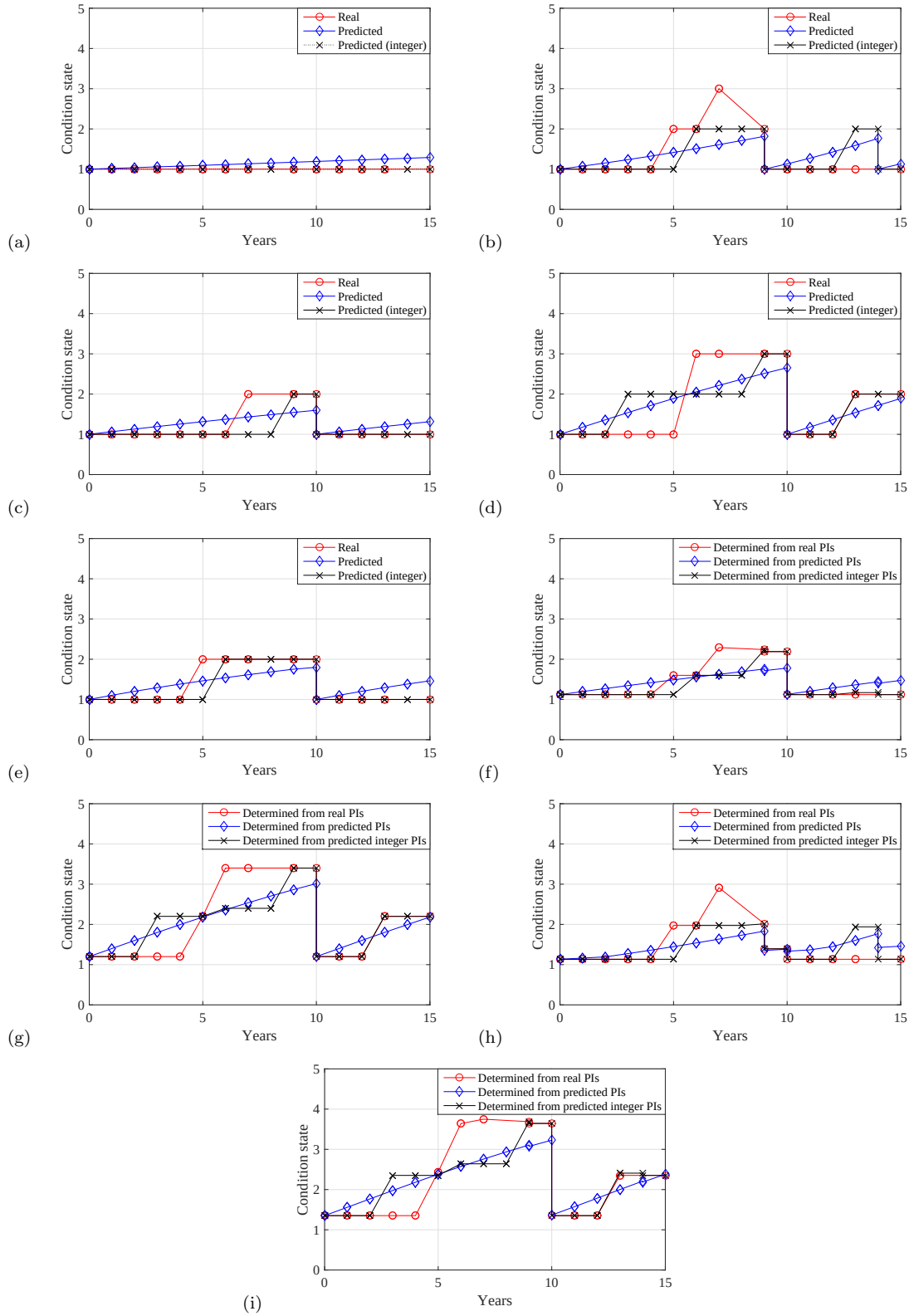


Figure 6.3: Real and predicted pavement performance evolution for section 48_1068: (a) PI_B, (b) PI_CR, (c) PI_E, (d) PI_F, (e) PI_R, (f) CPI_COM, (g) CPI_SFT, (h) CPI_STR, (i) GPI

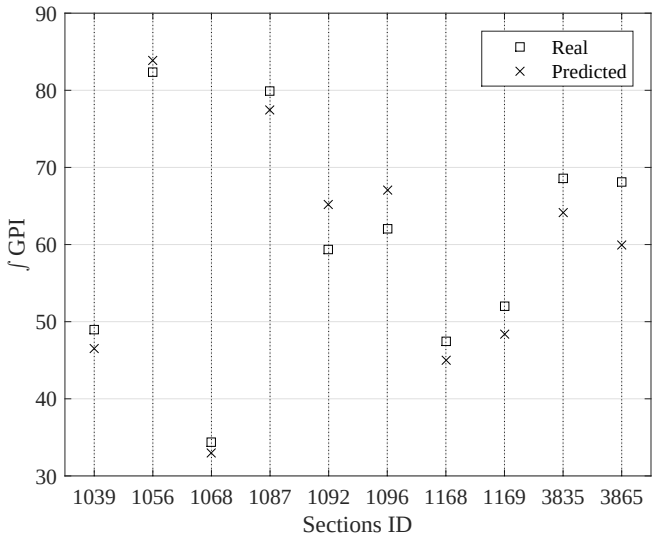


Figure 6.4: Real and predicted quality ($\int GPI$) for the considered sections of the State of Texas

conclusion that there is no clear trend about whether the models predict lower or higher quality than the actual one, which is an important finding to a better interpretation of the optimization results presented in the next subsection (6.2.4).

6.2.4 Optimization of maintenance and rehabilitation planning.

The main goal of this subsection is to compare the optimal results provided by the developed methodology with those actually observed in historical data.

Section-level

For each of the pavement sections, a section-level optimization is performed, looking for M&R strategies that minimize administration costs (C_A) and maximize the quality, as follows:

$$\begin{aligned} f_1 &= min \sum_{t=0}^{T} \frac{C_{A,t}}{(1+d)^t} \\ f_2 &= min \int_0^t GPI \end{aligned} \tag{6.1}$$

where T equals the period with available historical data indicated in Table 6.5, and the discount rate d is 2.5%. All sections are 152.4 m (500 ft) length and 3.66 m (12 ft) wide. Precise information related to minimum quality requirements and available budget was not found, so constraints for individual pavement performance indicators and

budget are not considered. Furthermore, preliminary tests from unconstrained problems seemed to give enough results regarding the purpose of this subsection.

The main options for the multi-objective genetic algorithm are the same as those previously mentioned in page 133. The main difference on the MOGA implementation refers to the lower and upper bounds for the decision vector, now defined as 1 and 6, respectively, in accordance with the new list of M&R operations (Table 6.2).

As an example, Figure 6.5 shows the Pareto front of solutions for section 1039, together with the objective function values for the actually implemented M&R strategy.

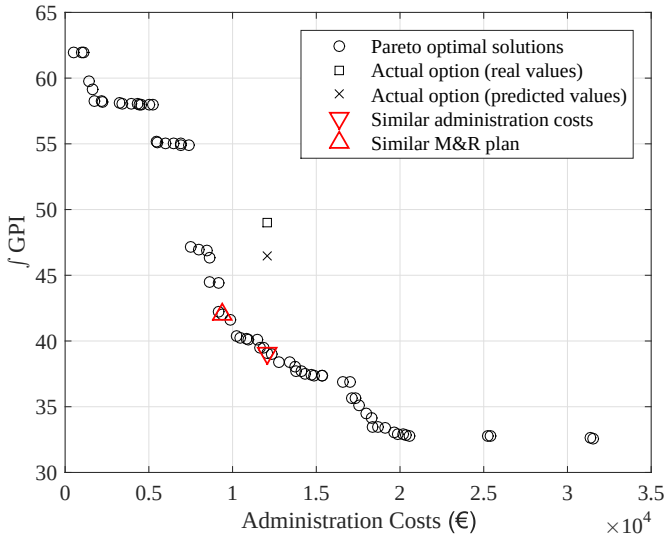


Figure 6.5: Pareto optimal solutions for section 1039 of the State of Texas

From all the 70 Pareto solutions, 16 and 13 of them dominate the actual solution measured by real and predicted values of performance indicators, respectively, because they are better in both objectives. The implemented solution could only be considered non-dominated if those were removed or identified as impossible solutions for some reasons not included in this case study. In further analysis and comparisons, the predicted quality for the actual M&R plan (represented by a cross in Figure 6.5) is going to be the reference value, since the Pareto results given by the optimization algorithm are calculated with the same prediction and preservation models.

A solution with a M&R plan for a very similar cost for administration is marked with a downward red triangle, resulting in a quality that is better in about 16% than the actual one (from $\int GPI = 46.48$ to $\int GPI = 39.10$). On the other hand, the upward red triangle represents a preservation plan that is similar to the actual one in terms of the type and application of M&R operations. The three plans are indicated in Table 6.7, and its respective consequences in terms of GPI evolution can be observed in

Figure 6.6, where the values obtained from the observed integer PIs are also illustrated. For this section, the prediction and preservation model is also quite accurate as noticed by the proximity between the red circles line and the black crosses line.

Table 6.7: Comparison of M&R plans for section 1039 of the State of Texas

Plan identification	Years																	
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Actual	1	1	1	1	1	1	4	1	1	1	1	5	5	1	1	1	1	–
Upward triangle	1	2	1	1	4	1	1	1	1	1	1	3	1	1	1	1	1	–
Downward triangle	1	4	1	1	3	1	1	1	3	1	1	3	1	1	1	1	1	–

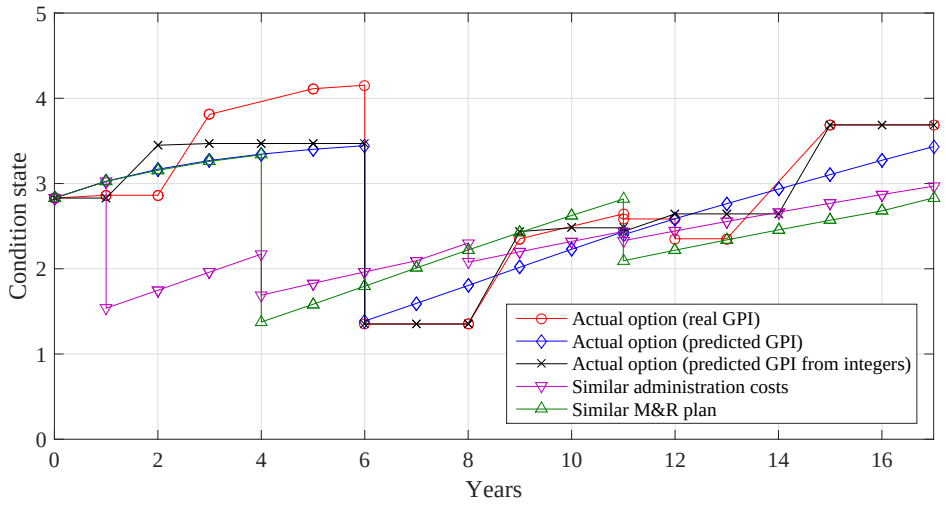


Figure 6.6: GPI evolution for different M&R plans for section 1039 of the State of Texas

The most significant difference from the actual to the *upward triangle* plan consists in the anticipation of the AC overlay in two years, causing an earlier improvement of the pavement performance and consequent reduction of $\int GPI$ for the whole period. Additionally, there is a crack sealing in the second year (year 1), and a surface shot blasting is planned to occur at the same year when surface treatments were verified, but causing more benefits. Although M&R operations are more costly in earlier years due to the discount rate affecting the value of money, the actual plan ends up being more expensive because of the consecutive application of surface treatments verified in the years 12 and 13.

Regarding the *downward triangle* plan, the predicted quality is better than the actual one for a very similar cost, not only due to an early AC overlay, but also because surface shot blasting is considered more often. This operation is cheaper than surface treatments and improves the friction indicator that is the one with faster deterioration and with important contribution for the GPI.

The previous results demonstrated the capabilities of the optimization methodology to provide a range of reasonable M&R plans at a section-level, in terms of the amount, types and distribution in time of M&R operations to be performed. It was observed, for the pavement section 48_1039, that the actual implemented solution was dominated by several suggested M&R plans in terms of global pavement performance and administration costs. A similar conclusion was depicted from many other optimization results for different pavement sections. As an illustrative example, Figure 6.7 shows the Pareto optimal results and the objective function values for the actual M&R plans implemented for sections 1096 and 3865 of Texas State.

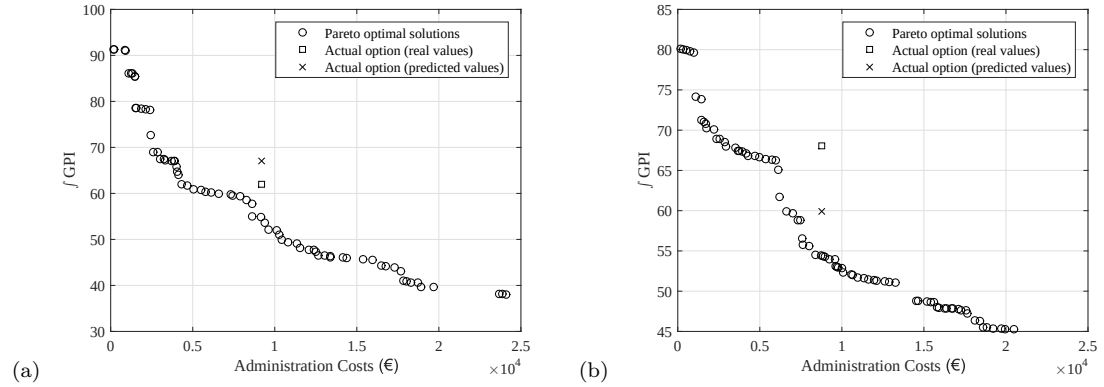


Figure 6.7: Pareto optimal solutions for sections 1096 and 3865 of the State of Texas

Network-level

Having obtained reasonable optimization results at the section-level (first-stage optimization), the methodology is now assessed by applying it for the group of sections simultaneously, i.e., at the network-level or second-stage optimization as defined before in Subsection 5.6.4. The objectives to be minimized are the administration costs (C_A) and society costs (C_S), defined as follows:

$$\begin{aligned} f_1 &= min \sum_{i=1}^{s} C_{A,i} \\ f_2 &= min \sum_{i=1}^{s} C_{S,i} \end{aligned} \tag{6.2}$$

where s is the number of sections to be considered.

Society costs are determined as exposed in Subsection 5.2.3, but some of the input values for Equations 5.9 to 5.13 are adapted to the USA reality. Fuel prices are defined according to the average values for the Gulf Coast region, where Texas State is located,

on the year of 2016 (U.S. Department of Energy, 2017b), and converted from USD to Euros according to the average exchange rate defined in Internal Revenue Service (2017) for the same year. The percentage of diesel vehicles in USA is much lower than the one verified in Portugal and Europe, as reported by Chambers and Schmitt (2015). Regarding environmental costs, there is no national wide system for carbon pricing in USA, so that the price defined in the State of California is adopted for this case study (World Bank Group and ECOFYS, 2016). In fact, the California's Global Warming Solutions Act (AB32) is the world's second largest carbon market, after the European Union's Emissions Trading System (Luckow et al., 2015). Table 6.8 summarizes the input values to determine user and environmental costs.

Table 6.8: Input values to determine user and environmental costs for the LTPP case study

Description	Designation	Value
Diesel cars	$ratio_{C,D}$	1.5 %
Gasoline cars	$ratio_{C,G}$	98.5 %
Diesel trucks	$ratio_{Tr,D}$	72.0 %
Gasoline trucks	$ratio_{Tr,G}$	28.0 %
Diesel cars average consumption	$FCR_{C,D}$	0.09491 l/km
Gasoline cars average consumption	$FCR_{C,G}$	0.10785 l/km
Diesel trucks average consumption	$FCR_{Tr,D}$	0.44731 l/km
Gasoline trucks average consumption	$FCR_{Tr,G}$	0.50831 l/km
Diesel price	D_{price}	0.5406 €/l
Gasoline price	G_{price}	0.5026 €/l
CO_2e emissions (diesel)	CO_2e_D	2.772 kg/l
CO_2e emissions (gasoline)	CO_2e_G	2.420 kg/l
CO_2e price	CO_2e_{price}	13 €/ton

Society costs are then calculated for each pavement section considering the actual implemented M&R plan and summed up to obtain the respective amount for the network. Similar to what was done for the global performance indicator, C_S are also determined considering the real and the predicted values of PI_E. The results are indicated in Table 6.9.

Society costs are under-predicted in 3 of the 10 considered sections. Accordingly, the predicted C_S for the network are higher than the calculated with the real values of PI_E.

The optimal M&R plans for each pavement section obtained at the first-stage optimization are now used as the input for the second-stage optimization, looking for

Table 6.9: Actual society costs for the sections and network of the LTPP case study

Section	Society costs (€)	
	Real	Predicted
1039	289 277	288 922
1056	53 613	54 101
1068	160 930	161 006
1087	373 425	375 875
1092	347 556	345 760
1096	418 920	419 451
1168	26 608	26 394
1169	88 689	89 374
3835	459 431	461 692
3865	150 787	151 811
Network	2 369 236	2 374 387

optimal M&R strategies at the network-level, i.e., sets of M&R plans for each pavement section. Results are shown in Figure 6.8, together with the real and predicted objective function values for the actual M&R strategy.

The Pareto front has 30 and 39 solutions that dominate the actual M&R strategy, respectively for the real and predicted values. The network strategy that costs 85 447 € for the road administration (red triangle), similar to the 86 591 € that were actually spent, represents 2 357 879 € of costs for society. Considering C_S resulted from the real PI_E of the actual M&R strategy, this solution would lead to savings of 11 357 € for society, i.e, 0.5%. Considering C_S derived from the predicted PI_E instead, the savings would be of 16 507 €, i.e, 0.7%.

Although these values seem to be insignificant, the relative savings are likely to increase as more and more pavement sections are included in the optimization at the second-stage level. Furthermore, the 10 considered sections comprise a total of 1 524 m ($152.4 * 10$) length of one lane only, with relatively low traffic, so the absolute savings of society costs definitely cause a great impact if all the road network is to be considered.

6.2.5 Conclusions

From all the LTPP database, pavement sections of Texas were the ones with more historical information and, thus, selected to assess the developed optimization methodology. Likewise all other states, the pavement sections recorded in LTPP are very disperse in terms of location, as observed in the map of Figure 6.1. Thus the variety

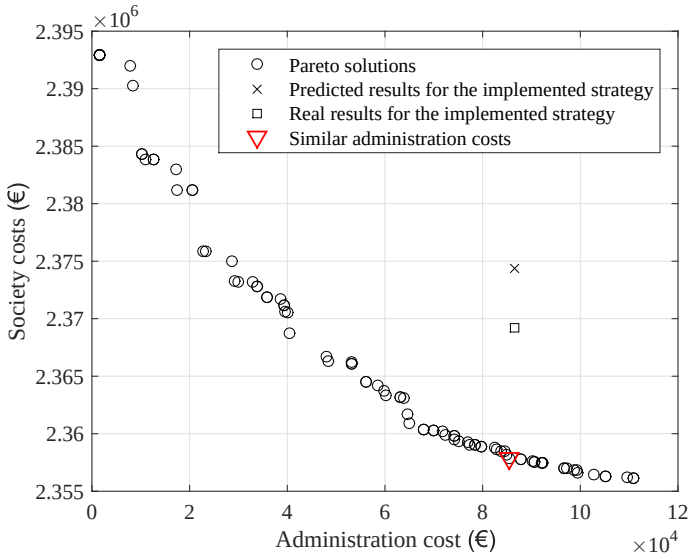


Figure 6.8: Pareto optimal solutions at the network-level for the State of Texas, considering administration and society costs

of pavement sections in terms of structure, affected traffic and deterioration patterns is quite high. Nevertheless, they were considered to be part of the same network, as they are in same administrative state.

The versatility of the methodology was demonstrated, since it was possible to adopt new input data such as M&R operations and respective effects, as well as all traffic and environmental related data needed to determine society costs.

In order to assess the methodology operation and effectiveness, it is necessary to admit that the prediction and preservation models are reliable. In fact, the prediction models were built with LTPP data so its efficiency is moderately expected. On the other hand, a clear definition of M&R effects and costs could not be done with the available historical data. Furthermore, these highly depend on project-level decisions that are not considered in the developed methodology.

Bearing that in mind, the optimality of M&R plans at the section-level suggested by the optimization methodology was verified, as they always provided solutions that dominated the actually implemented ones. However, the considered objective functions might differ from the priorities of the road administration responsible for those sections. In addition, there are other possible ways to measure the quality of a pavement section. Nevertheless, the functionality and potential of the methodology was successfully demonstrated for the section-level optimization.

The selected sections were grouped and an optimization for the network was performed in order to minimize the user and environmental costs, considered together as

society costs. The methodology also provided M&R strategies that could minimize society costs for the same road administration expenditures. The comparison of the network strategies with what was actually implemented became less relevant in this case, because it is not clear whether or not the considered sections are part of the same network and it is very unlikely that the environmental criteria was taken into account in the considered time period (from 1990 to 2010 approximately). Summing up, it cannot be clearly stated that the M&R strategies plans suggested by the methodology are better or worst than those actually implemented, because there are several aspects with high degree of uncertainty and some others that just cannot be considered in a mathematical approach. It can be stated, however, that the developed methodology suited well the case study for the LTPP sections and provided results that are potentially optimal and good to be considered by a decision maker.

6.3 Case study with data from a Portuguese road administration

6.3.1 Selection of pavement segments

The network of ASCENDI is composed by seven concessions. Each can be further divided in several segments that extend in between consecutive interchanges. Logically, a segment is affected with the same traffic and, generally, similar climate conditions, so that deterioration factors are similar, except for the differences in the vertical and horizontal alignment and drainage conditions within the segment. In addition, there are differences in the number of inspections performed among segments. For these reasons, and according to suggestions of ASCENDI, the application of the methodology is to be made per segment.

Information about several segments of three different concessions, located in the center and north of Portugal, was provided by ASCENDI. Segments with available data for more years and with some records of preservation operations were preferred in order to have a more complete and complex group of real data to compare with the optimization methodology results. Table 6.10 indicates the number of inspections, for which information was provided, that occurred in different time periods for three pre-selected segments.

Pavement preservation treatments were applied in parts of the segments A and B 8 years after their opening to traffic and on segment C 9 years after opening. No data after these dates are available. Each segment includes two carriageways in opposite directions

Table 6.10: ASCENDI network segments selected for further analysis

Segment	Number of inspections for each PI				
	PI_B	PI_CR	PI_E	PI_F	PI_R
A	1	2	3	3	2
B	2	2	3	3	2
C	2	1	3	3	2

of approximately 7 km, 20 km and 2 km length, respectively. Each carriageway is composed by two lanes (right-lane and left lane) for the whole extension and a third lane, known as the slow-lane, for shorter lengths.

To test the applicability of the methodology, only the most heavily loaded lane is considered, as it is normally the one with faster deterioration, thus demanding more M&R interventions. Therefore, a total of 136, 386 and 78 sections were analysed for segments A, B and C, respectively.

6.3.2 Definition of maintenance and rehabilitation operations effects and costs

Although the M&R operations previously defined in Section 4.6 were based on a list from ASCENDI, some changes were made in order to address this practical case study, according to suggestions made by the road administration.

On one hand, the operation consisting in an overlay of a bituminous layer was removed, because current maintenance practices for short lengths consist in milling off and applying a new pavement layer. This operation is preferred because adjacent lanes (left and right, for instance) are often in different preservation conditions and the overlay can only be used if applied to both lanes, as they must be at the same elevation. On the other hand, an operation consisting in milling off and replacing with new layer, including the addition of an overlay was included in the list of M&R operations. This is the option usually used to perform their major rehabilitation campaigns that are normally scheduled every 10 or 12 years. Obviously, this operation must include all the lanes in the same longitudinal extent.

The changes mentioned in the previous paragraph were the most significant ones. Other slight modifications based on preliminary results and discussions with experts from the road/highway sector were made. The list of M&R operations to be considered and their costs are presented in Table 6.11.

Table 6.11: M&R operations and costs considered for the second case study

M&R ID for the case study	Cost (€/m^2)
1 - Do nothing	0.0
2 - Crack sealing	3.70
3 - Surface shot blasting	2.70
4 - Surface treatment	5.60
5 - Mill off (5 cm) and replacement with AC	21.00
6 - Mill off (> 5 cm) and replacement with AC	57.30
7 - Mill off, replacement, and overlay	71.46

The M&R effects are presented in Appendix C. In opposition to what was made for the LTPP case study (Section 6.2), the defined effects could not be assessed by comparison with real data, as there were not available data for years after some M&R operations were actually applied. Nevertheless, the immediate effects of the M&R operations on the condition state is quite reliable and supported with the experience of those who helped in the definition of the effects. The most doubtful effects are related to the change of deterioration rate for performance indicators after applying preservation treatments. In fact, the new deterioration rate can only be noticeable on the long term and might be influenced by the change of several other deterioration factors.

6.3.3 Assessment and calibration of the pavement performance prediction models

The pavement performance prediction models (PPPM) implemented in the optimization methodology were developed with data from the LTPP database. Therefore, some disparities are expected to be observed when the same PPPMs are applied to data from ASCENDI. An assessment and calibration is then needed.

The classification system to be used in this case study is also the one suggested by the COST354 (as presented in Section 3.3) in accordance with ASCENDI, although that road administration has been adapting the COST354 transfer functions in order to be more compatible with their procedures of pavement quality assessment and control.

Besides the variable *Time*, the *Traffic* and *Traffic/SN* are also used as the Markov parameters to assess the adaptability of the PPPMs. The last two models were developed with data of heavy traffic only, since this is the type of traffic that causes pavement deterioration. For this reason, only the most heavily loaded lane is considered to assess the reliability of the PPPM. Available data of traffic in the selected

highway segments refer to the average annual daily traffic in both directions. It is assumed that each direction is affected by half of it. The distribution among the lanes follows the indications of the *Manual of pavement structures for the Portuguese road network* (JAE, 1995), as shown in Table 6.12.

Table 6.12: Percentage of the heavy traffic in the most heavily loaded lane (adapted from JAE (1995))

Number of lanes	Most heavily loaded lane
2	90 %
3	80 %

As mentioned before in Subsection 6.3.1, historical information about pavement performance is available for sections of 100 m length of lane. Therefore, the pavement performance of a segment can be evaluated according to the percentage of sections in a certain condition state (CS) for each PI. This is coherent with the nature of Markov prediction models that provide probabilities of a pavement stretch to be in a certain CS, or, in another perspective, the relative number of sections or relative area in that CS. In any case, an average value for the CS can be calculated as the representative condition of the whole segment. As an example, the condition of the segment A is presented in Table 6.13.

Table 6.13: Historical pavement condition for segment A since opening to traffic

	PI_B	PI_CR		PI_E			PI_F			PI_R	
Year	0	5	8	0	5	8	0	5	8	5	8
CS 1 (%)	100	86	76	68	58	46	91	1	0	99	96
CS 2 (%)	0	1	9	32	42	54	9	18	12	1	3
CS 3 (%)	0	2	1	0	0	0	0	60	40	0	1
CS 4 (%)	0	1	1	0	0	0	0	21	40	0	0
CS 5 (%)	0	10	13	0	0	0	0	0	9	0	0
Average CS	1.0	1.5	1.6	1.3	1.4	1.5	1.1	2.6	2.7	1.0	1.0

Data for the bearing capacity indicator (PI_B) is only available for the opening year of the segment. However, the deterioration rate of this indicator is known to be significantly low. Similarly, the deterioration of rutting is almost unnoticed as 5 and 8 years after opening to traffic, 99% and 96% are still in CS_1 regarding the PI_R. It is observed that the longitudinal evenness (PI_E) is not in perfect conditions in the opening year, which might be due to construction issues, but also because the transfer function of COST354 might not be fully suitable to quantify the CS of longitudinal evenness according to the administration standards. The PI_E never achieved the CS_3

in the first nine years of the pavement life. The skid resistance indicator (PI_F) is the most critical one as it deteriorates much faster than the others. Indeed, in the year 8, there is no section remaining in CS_1, and most of them are in CS_3 and CS_4. Regarding the cracking indicator (PI_CR), if a section is not in CS_1, the probability of being in the worst CS is quite high. This fact is partially explained by the cracking quantification procedure of ASCENDI, that assumes the full lane width is cracked if some alligator cracking is visible, thus affecting a big percentage of the section area.

Table (6.13) comprises all the sections of the most heavily loaded lane, which can all be used to compare with the predicted performance when the Markov parameter in use is the *Time*. If predictions are based on the parameters *Traffic* or *Traffic/SN*, the existence of the slow-lane (SL) must be taken into account, because it is affected with different traffic loads and possibly with different structure than the right-lane (RL). The pavement structure is characterized by the structural number (SN) obtained as explained in Subsection 3.5.3. A schematic representation of the pavement structure for segment A is presented in Figure 6.9, which happens to be the same for the RL and SL in both directions.

Surface course	e = 0.04m	$SN_{coefficient}$ = 0.44
Regulating course	e = 0.05m	$SN_{coefficient}$ = 0.34
Bituminous base	e = 0.14m	$SN_{coefficient}$ = 0.34
Granular base	e = 0.15m	$SN_{coefficient}$ = 0.14
Granular sub-base	e = 0.15m	$SN_{coefficient}$ = 0.14
Subgrade		

SN = 4.9

Figure 6.9: Pavement thickness and structural number for segment A

In order to assess the reliability of the *Traffic/SN* based models, these were used to predict pavement deterioration of two segments (A and B) with different traffic volumes and were compared with the real pavement performance values. Segment A is composed of 136 sections of the most heavily loaded lane, from which 99 are in the RL of a two-lane cross section, while the remaining 37 are in the SL of a three-lane cross section. Segment B is composed of 386 sections of the most heavily loaded lane,

from which 334 are in the RL of a two-lane cross section, while the remaining 52 are in the SL of a three-lane cross section. Tables 6.14 and 6.15 indicate the affected traffic for the referred segments, in equivalent single axle load (ESAL) of 80 kN, which was obtained from the number of heavy vehicles using a factor of 4.5 and 3.0, respectively for segments A and B, as recommended by JAE (1995). The indicated values refer to the traffic on the RL and the SL in the situations where they are the most-heavily loaded lanes. For instance, in the opening year of segment A, the number of kESAL passing on the most-heavily loaded lane was of 1119 for stretches with two-lanes and of 994 for stretches with three-lanes.

Table 6.14: Heavy traffic, in kESAL of 80 kN, for the most heavily loaded lane (right-lane or slow-lane) of segment A

Year	0	1	2	3	4	5	6	7	8	9
RL	1119	2229	3275	4393	5443	7248	9100	10944	12543	14165
SL	994	1981	2911	3905	4838	6443	8089	9728	11149	12591
Year	10	11	12	13	14	15	16	17	18	19
RL	15812	17483	19182	20914	22679	24479	26313	28183	30096	32051
SL	14055	15541	17051	18590	20159	21759	23390	25052	26752	28489

Notes: RL - right-lane; SL - slow-lane.

Table 6.15: Heavy traffic, in kESAL of 80 kN, for the most-heavily loaded lane (right-lane or slow-lane) of segment B

Year	0	1	2	3	4	5	6	7	8	9
RL	156	208	227	237	252	336	335	346	359	361
SL	138	185	202	211	224	299	297	307	319	321
Year	10	11	12	13	14	15	16	17	18	19
RL	364	366	370	375	379	383	388	394	400	406
SL	323	325	329	333	337	341	345	350	355	361

Notes: RL - right-lane; SL - slow-lane.

Figure 6.10 shows the comparison between the predicted and real average pavement performance using the *Traffic/SN* based Markov prediction model (as presented in Chapter 4). Indicators for bearing capacity and rutting are not presented because their deterioration is very low for the studied segments, as it is for the whole highway network of ASCENDI.

A clear over-prediction of deterioration for all the PIs is observed for both lanes of segment A. Predictions for segment B have better approximation to the real values.

PI_F and PI_E are slightly over-predicted. In fact, the PI_E has almost null deterioration. The real cracking performance indicator exceeds the predicted value, namely in the slow-lane sections where the difference between real and predicted average PI_CR is very high.

As expected, the predicted values for segment A are higher than for segment B, because the traffic volume is significantly higher for the former, while the structural number is similar for both segments: 4.9 for segment A and 4.6 for segment B. However, the differences of real deterioration between both segments is not so notorious. Furthermore, the cracking evolution is stronger for the segment with lower traffic volume, which can be explained by other factors besides the traffic load. The main purpose of using *Traffic/SN* based models is to adopt the same prediction model to pavement segments with different traffic volume and structure. In the present case, however, it can be concluded that the model could be reasonably adapted for segment B, but significant gaps between predicted and real performance of segment A could be identified. Similarly, the adjustment of the model to be compatible with the segment A would consequently represent a very slow deterioration prediction for segment B, as it could

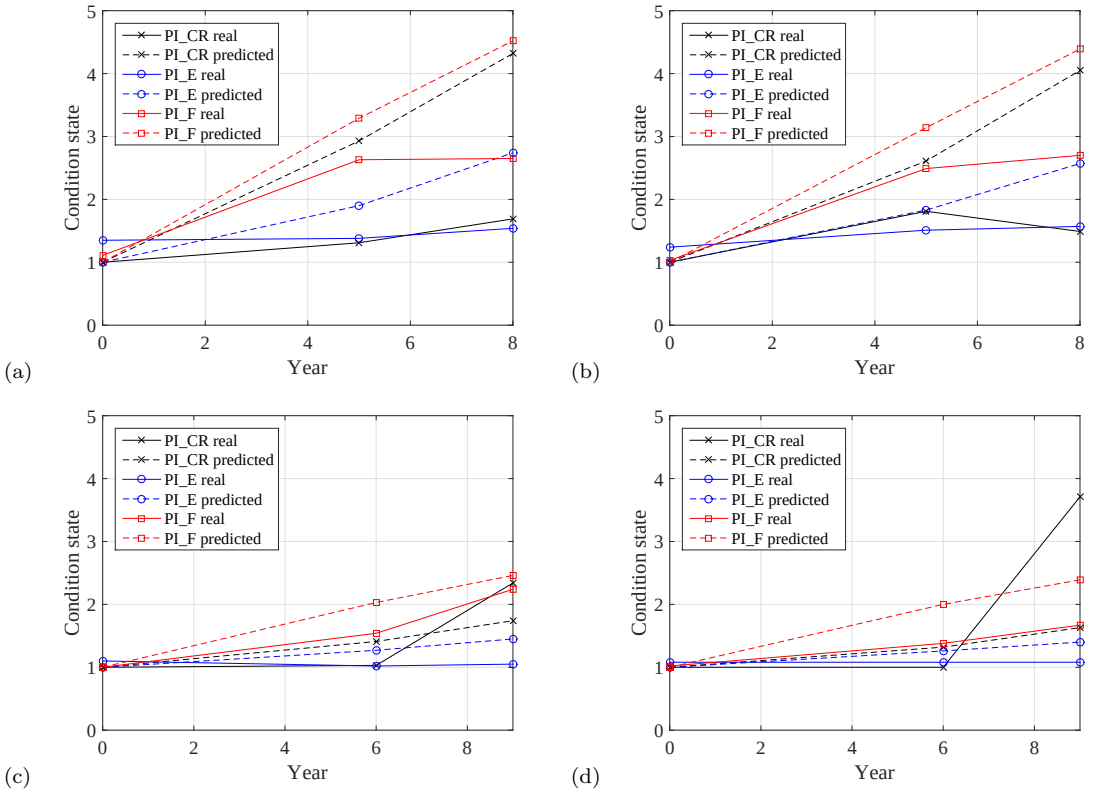


Figure 6.10: Real and predicted average pavement performance with the *Traffic/SN* based model: (a) right-lane sections of segment A; (b) slow-lane sections of segment A; (c) right-lane sections of segment B; slow-lane sections of segment B

be perceived by the author from some preliminary experiences.

Due to the aforementioned reasons, the parameter *Time* is used to predict pavement performance evolution, as the *Time* based model can be less arguably adjusted to different pavement segments. In fact, *Time* implicitly includes several deterioration factors besides traffic and pavement structure.

Figure 6.11 illustrate the real and the predicted pavement performance for segment A, considering the Markov parameter *Time*. In this case, both the right-lane and the slow-lane sections are considered together, because they are affected with the same independent variable (*Time*), in opposition to the case of Figure 6.10 (*Traffic/SN*).

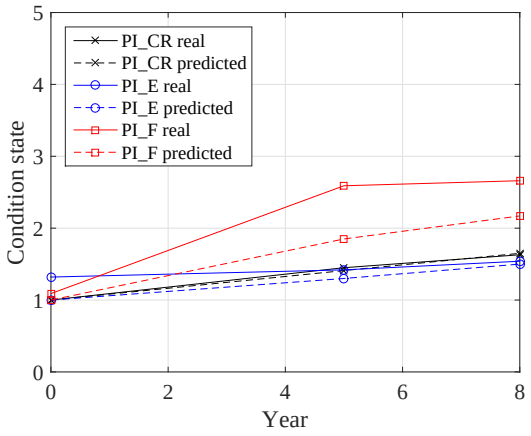


Figure 6.11: Real and predicted average pavement performance evolution for segment A with the *Time* based model

A reasonably good accuracy of the *Time* based prediction model for segment A is depicted from the Figure 6.11. The predicted and real lines are quite coincident for PI_CR. Regarding the PI_E, the predicted and real average condition state for the last year with available historical data are very close. The average predicted PI_F differs from the real one in less than a unitary condition state, but enough to be in different CSs. Thus, in order to use the prediction model for optimization purposes, an adjustment on the intensity matrix for PI_F (Q_F) should be made. In addition, the model PI_R is also adjusted in accordance with the very low deterioration of these indicators in segment A.

The new Q_F is obtained through the multiplication of the original matrix by a factor of 1.7, as indicated in Equation 6.3:

$$Q_F_{new} = \begin{bmatrix} -0.1773 & 0.1773 & 0 & 0 & 0 \\ 0 & -0.2108 & 0.2108 & 0 & 0 \\ 0 & 0 & -0.1071 & 0.1071 & 0 \\ 0 & 0 & 0 & -0.0765 & 0.0765 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} * 1.7 \Leftrightarrow$$
$$Q_F_{new} = \begin{bmatrix} -0.3014 & 0.3014 & 0 & 0 & 0 \\ 0 & -0.3584 & 0.3584 & 0 & 0 \\ 0 & 0 & -0.1821 & 0.1821 & 0 \\ 0 & 0 & 0 & -0.1300 & 0.1300 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (6.3)$$

A summary of the θ_i values for all PIs is presented in Table 6.16. The Q matrices for the first three PIs remain unchanged.

Table 6.16: θ values used for the prediction model for the second case study

	PI_B	PI_CR	PI_E	PI_F	PI_R
θ_1	0.0186	0.0736	0.0671	0.3014	0.0011
θ_2	0.0256	0.1178	0.0390	0.3584	0.0004
θ_3	0.0113	0.1777	0.0489	0.1821	0.0004
θ_4	0.0420	0.3542	0.0743	0.1300	0.0003

Considering the adjusted version of the *Time* based prediction model, the average CS for PI_F is now more accurate, as it is noticed on Figure 6.12.

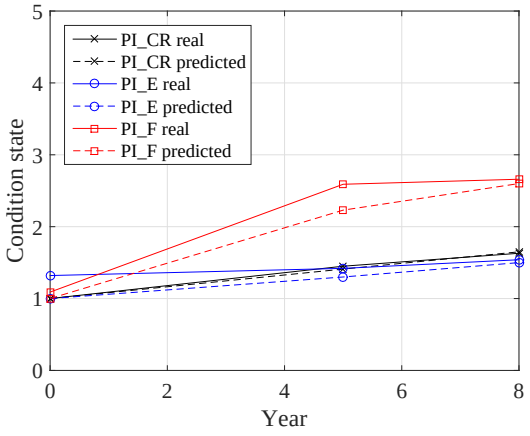


Figure 6.12: Real and predicted pavement performance evolution for segment A, considering the modified version of prediction model with parameter *Time*

Although the average predicted CSs is quite well adjusted, a perfect calibration would require the probabilities of being in each CS to be equal to what is actual verified in the relative number of pavement sections in each CS within a segment. The percentages indicated in Table 6.17 point out that aspect. In general, the transition for

Table 6.17: Real and predicted probabilities of finding a pavement section in each CS within a segment

Year 8	PI_CR		PI_E		PI_F	
	Real	Predicted	Real	Predicted	Real	Predicted
CS 1	76%	54%	46%	58%	0%	8%
CS 2	9%	30%	54%	36%	12%	18%
CS 3	1%	10%	0%	6%	40%	38%
CS 4	1%	3%	0%	1%	40%	27%
CS 5	13%	3%	0%	0%	9%	10%
Average CS	1.63	1.65	1.54	1.50	2.66	2.60

higher CSs is smoother for the predicted model than the actually verified, i.e., there is more evidence of passing by every CS before achieving the worst one. For instance, the predicted probability for the PI_E to be in the CS_2 and CS_3 is higher than what actually happens, in contrary to the probability of being in the worst CS. The actual probability of finding pavement sections in CS_3, CS_4 or CS_5 for PI_E is null, while the prediction model shows a decrease in the probabilities from CS_1 up to CS_4.

The determination of these probabilities is essential to define potential optimal preservation plans, as it is explained in the next subsection.

6.3.4 Application of the optimization methodology to suggest M&R plans

Adaptation of quality control plan to COST354 indicators

All the pavement network of ASCENDI is subjected to a quality control plan (QCP) that must be respected to avoid contractual punishments. The QCP consists in defining threshold values for the technical parameters for bearing capacity, cracking, longitudinal and transversal evenness, rutting and texture. The later one is not considered in this thesis since prediction models for the respective PI could not be developed due to the lack of data.

The requirement for bearing capacity is defined in accordance to the predicted loading the pavement will be subjected until the next major rehabilitation, so there

is no pre-specific threshold values. The quality requirement for cracking is defined in terms of relative cracked area within the total area of a segments. Similarly, the longitudinal evenness is constrained by relative lengths in which the IRI must be below specified values. Technical parameters for skid resistance and transversal evenness are limited for every section of 100 m length.

The technical parameters thresholds as specified in ASCENDI QCP are:

- Cracking: cracked area cannot exceed 20% of the segment area;
- Longitudinal evenness: IRI cannot exceed 2.5 m/Km in 50% of the segment length, 3.5 m/Km in 80% and 4.5 m/Km in 100% of the segment;
- Transversal evenness: the rut depth is limited to a maximum of 20 mm for continuous measurements in 100 m intervals;
- Skid resistance: the friction coefficient (grip number), measured in continuous for 100 m intervals must be higher than 0.35.

A compatibility analysis between the QCP and the adopted performance indicators from COST354 is necessary in order to define quality constraints to be imposed in the application of the optimization methodology to this case study. For an easier interpretation, readers are encouraged to revisit Table 3.1 and Tables 3.3 to 3.6 on Section 3.3 of this thesis.

The performance indicators for friction (PI_F) and rutting (PI_R) should never exceed the CS_4, corresponding to a minimum longitudinal friction coefficient of 0.38 and a maximum rut depth of 20.1 mm, respectively. This constraint for PI_F is a bit more demanding than the actual QCP, while for PI_R there is a very good approximation with the real requirement.

For longitudinal evenness (PI_E), a unique limit for its CS is not defined. Hence, the imposed constraints define that 50% of the length must be in CS_2 or better, 80% must be in CS_3 or better, and that CS_4 is the worst admissible condition for the whole extension. These are cumulative conditions so that all must be respected simultaneously. The IRI values corresponding to the mentioned CSs are slightly less strict than those defined in the QCP.

Regarding the cracking indicator (PI_CR), if a group of segments is considered just as one element, the PI_CR would be constrained to a maximum of CS_4. However, in the probabilistic approach as presented herein, and considering that different pavement sections within the same segment can differ in their CS, the definition of constraints for PI_CR is not so straightforward. In fact, if some pavement sections are in the worst CS

regarding the PI_CR (i.e., more than 25% of the section is cracked), the QCP might still be in compliance as the cracked area of the group of segments can still be less than the maximum admissible cracking rate. Due to the range of possible cracking rate correspondent to each CS (namely for CS_5), it is hard to define constraints for PI_CR that are clearly compatible with the QCP demands. Therefore, and in accordance with ASCENDI recommendations, it is defined that at least to 85% of the sections within a segment should be in CS_1, CS_2 or CS_3.

Although there is no pre-specified thresholds for PI_B in the QCP, a CS_3 is defined as the maximum admissible condition state for every pavement section.

In summary, threshold CSs for the PIs and corresponding values for the respective technical parameters are as follows:

- PI_B: cannot exceed CS_3 ($SCI_{300} \leq 759$ µm) at any pavement section;
- PI_CR: 85% of the segment area must be in CS_1, CS_2 or CS_3 (cracking rate $\leq$ 18.8%);
- PI_E: 50% of the segment length must be in CS_1 and CS_2 (IRI $\leq$ 2.5 mm/m), 80% in CS_1, CS_2 and CS_3 (IRI $\leq$ 3.7 mm/m) and none of the pavement sections can achieve the CS_5 (IRI *leq* 4.9 mm/m);
- PI_F: cannot exceed CS_4 (LFC $\geq$ 0.38) at any pavement section;
- PI_R: cannot exceed CS_4 (Rut depth $\leq$ 20.1 mm) at any pavement section.

It must be noticed that the QCP is not rigorously compatible with the thresholds defined for the PIs. In addition, some measurement procedures of ASCENDI might differ from the ones referred in COST354 to quantify the technical parameters. Therefore, the thresholds for PIs proposed herein cannot be used to assess the compliance with the QCP in real terms. For instance, the "real" probabilities previously presented in Table 6.17 have no direct translation with the QCP. This note is also particular important in order to avoid misinterpretations of the next subsubsection, in which a M&R plan that is expected to be similar to what is being defined by ASCENDI is analysed.

Preservation plan considering past M&R operations and future expectations

This subsubsection consists in simulating results for a M&R plan for segment A for a 20 years period. This period is composed by two parts. One is already past, starting on the very beginning of the segment A life-cycle until the present date. The second part includes the years to come until the time horizon of 20 years is reached. Therefore,

for the past years, the actually implemented M&R operations are considered. For the years to come, an approximation to what is expected to occur is assumed. This M&R plan is referred to as plan Z hereinafter.

Table 6.18 indicates the M&R plan Z, divided in three sub-plans, to be analysed. The respective costs and quality, measured by $\int GPI$, are presented in Table 6.19.

Table 6.18: M&R plan Z for segment A

M&R sub-plan	No. of sections	Years																			
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Z-1	65 (46%)	1	1	1	1	1	1	1	1	1	1	1	1	1	7	1	1	1	1	1	1
Z-2	8 (6%)	1	1	1	1	1	1	1	1	6	1	1	1	1	7	1	1	1	1	1	1
Z-3	63 (48%)	1	1	1	1	1	1	1	1	5	1	1	1	1	7	1	1	1	1	1	1

Table 6.19: Costs (€) and quality ($\int GPI$) of M&R plan Z for segment A

M&R sub-plan	No. of sections	Cost per section	Cost for all sections	Cost for the whole segment	Quality ($\int GPI$)	Weighted average quality
Z-1	65 (46%)	19 439	1 263 564		56.89	
Z-2	8 (6%)	37 075	296 602	3 192 044	47.86	52.18
Z-3	63 (48%)	25 903	1 631 879		47.87	

On the year 13, the M&R operation 7 is expected for the whole segment length, thus affecting all the 136 pavement sections. The M&R 6 was already applied in 8 sections on the year 8, while the M&R 5 was applied to 63 sections in the same year. As an example, for these 63 sections, the probabilities of finding the PI_CR in each CS along the 20 years is indicated in Table 6.20. For instance, according to that M&R plan, the probability for the group of those 63 sections to be in the worst CS is about 3% on year 8. In other words, it can be said that, probably, 3% of the 63 sections, i.e., 2 sections, were in the CS_5. The mill off and replacement operation that occurs in that year brings the PI_CR to the best condition state, as it is noticed on the column

Table 6.20: Probabilities (%) for PI_CR to be in each CS considering the M&R sub-plan 3

Year	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
CS_1	100	93	86	80	74	69	64	59	55	91	83	76	68	62	91	84	76	70	64	59	54
CS_2	0	7	12	17	21	23	25	27	28	8	15	19	24	25	8	14	19	22	24	26	28
CS_3	0	0	1	3	4	6	8	9	11	1	2	4	6	9	1	2	4	6	8	9	11
CS_4	0	0	0	0	1	1	2	3	4	0	0	1	1	2	0	0	1	1	2	3	3
CS_5	0	0	0	0	0	1	1	2	3	0	0	0	1	2	0	0	0	1	2	3	4

referent to year 9. The difference in the quality resulting from the sub-plans Z-2 and Z-3 is insignificant. Indeed, the effects of M&R operation 5 and 6 are very similar. The choice among those two operations depends more on a project analysis at the moment of application rather than on the future effects.

Identical calculations are performed to the other group of sections with different M&R sub-plan, allowing to conclude about the condition of all PIs for the whole segment. Figure 6.13 graphically represents the probabilities of finding sections in each CS for each PI, as well as the average condition of the whole segment. As expected, discontinuities on the graphs are seen for years 8 and 13. For year 8, the increase of probabilities associated with CS_1 are more significant for PI_CR and PI_F, because these PIs are in worse condition and the applied treatment (mill off (5 cm) and replacement with asphalt concrete) suits the related distresses. For instance, the longitudinal evenness indicator was not so improved because the treatment is defined not to produce improvement effects if the PI_E is on CS_1 or CS_2. In the year 13, when the major rehabilitation occurs, all the PIs are affected and return to the best condition state in all the segment extension.

From Figure 6.13 (f), it can be observed that the average CS for PI_F is quite similar for years 8 and 13, immediately before the application of the M&R operations. However, there is higher probability of finding pavement sections in the worst CS in year 13, as it can be depicted from Figure 6.13 (d). This fact highlights the importance of considering both the average condition and the probabilities associated with each CS to analyse and define M&R plans, as they are not necessarily "proportional".

M&R plans suggested by the methodology

The optimization approach for this case-study is in line with the approach previously presented for the M&R plan Z, i.e., allowing the definition of different M&R sub-plans for segment A. However, it is not reasonable to solve an optimization problem for each of the 136 pavement sections due to the long processing time it would require. Furthermore, the randomness associated with the deterioration process would suggest individual M&R plans that would be hard to merge into a wider plan covering several pavement sections. This conclusion was deduced from results of preliminary experiences for fewer number of sections, for which common M&R patterns could not be identified.

For this reason, the optimization is performed for the whole segment as a single unit to be optimized:

- Number of pavement sections: 136;

- Section length: 100 m;
- Section width: 3.75 m;
- Total area: 51 000 m^2.

The probabilistic character of the prediction models is then used to quantify the number of sections, or relative area, that are actually receiving the M&R operations, in line with the pre-defined effects on each PI in each CS. For instance, if the M&R operation 3

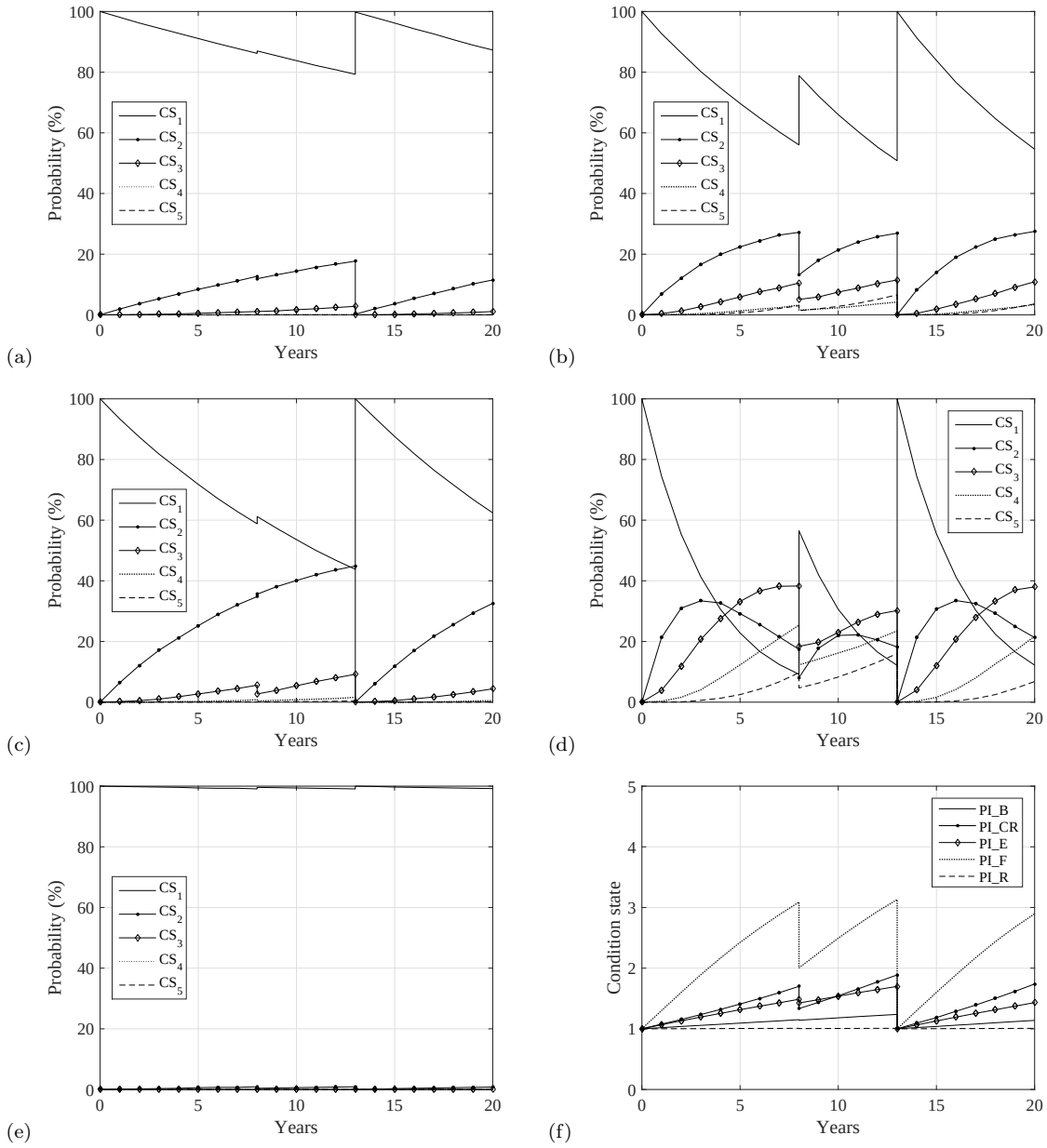


Figure 6.13: Probabilities of finding a pavement section of segment A in each condition state, and average condition, assuming the M&R plan Z: (a) PI_B, (b) PI_CR, (c) PI_E, (d) PI_F, (e) PI_R, (f) average condition of the segment

(surface shot blasting) is selected as optimal for a certain year, only the relative segment area with PI_F in CS_2 to CS_5 are affected.

The objective functions to optimize are defined as:

$$\begin{aligned} f_1 &= min \sum_{t=0}^{T} \frac{C_{A,t}}{(1+d)^t} \\ f_2 &= min \int_0^t GPI \end{aligned} \tag{6.4}$$

where T is the period to be analysed, in years, $C_{A,t}$ is the M&R cost for administration in year t, d is the discount rate and GPI is the average global performance indicator for the whole segment. A value of 2.5% for the discount rate was assumed, as it approximates its value on the beginning of the segment A life-cycle (Trading Economics, 2017). The constraints to be effectively used are based on those itemized on page 209, with slight modifications to attend some probabilistic particularities of the optimization procedure, as indicated in the group of equations 6.5:

$$\begin{gathered} p(PI_B = CS_4) + p(PI_B = CS_5) = 1\% \\ p(PI_CR = CS_4) + p(PI_CR = CS_5) \leq 15\% \\ p(PI_E = CS_3) + p(PI_E = CS_4) + p(PI_E = CS_5) \leq 50\% \\ p(PI_E = CS_4) + p(PI_E = CS_5) \leq 20\% \\ p(PI_E = CS_5) \leq 1\% \\ p(PI_F = CS_5) \leq 2\% \\ p(PI_R = CS_5) \leq 1\% \end{gathered} \tag{6.5}$$

The low probabilities for $[PI_B = CS_4 + PI_B = CS_5]$, $PI_E = CS_5$, $PI_F = CS_5$ and $PI_R = CS_5$ are actually beyond the real desirable limit (0%), but if they were defined to be 0%, the optimization algorithm would often face difficulties to converge to feasible solutions. Due to the probabilistic character of the prediction models, there is always a tiny chance of a PI to suddenly achieve the worst condition state. This fact is, however, negligible for PI_B and PI_R, because their deterioration probabilities are very low. Finally, a rehabilitation constraint is also considered, so that M&R operations within the segment cannot occur in consecutive years.

The intrinsic options for the multi-objective genetic algorithm remain the same as exposed in page 133. The lower and upper bounds for the decision vector are now defined as 1 and 7, respectively, in accordance with the new list of M&R operations (Table 6.11). Preliminary tests showed that no feasible solutions would be given if a

priori constraints were not imposed to the optimization problem, even for population size of 2000 or 5000 individuals. In fact, the optimal solutions were converging to a region of the Pareto front with lower administration costs than the necessary. Thus, the aforementioned constraints (Equation 6.5) were imposed *a priori* as a non-linear constraint function.

Results from the constrained optimization are plotted in Figure 6.14, where it is observed that the average quality for the segment ranges from 36.67 to 34.31 and the administration costs range from 1 391 212 € to 11 552 085 €. Four solutions are highlighted as potential choices for the administration: solution A for being the cheapest one; solution B for causing significantly better quality for a slight increase of costs; solution C for being the cheapest one from a group of solutions with intermediate levels of quality; and solution D for being the last one after which administration costs significantly increase for just slight improvements of quality. The respective M&R plans, quality and administration costs are indicated in Tables 6.21 and 6.22.

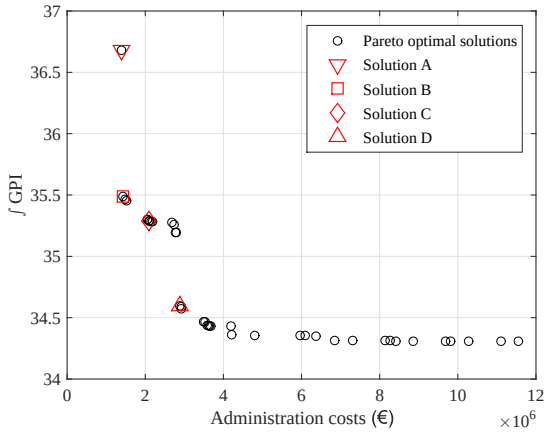


Figure 6.14: Pareto solutions suggested for the second case study

Table 6.21: M&R plans for the highlighted solutions for segment A

M&R plan	Years																			
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Sol. A	1	3	1	3	1	3	1	4	1	2	1	5	1	4	1	3	1	4	1	3
Sol. B	1	4	1	3	1	3	1	4	1	3	1	5	1	3	1	3	1	4	1	3
Sol. C	1	3	1	3	1	3	1	4	1	5	1	4	1	3	1	5	1	3	1	3
Sol. D	1	3	1	3	1	3	1	4	1	4	1	6	1	3	1	4	1	3	1	3

From almost all the solutions represented in Figure 6.14, there is a M&R operation that improves friction every two years, which is quite expected given the fast deterioration rate of this PI in this case study and the very low allowance to achieve CS_5. The solutions exposed in Table 6.21 are not exception.

Table 6.22: Pavement quality and administration costs resulting from the M&R plans for the highlighted solutions for segment A

M&R plan	Quality ($\int GPI$)	Relative quality (%)	Administration costs (€)	Relative costs (%)
Sol. A	36.68	94.0	1391212	48.3
Sol. B	35.49	97.4	1435218	49.8
Sol. C	35.29	98.0	2100528	72.9
Sol. D	34.59	100.0	2881153	100.0

The difference between the quality provided by solutions A and B is mainly caused by the crack sealing on the year 9 for solution A, instead of a surface shot blasting as suggested for solution B, which increases the cost in 44 006 € (3.2%) while improving the quality in 1.2 units (3.2%). Solution C differs from the others because it suggests the replacement of part of the pavement layer (M&R 5) in two moments, separated by six years. Solution D differs from B mainly due to the predicted thickness to mill off and replace, as the former suggests the M&R 6 instead of M&R 5. Thus, it brings more benefits for pavement quality because it improves the CS of PI_B and has a more positive effect on PI_E for all condition states. Consequently, solution D is more expensive. In practical terms, the appropriate thickness to mill off is chosen at the project level, in accordance with a more detailed analysis on the distresses to repair. The consideration of M&R 6 for few pavement sections in worst condition, and of M&R 5 for the remaining extension is, perhaps, a more realistic scenario.

Assuming that solution B is preferred over solution A, because it represents better safety conditions (due to increasing of friction) for a relatively small amount of extra costs, a comparison of the average condition for PI_B, PI_CR, PI_E and PI_F for solutions B, C and D is presented in Figure 6.15. The evolution of rutting performance indicator is not presented because it is negligible and very similar for all the solutions. It can be observed that solution C improves PI_E and PI_CR in two moments, being the best solution in terms of the cracking performance. For PI_E, the best solution is D, being the only one capable of bringing all the pavement sections to CS_1 for PI_E and PI_B. The friction indicator evolution is quite similar for all the solutions.

From these three solutions, the cheapest one (solution B) is very likely to be elected, since it respect the constraints for the least cost. It matters, then, to assess how far are the PIs to fail with the constraints. The probabilities of achieving each condition state for PI_B, PI_CR, PI_E and PI_F are illustrated in the graphs of Figure 6.16. In coherence with the respective graph in Figure 6.15, the year 11 is the only moment when all the pavement sections return to the best condition state in terms of PI_CR and PI_F. In that year, PI_E is only improved in pavement sections that are in CS_3 and CS_4, reducing it to CS_2. The solution does not suggest any M&R operation capable

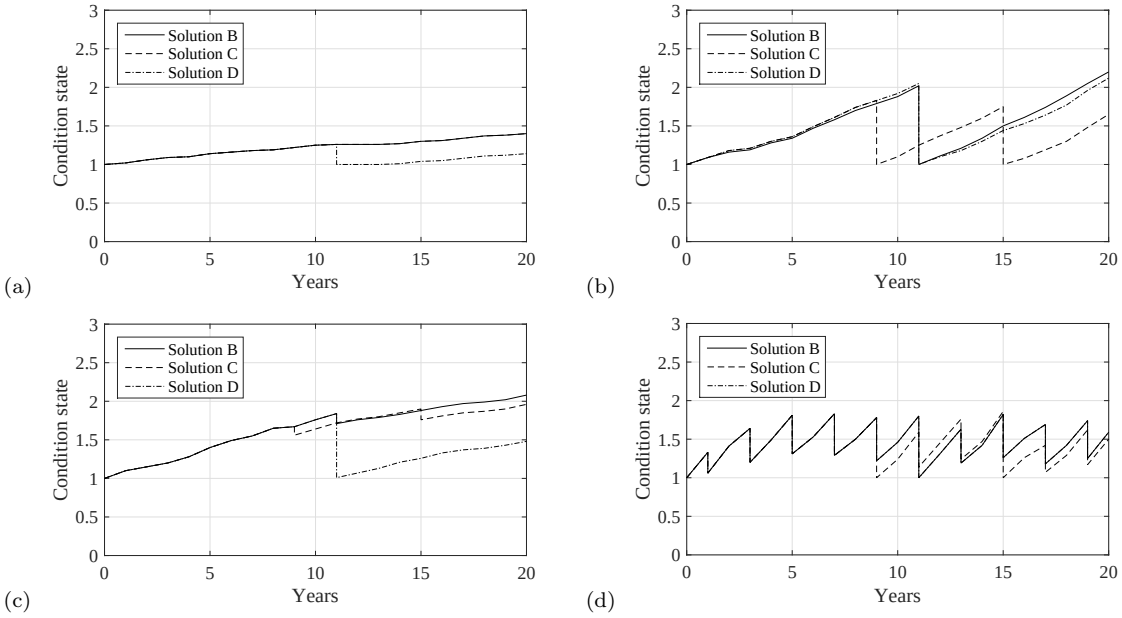


Figure 6.15: Evolution of the average condition resulting from solutions B, C and D, for: (a) PI_B, (b) PI_CR, (c) PI_E and (d) PI_F

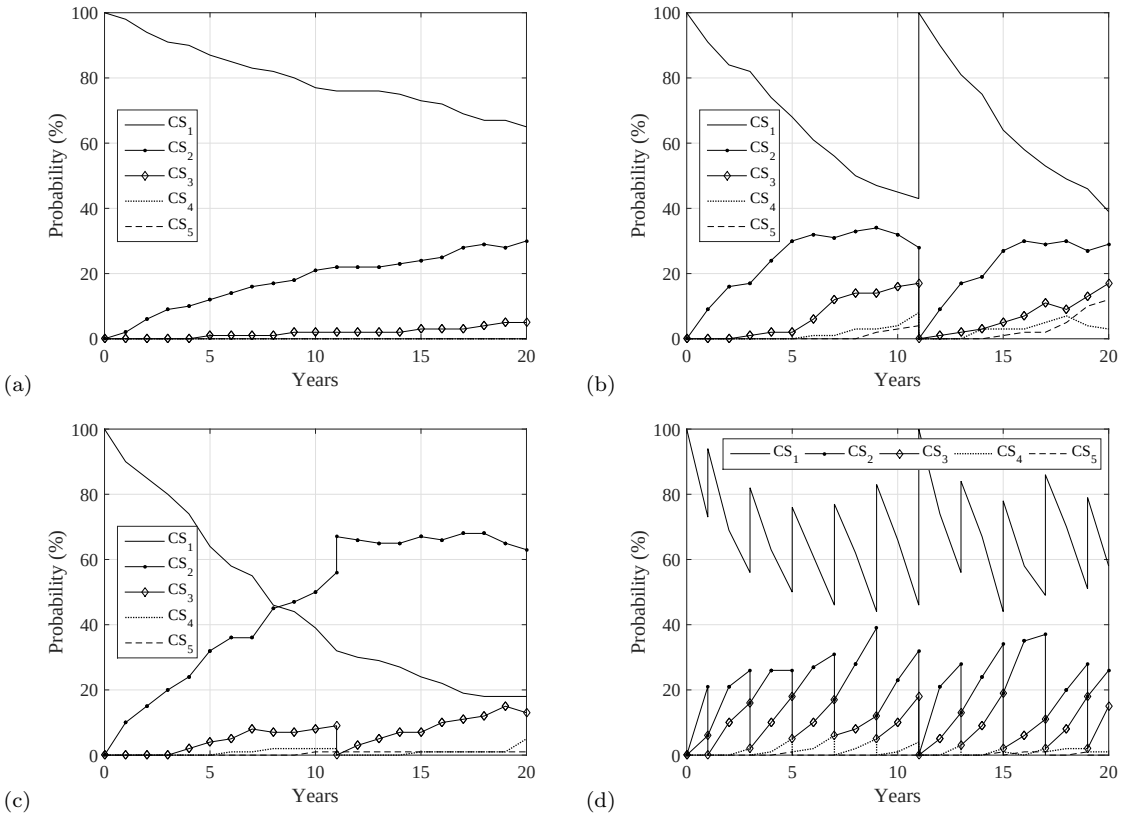


Figure 6.16: Probabilities of finding a pavement section of segment A in each condition state, assuming the M&R plan of Solution B: (a) PI_B, (b) PI_CR, (c) PI_E, (d) PI_F

of treating pavement sections in the worst condition state for PI_E, which comprises 1% of the segment in this example. It is expected that any administration, after a project-level analysis, would apply some other M&R operation to this small segment area to account for these rare events. Nevertheless, the probability of finding pavement sections in CS_5 for PI_E remains equal to 1% during the whole period, thus respecting the mathematically imposed constraints. Regarding the bearing capacity indicator, the only effect produced by the M&R operations 4 and 5 consists in reducing its deterioration rate for some period, barely noticed in Figure 6.16 (a).

Another potentially interesting M&R plan for a road administration could be the one of solution C, because it is more conservative in terms of cracking deterioration and it represents a better distribution of the M&R costs along the time. Furthermore, the administration costs can possibly be reduced if the mill off and replacement operation is only applied to pavement sections that are actually proved to be deteriorated after a project-level analysis. In fact, the methodology considers that M&R operations 5, 6 and 7 are applied to all the segment extension, because the probability of finding pavement sections in some degree of deterioration is high for more than one PI and the methodology is not capable to identify whether or not some pavement sections are still in the best CS for all PIs. Regarding the other operations indicated in the M&R plan, only the relative extension that are actually influenced by that operation is treated. M&R 3 only affects pavement sections in CS_2 to CS_4, whereas M&R 4 is also mainly applied to reduce PI_F in the same CSs, although it causes the reduction of deterioration rate for other PIs. The proportion of the affected segment in each year of the analysis period is indicated in Table 6.23.

Table 6.23: Proportion of the segment actually affected by the M&R operations suggested by solution C

Year	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
M&R plan	1	3	1	3	1	3	1	4	1	5	1	4	1	3	1	5	1	3	1	3
Affected area (%)	-	27	-	44	-	50	-	54	-	100	-	45	-	52	-	100	-	35	-	45
Number of sections	-	37	-	60	-	68	-	73	-	136	-	61	-	71	-	136	-	48	-	61

The number of sections treated by surface shot blasting increases until the moment when all the segment is reduced to CS_1 for PI_F due to a replacement of the surface layer. In fact, according to the opinion of the experts listen in this work, surface shot blasting stops being effective after the third application in the same surface, a fact that was taken into consideration in the methodology. The main purpose of M&R 5 on years 9 and 15 is to treat cracking and longitudinal evenness, despite improving

other PIs. Thus, a more risky approach to reduce administration costs is to assume that sections in need of cracking and longitudinal evenness repair are coincident, and these are also the ones in worse condition of skid resistance. If so, the segment area to be affected by M&R 5 can be reduced, providing that the constraints are met.

An analysis to the probabilities of finding pavement sections in each CS for PI_CR, PI_E and PI_F for solution C suggested that 50% to 60% of the sections should be treated with M&R 5 in year 9 and 15. Few trial-error tests led to conclude that an affection on 56% of the sections for both years would be sufficient to respect the constraints defined for the whole segment, while reducing the costs for administration. Therefore, three M&R sub-plans are defined and indicated in Table 6.24 and the resulting probabilities for the segment to achieve each CS are graphically presented in Figure 6.17. For

Table 6.24: M&R sub-plans of solution C for segment A

M&R sub-plan	No. of sections	Years																			
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	44%	1	3	1	3	1	3	1	4	1	**5**	1	4	1	3	1	**1**	1	3	1	3
2	44%	1	3	1	3	1	3	1	4	1	**1**	1	4	1	3	1	**5**	1	3	1	3
3	12%	1	3	1	3	1	3	1	4	1	**5**	1	4	1	3	1	**5**	1	3	1	3

the presented scenario, none of the PIs returns to the best CS at the same time for the whole segment. The years 15 and 20 are those when the pavement performance is nearly passing the imposed constraints, with $p(PI_CR = CS_4) + p(PI_CR = CS_5) = 14\%$ and $p(PI_E = CS_5) = 1\%$. $p(PI_F = CS_5) = 1\%$ occurs in several occasions. The division of solution C in three sub-plans led to a significant reduction of administration costs, from 2 100 528 € to 1 458 105 €, for a small decrease of the overall pavement quality, i.e., a small increase of the $\int GPI$, from 35.29 to 36.58. Although these values denote the non-optimality of dividing solution C in three different sub-plans regarding objective functions for administration costs and quality, it is an option to be taken into consideration by the administration as a potential choice.

It often happens that administrations are only concerned in minimizing preservation costs while keeping the pavement performance within the quality requirements, either because of management policies, financial constraints or both. In such cases, solving a single-objective optimization problem is enough to find an optimal solution. A genetic algorithm for single-objective optimization, as previously presented in page 133 was used to solve such problem, resulting in the solution indicated in Table 6.25 (hereinafter called "solution SO"), with a quality of 43.24 and costs for administration of 1 121 378 €. Comparing to the solutions given for the multi-objective problem, solution SO suggest less friction related treatments, which is, indeed, the PI that often contributes the most to the increasing of the GPI. On the other hand, this solution sug-

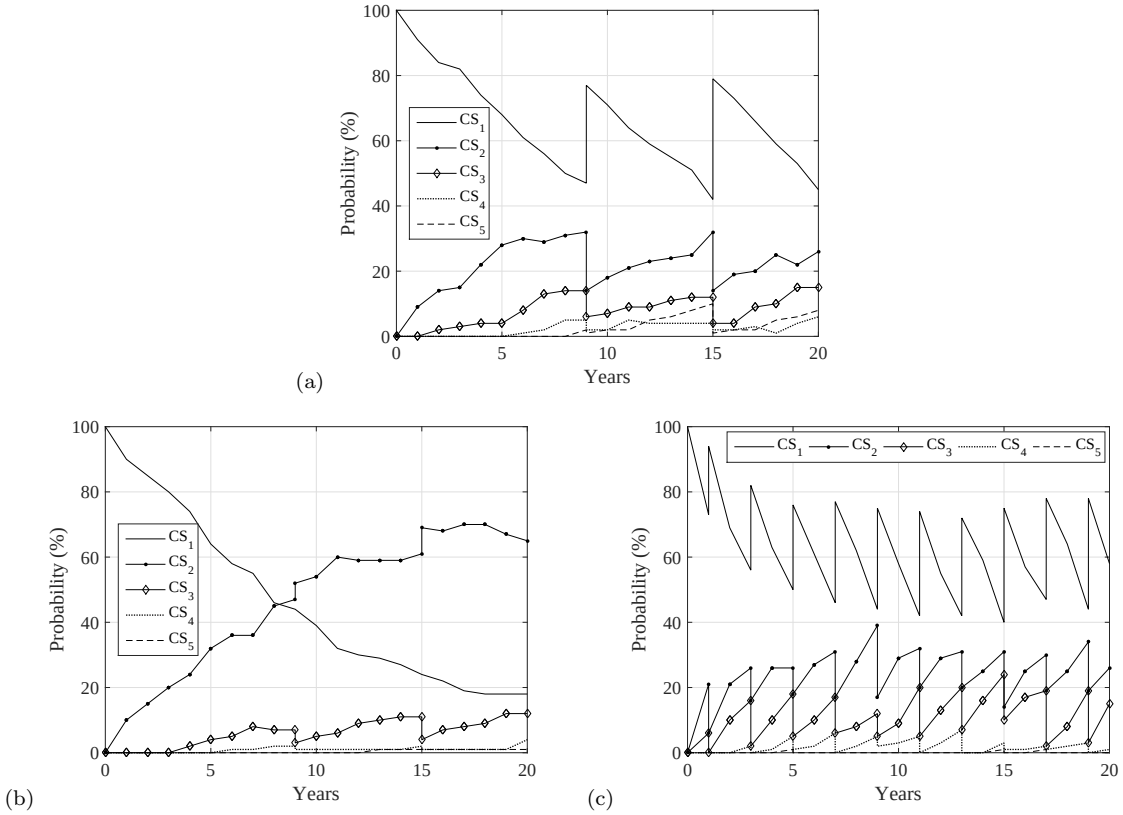


Figure 6.17: Probabilities of finding a pavement section of segment A in each condition state, assuming the M&R sub-plans of Solution C as indicated in Table 6.24: (a) PI_CR, (b) PI_E, (c) PI_F

Table 6.25: M&R plan that minimizes administration costs only

Year	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
M&R plan	1	2	1	3	1	3	1	3	1	2	1	5	1	2	1	2	1	3	1	2

gests crack sealing several times, as it is a very cheap treatment that reduces cracking, bearing capacity and rutting deterioration.

In fact, from all the exposed solutions so far, solution SO is the cheapest one, costing 19% less than solution A, with a decrease in quality of 18%.

Finally, all the exposed solutions and the M&R plan Z are plotted together regarding the administration costs and quality to ease the visualization of the trade-off among the conflicting objectives. Solution D is the one that approximates the most with the plan Z in terms of administration costs due to the occurrence of the M&R 6, that is significantly more expensive than M&R 5, and closer to the cost of M&R 7 predicted in the plan Z. In terms of quality, the plan Z presents a relatively high value because there are not as many friction related treatments as there are in the optimized solutions.

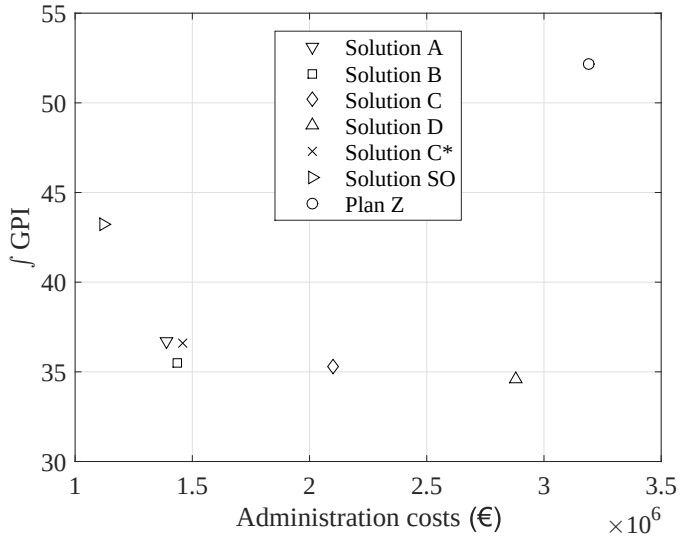


Figure 6.18: Exposed solutions for the second case study and current M&R plan

Solutions B and C provide similar quality but at very different costs. However, if the M&R plan of solution C is split in three sub-plans (solution C*), affecting different areas of the road segment, costs can be reduced to similar levels of solution B. A possible advantage of C* is in the smoother distribution of administration costs, which might be necessary due to annual financial constraints. Solution D is probably the least relevant option, but it provides an idea on the amount of money needed to renew the whole segment for the best pavement condition at the middle of its life-cycle. In the other extreme, solution SO represents the minimum necessary amount of money to keep the pavement within the quality requirements.

At last, user and environmental costs are indicated in Table 6.26, serving as another input to support decision making, although these were not part of the objective functions to minimize. These costs are calculated as explained in Subsection 5.2.3 and with the same input values, considering an approximation of real traffic data for segment A, which varies from about 1.5 at the beginning to 2.7 million vehicles per year at the end of the analysis period, with a ratio of around 17% of heavy vehicles. In general, the change of society costs ($C_U + C_{CO2e}$) is not so significant as the change of administration costs, because the former depend only on the PI_E which deterioration is not so different among the solutions. Therefore, the variation trend of total costs is quite similar to the variation trend of the administration costs. Nevertheless, it is worth noting the most costly plans (plan Z and Solution D) are the ones with less costs for users. The minimum total costs ($C_S + C_A$) occurs for the solution SO. Solution C* sacrifices a small amount of user costs by significantly reducing costs with M&R operations, thus resulting in less total costs.

Table 6.26: User and environmental costs for the exposed solutions for the second case study and M&R plan Z

M&R plan	C_A	C_U	C_{CO2e} (thousands of €)	C_S	C_T
Sol. A	1 391	99 023	1 758	100 781	102 172
Sol. B	1 435	99 023	1 758	100 781	102 216
Sol. C	2 101	98 987	1 757	100 744	102 845
Sol. D	2 881	98 452	1 748	100 199	103 080
Sol. C*	1 458	99 054	1 758	100 812	102 271
Sol. SO	1 121	99 023	1 758	100 781	101 902
Plan Z	3 192	98 440	1 747	100 187	103 379

Notes: C_A - administration costs; C_U - user costs; C_{CO2e} - cost of CO2e emissions; C_S - society costs; C_T - total costs.

6.3.5 Conclusions

Due to the type and amount of available data, as well as the time window to apply the methodology in this case study, focus was given to a pavement segment only. The selected segments to perform a first analysis were the ones with more available data in terms of years with distress measurements.

The M&R operations list was adapted to meet practical aspects of current practices of the administration and some particularities of the algorithm. In fact, the definition of M&R costs and effects highly affect the results given by the optimization methodology.

One of the difficulties of this case study was expected to be related to the use of the pavement performance prediction models (PPPM) developed with LTPP data. This was demonstrated for the PPPM based on *Traffic/SN*, because it could not suit well two segments with different traffic levels, but similar structural number. Regarding the *Time* based model, its adjustment to ASCENDI data by multiplying the original intensity matrices with an adjustment factor was easier and more reliable than expected, supporting the adaptability of the Markov prediction models. Nevertheless, a better precision could only be achieved if historical data for a higher number of inspections was available and used to train the Markov models.

Regarding the optimization of M&R plans, the quality control plan (QCP) of ASCENDI was adapted as much as possible to the performance indicators defined by the COST354 and the original transfer functions. Therefore, for some PIs, the defined constraints were more demanding than the QCP, and vice versa. The M&R plan Z was analysed in order to have an idea of the objective function values and relative performance condition of the segment. Due to the adoption of prediction models and transfer functions that are not used by ASCENDI, nothing can be concluded regarding

the real feasibility of the M&R plan Z.

To find optimal solutions, the optimization algorithm is deterministically applied to one pavement segment, but the constraints are evaluated in a probabilistic base. This option strongly reduces the processing time of the algorithm, comparing to what would be necessary to run the optimization algorithm for each segment section. In addition, the consideration of several pavement sections associated with random performance deterioration led to several individual M&R plans that were hard to merge into fewer solutions to be considered at the segment level. In opposition, the optimization for the whole segment at once allows the definition of few different sub-plans in accordance to the relative area that actually needs to be treated at a specific time in order to respect the constraints, as it was demonstrated by dividing the M&R of solution C into three sub-plans (solution C*). The Pareto solutions are, then, good initial suggestions from which a decision maker can test some sub-plans while numerically and graphically observing the advantages and risks that comes with it.

In this case study, user and environmental costs were only quantified for the presented solutions as a reference and an extra input to help decision making. The consideration of those costs would be reasonable if more segments were being analysed simultaneously, so that a second-stage level optimization as it was made for the LTPP case study would be possible.

According to the feedback obtained from the administration, the solutions provided by the methodology are reasonable in terms of real costs and operation, thus useful to support decision making. It is also an useful tool to assess risks and advantages of other possible proposed M&R plans. Finally, likewise the previous case study, it cannot be said that the suggested M&R plans are better or worse than what was defined as the M&R plan Z, as there are several other variables and constraints not numerically defined that affect decision making, besides the uncertainty of the prediction and preservation models used in this thesis.

Chapter 7

Conclusions and future works

7.1 Conclusions

This thesis focused on the development of an optimization methodology for pavement management systems (PMSs), capable of providing a decision maker with a group of potentially optimal preservation plans for a pavement network within a specified period of analysis. A big amount of data was necessary for developing and continuously testing the methodology. The Long Term Pavement Performance (LTPP) database was the main source of pavement related data. Then, the European COST Action 354 was used to transform the provided data in performance indicators (PIs). The conjugation of LTPP data with the PIs proposed by COST354 led to the usage of the following indicators to assess pavement condition: PI_B for bearing capacity; PI_CR for cracking; PI_E for longitudinal evenness; PI_F for skid resistance; PI_R for rutting; CPI_COM for comfort; CPI_SFT for safety; CPI_STR for structure and GPI, a global performance indicator. Their quantification in integer values was also necessary to develop the pavement performance prediction models (PPPM).

A major problem of PMSs is related to the reliability of the PPPMs, which was also a difficulty felt in this thesis. With the selected data, Markov based models were developed to predict pavement performance evolution. Typically, they define the probabilities of finding a pavement section in a certain condition state as a function of the time passed. In order to distinguish pavement deterioration of roads with different traffic and pavement structure, the Markov models were also trained using traffic and structural information. These models showed to be actually useful to distinguish the predicted deterioration in different roads. However, they are not necessarily more accurate than the *Time* based model, as it could be noticed in the case study presented in Section 6.3, because there are several other unaccounted deterioration factors. Ide-

ally, Markovian prediction models should be developed with a significant amount of historical data. Nevertheless, the *Traffic* or *Traffic/SN* based models have shown some potential for further improvements by including more variables, for instance.

Chapter 5 describes the development of the optimization methodology starting by the definition of the objective functions. Administration costs is the most common and usually considered objective to be minimized by road administrations, provided that pavement condition constraints are met. The pavement quality was defined in this thesis as the area under the GPI graph along time ($\int GPI$), although other options were tested. The simultaneously consideration of both objectives allow the definition of several maintenance and rehabilitation (M&R) plans that constitute a trade-off among pavement quality and costs for the administration. A third objective related to user and environmental costs was also defined, in line with the increasing importance that society has been giving to these costs. In fact, they represent a very significant parcel of the pavement life-cycle costs and their reduction can bring benefits to the whole society.

The inclusion of user and environmental costs, referred as society costs in this thesis, in the decision making process of road administrations is usually considered to be unpractical, thus, they are ignored by the administrations. This fact is explained by the higher magnitude that user and environmental costs typically represent in comparison to administration costs. This problem was addressed in Section 5.6.5, where a two-stage optimization approach was presented, which is capable of including all the mentioned objectives in a practical way for a network of pavement sections. Genetic algorithm was selected as the solver for the multi-objective optimization problems. Additionally, the methodology allows the results to be analysed in a probabilistic way and to include uncertainty originated by the prediction models and by the stochastic character of the optimization algorithm.

The two-stage optimization approach was applied in a case study with real data from the LTPP database for in-service pavement sections differing in their initial condition state (Section 6.2). The PPPM were reasonably accurate as they were developed with LTPP data as well. The list of M&R operations was adapted to be compatible with the preservation activities registered in the LTPP database. The methodology proved to be capable of providing optimal solutions of M&R plans at the pavement section level, considering administration costs and pavement quality as the conflicting objectives. Society costs were considered for the optimization of a group of sections simultaneously, i.e., for a network. Some of the resulting solutions demonstrated that, for approximately the same observed expenditure, a reduction in user and environmental costs at the network level, as quantified by the methodology, could be achieved.

Another case study was presented in Section 6.3, where the methodology was applied using historical data from the highways of ASCENDI, a Portuguese road administration. This case differs from the one previously mentioned because of the type and amount of available data. In this case, there was a much higher quantity of available data, but for a few number of years only. Furthermore, data were available for many adjacent pavement sections within the same segment and within the same highway, which allow and demand a different approach in the use of the methodology. In fact, for this case study, the probabilistic features of the methodology were exploited more extensively, because they allowed to predict the relative pavement area of a road segment that would achieve different condition states and, therefore, would be affected by the suggested M&R operations. Furthermore, the probabilities of finding pavement sections in each condition state can be directly related to the constraints defined by the quality control plan (QCP) of ASCENDI. Similar ways of defining constraints are likely to be found in the QCP of other road administrations. This case study was developed in collaboration with an ASCENDI engineer, so that the expectations of the administration in terms of useful information for their decision making process was taken into consideration in order to define the type of results to be provided by the methodology.

The versatility of the methodology could be verified by its application in two different case studies. In fact, the intensity matrices for the Markov prediction model and the M&R costs and effects are external inputs that can be easily modified. The optimization approach and type of results to be obtained can also be adapted to different needs. There is, however, difficulty in imposing some technical and/or political aspects that influence the decision making and are hardly converted into a mathematical or algorithmic form. Nevertheless, such aspects can be considered by the decision maker when analysing the solutions provided by the methodology.

Summing up, the developed methodology is able to define a group of optimal (or near optimal) solutions for preservation plans considering two or three conflicting objectives, either for a pavement section only or for a group of sections. User and environmental costs, which are expected to be more and more important for decision making in the years to come, were included in the methodology in a balanced way with costs for administration. The quantification of pavement quality and constraints was based in an European COST Action that intended to standardize pavement quality assessment at the European level, but has not been widely used so far. Its suitability for decision making was shown in this methodology. The case studies helped to validate the functionality of the methodology, that is able to define approximate administration costs to meet different levels of pavement quality and society cost, but also to evidence

some drawbacks that might be addressed in future works.

7.2 Future works proposals

The developed optimization methodology is, indeed, capable of providing results that support decision making. However, it cannot be said that it is a ready-to-use methodology, because the inputs definition and the use of the optimization tool still requires some "manual" work that cannot be rapidly understood by a new user of the methodology. The development of a software with a simple front-end would be an interesting task to be carried out. Ideally, this would be an open source software that would allow the methodology to increase its complexity in terms of considered aspects, while keeping it simple for the end user. For instance, the methodology considers a significant part of user and environmental costs within a pavement life-cycle. However, it could have been more complete if more parcels of user and environmental costs were added, most of which are already well studied and quantified in existent literature and practice.

Regarding the second case study (Section 6.3), the consideration of all the lanes of the pavement segment and of more segments within the same concession would have been an interesting study in order to face an even more realistic problem of decision making. In that case, the consideration of user and environmental costs could have been addressed by the developed two-stage approach. This would allow to observe the real impact of considering other costs rather than administration costs only and to understand ASCENDI's perspective about it. Nevertheless, this case study was a promising first approach considering the amount of information provided and the short time window available to address the problem. It is a good base for further studies with more available time and data, which will allow a more comprehensive analysis to be made. It would be interesting to observe how the methodology would perform if applied to other type of roads rather than highways, such as national or regional roads that are usually repaired more often. Perhaps other type of constraints and objective functions would have to be included. Naturally, new types of preservation treatments and prediction models could have to be defined.

The selection of reliable pavement performance prediction models (PPPM) consisted in one of the main difficulties of this work. In fact, new models had to be developed in the scope of this doctoral thesis. Despite not being the major focus of this work, a significant and time-consuming effort was made to improve the reliability of the PPPMs to be used. It was well noticed that a lot of work remains to be done in order to have more accurate prediction models, essential to enhance pavement

management systems. Additionally, efficient monitoring and organization of pavement related data should continue to be part of future applied research projects.

Finally, the application of the case studies in existent pavement management systems (PMSs) capable of providing optimal preservation plans would be an important step to validate the developed methodology. This comparison was not made due to limited time to finish the doctoral thesis but also because existing reliable PMSs are usually developed to specific road administrations and are not accessible to general use.

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Appendices

Appendix A

Description, costs and effects of maintenance and rehabilitation operations as defined in the original maintenance model (Section 4.6) and used for problems presented in Chapter 5.

Table A1: Description and cost of M&R operations

ID	Description	Cost (€/m^2)		
		min.	mean	max.
1	Do nothing		0.0	
2	Crack sealing	3.51	3.70	3.89
3	Milling ($\leq$ 5cm) + TC + RC	14.25	15.00	15.75
4	TC + overlay	13.40	15.30	16.90
5	Milling ($\leq$ 5cm) + TC + SC	19.10	21.00	22.30
6	Milling (5-10cm) + TC + BC + TC + SC	37.80	41.55	44.70
7	Milling (>10cm) + TC + BaseC + TC + BC (5-10cm) + TC + SC	63.60	68.90	73.30
8	Milling (5cm) + TC + SAMI + SC	32.60	34.50	35.80
9	Milling (5-10cm) + TC + SAMI + BC + TC + SC	15.30	55.05	58.20
10	Milling (>10cm) + TC + SAMI + BaseC + TC + BC (5-10cm) + TC + SC	77.10	82.40	86.80
11	Surface shot blasting	2.56	2.70	2.84
12	Surface treatments	5.32	5.60	5.88

Notes: BaseC = Base Course; BC = Binder Course; RC = Regulating Course; SAMI = stress absorbing membrane interlayer; SC = Surface Course; TC = tack coat.

Table A2: Effects on PI_B

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	1	0	0	0	20	20	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	2	2	0	0	per.	per.	per.	0	0	-20	-40	-60	0
5	0	0	0	0	0	0	5	4	3	0	0	30	20	10	0
6	0	1	2	2	0	0	0	0	0	0	0	0	0	0	0
7	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	6	5	4	0	0	30	20	10	0
9	0	1	2	2	0	0	0	0	0	0	0	0	0	0	0
10	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	3	2	1	0	0	30	20	10	0

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Table A3: Effects on PI_CR

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	2	1	0	0	20	10	10	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	2	3	4	0	per.	per.	per.	per.	0	-70	-80	-90	-100
5	0	1	2	3	4	0	per.	per.	per.	per.	0	-60	-70	-80	-90
6	0	1	2	3	4	0	per.	per.	per.	per.	0	-50	-60	-70	-80
7	0	1	2	3	4	0	per.	per.	per.	per.	0	-40	-50	-60	-70
8	0	1	2	3	4	0	per.	per.	per.	per.	0	-50	-60	-70	-80
9	0	1	2	3	4	0	per.	per.	per.	per.	0	-40	-50	-60	-70
10	0	1	2	3	4	0	per.	per.	per.	per.	0	-30	-40	-50	-60
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	3	2	1	0	0	30	20	20	0

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Table A4: Effects on PI_E

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	1	2	2	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
5	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
6	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
7	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
8	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
9	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
10	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A5: Effects on PI_F

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
5	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
6	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
7	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
8	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
9	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
10	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
11	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A6: Effects on PI_R

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	1	0	0	0	20	20	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
5	0	1	2	3	0	0	per.	per.	per.	0	0	-40	-50	-60	0
6	0	1	2	3	0	0	per.	per.	per.	0	0	-30	-40	-50	0
7	0	1	2	3	0	0	per.	per.	per.	0	0	-20	-30	-40	0
8	0	1	2	3	0	0	per.	per.	per.	0	0	-30	-40	-50	0
9	0	1	2	3	0	0	per.	per.	per.	0	0	-20	-30	-40	0
10	0	1	2	3	0	0	per.	per.	per.	0	0	-10	-20	-30	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	3	2	1	0	0	30	20	10	0

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Appendix B

Description, costs and effects of maintenance and rehabilitation operations used for the first case study (presented in Section 6.2).

Table B1: Description and costs of M&R operations for the first case study

LTPP M&R code	M&R ID for the case study and description	Cost (€/m^2) min.	mean	max.
not applicable	1 - Do nothing		0.0	
1	2 - Crack sealing	3.51	3.70	3.89
12	3 - Surface shot blasting	2.56	2.70	2.84
19	4 - AC overlay	13.40	15.30	16.90
28, 31, 33, 34, 36	5 - Surface treatment	5.32	5.60	5.88
51	6 - Mill off and overlay with AC	19.10	21.00	22.30

Table B2: Effects on PI_B

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	1	0	0	0	20	20	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	1	2	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	3	2	1	0	0	30	20	10	0
6	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0

Table B3: Effects on PI_CR

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	2	1	0	0	20	10	10	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	2	3	4	0	per.	per.	per.	per.	0	-60	-70	-80	-90
5	0	1	1	2	2	0	per.	per.	per.	per.	0	-70	-80	-90	-90
6	0	1	2	3	4	0	per.	per.	per.	per.	0	-40	-50	-60	-80

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Table B4: Effects on PI_E

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	1	2	2	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	1	2	3	3	0	0	0	0	0	0	0	0	0	0

Table B5: Effects on PI_F

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
4	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0

Table B6: Effects on PI_R

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	1	0	0	0	20	20	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	2	3	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	3	2	1	0	0	30	20	10	0
6	0	1	2	3	3	0	0	0	0	0	0	0	0	0	0

Appendix C

Description, costs and effects of maintenance and rehabilitation operations used for the second case study (presented in Section 6.3).

Table C1: Description and costs of M&R operations for the second case study

M&R ID for the case study	Cost (€/m^2)
1 - Do nothing	0.0
2 - Crack sealing	3.70
3 - Surface shot blasting	2.70
4 - Surface treatment	5.60
5 - Mill off (5 cm) and replacement with AC	21.00
6 - Mill off (> 5 cm) and replacement with AC	57.30
7 - Mill off, replacement, and overlay	71.46

Table C2: Effects on PI_B

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	1	0	0	0	20	20	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	3	2	1	0	0	30	20	10	0
5	0	0	0	0	0	0	5	4	3	0	0	30	20	10	0
6	0	1	2	2	0	0	0	per.	per.	0	0	0	-10	-20	0
7	0	1	2	2	3	0	0	0	0	0	0	0	0	0	0

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Table C3: Effects on PI_CR

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	2	1	0	0	20	10	10	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	3	2	1	0	0	30	20	20	0
5	0	1	2	3	4	0	per.	per.	per.	per.	0	-60	-70	-80	-90
6	0	1	2	3	4	0	per.	per.	per.	per.	0	-50	-60	-70	-80
7	0	1	2	3	4	0	per.	per.	per.	per.	0	-10	-20	-30	-40

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.

Table C4: Effects on PI_E

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
6	0	1	2	3	3	0	0	0	0	0	0	0	0	0	0
7	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0

Table C5: Effects on PI_F

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
4	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
5	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
6	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0
7	0	1	2	3	4	0	0	0	0	0	0	0	0	0	0

Table C6: Effects on PI_R

	Actual CS														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M&R ID	Reduction of CS					Years with changed deterioration rate					Change of deterioration rate (%)				
2	0	0	0	0	0	0	2	1	0	0	0	20	20	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	3	2	1	0	0	30	20	10	0
5	0	1	2	3	0	0	per.	per.	per.	0	0	-40	-50	-60	0
6	0	1	2	3	3	0	per.	per.	per.	per.	0	-30	-40	-50	-50
7	0	1	2	3	4	0	per.	per.	per.	per.	0	-20	-30	-40	-50

Notes: per. stands for permanently, so the effect remains until another M&R operation occurs.