Prescriptive maintenance for optimal management of systems subject to degradation : Application to the joint prescription of usage modes and maintenance actions for heavy vehicles

Pedro Dias Longhitano

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Présentée par :

Pedro DIAS LONGHITANO

Direction de thèse :

Christophe BERENGUER PROFESSEUR DES UNIVERSITES, GRENOBLE INP	Directeur de thèse
Benjamin ECHARD Docteur en sciences, Volvo	Co-encadrant de thèse

Rapporteurs :

Peter ZEILER
FULL PROFESSOR, Hochschule Esslingen
Bruno CASTANIER
PROFESSEUR DES UNIVERSITES, UNIVERSITE D'ANGERS

Thèse soutenue publiquement le **2 février 2024**, devant le jury composé de :

Gülgün ALPAN-GAUJAL, PROFESSEURE DES UNIVERSITES, GRENOBLE INP	Présidente
Christophe BERENGUER, PROFESSEUR DES UNIVERSITES, GRENOBLE INP	Directeur de thèse
Peter ZEILER, FULL PROFESSOR, Hochschule Esslingen	Rapporteur
Bruno CASTANIER, PROFESSEUR DES UNIVERSITES, UNIVERSITE D'ANGERS	Rapporteur
Mihaela MITICI, ASSISTANT PROFESSOR, Universiteit Utrecht	Examinatrice
Phuc DO, MAITRE DE CONFERENCE HDR, Université de Lorraine	Examinateur

Invités :

Khaoula Tidriri
MAITRESSE DE CONFERENCES,
Benjamin ECHARD
Docteur en sciences, Volvo

UNIVERSITÉ DE GRENOBLE ALPES

EEATS

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Pedro DIAS LONGHITANO

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Thèse dirigée par Christophe BÉRENGUER

préparée au Laboratoire de Grenoble-Images, Parole, Signal et Automatique (GIPSA-lab)

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Jury :

Rapporteurs :	Bruno CASTANIER	-	Université d'Angers
	Peter ZEILER	-	Esslingen University
Directeur :	Christophe BÉRENGUER	-	Grenoble INP - UGA
Encadrant :	Benjamin ECHARD	-	Volvo Group
Présidente :	Gülgün ALPAN	-	Grenoble INP - UGA
Examinateur :	Phuc DO	-	Université de Lorraine
	Mihaela MITICI	-	Utrecht University

A very personal foreword and acknowledgments

As I write down those last pages of my manuscript, I cannot help but having mixed feelings and somewhat contradictory thoughts about ending this journey. It is impossible not to feel immensely relieved. Those almost four years of work have been extremely challenging. Not intellectually, as I would have guessed before beginning this PhD, but in a much deeper and personal level. Doing research can be extremely taxing and lonely at times, and the months before sending this manuscript to the jury were some of the hardest I have ever gone through.

At the same time, it is also impossible not to think about all the different things I would have liked to include here. We always think that an elegant solution for that hairy optimization problem is right around the corner and, with just two extra weeks, we would have delivered the perfect PhD manuscript. In one of the many amazing talks I've had with my advisor, Christophe, he reminded me of a quote from Fernando Pessoa that captures this feeling perfectly:

"I'm astounded whenever I finish something. Astounded and distressed. My perfectionist instinct should inhibit me from finishing; it should inhibit me from even beginning [...]. I begin because I don't have the strength to think; I finish because I don't have the courage to quit."

Another thing that crosses my mind as I write my last paragraphs, is a brief conversation I had a couple of years ago, with Bruno Castanier, who would later evaluate this manuscript. After I complained about being unsure of the relevance of what I had achieved in my PhD until that point, Bruno kindly told me not worry that much: "After spending so much time and putting so much of yourself into it, your manuscript becomes your baby. You will love and be proud of it at the end". Time proved him right and despite the rough patches along the way, I grew proud of this work, not only for its content, but for all the personal growth that came with it.

But more than relief, regret or pride, the strongest among all the feelings I feel at this point is gratitude towards the amazing people that, in a way or another, have helped me through this adventure. Hence, without further ado:

I would like to thank my colleagues at Volvo, in particular my predictive maintenance partners, Christophe, Emmanuel and Elodie for the patience and all the good work we have done together through those years. I also want to thank my managers Ismael, for contributing actively with this manuscript and helping me whenever he could, and Marc for giving me the opportunity and idealizing this research project.

I am thankful to Bruno and Peter for their valuable insights, relevant comments and extremely gentle feedback. I also want to thank the remaining members of my jury: Mihaela,

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I am thankful to my dear friends Ian, for the uncountable laughs, deep conversations and for always looking after me on his own way; Mônica for being such a caring friend and for, in several occasions, effortlessly making my life better just by being the kind and simple person she is; Arthur for being extremely positive, making the atmosphere around him always lighter and for never refusing a beer; and Bia for being such a generous friend who knows me deeply, and for saving some of my hardest days with her music.

I also want to thank my friends and family in Brazil, in particular, my parents, Margarete and Paulo, for their empathy, unconditional love and all the advice they give me. Being far from them is one of the hardest parts of living abroad and yet, I never truly felt distant.

Finally, I want to thank Khaoula for the guidance in my first years of PhD. And last, but far from least, my two other advisors:

Thank you Christophe for your patience - which I tested several times - and for understanding me so well, specially at the end. You really made this journey worth it and I hope you know that you taught me things that go far beyond mere good research practices.

Thank you Ben for being so educated, smart and extremely present. I know that you often made an extra effort as advisor because you knew what this work meant to me. Our regular discussions - not only the technical ones - are probably the thing I will miss the most from my time in TSD Lyon.

Extended abstract

With digitalization, the internet of things and the popularization of data-centric services, different economy sectors have gone through significant changes in their business model. For the automotive sector in particular, those changes relate to moving towards more service-oriented offers. Selling a vehicle is no longer the last contact with the client, as aftermarket services are responsible for a significant part of vehicle manufacturer's revenue. With that in mind, the main concern of this research project is to lay down the foundations for enabling future services for heavy vehicles.

This work stresses the importance of maintenance optimization as well as its relationship with vehicle usage. In the past, maintenance was limited to corrective replacements of faulty parts resulting in long idle periods. This impacted the activity of the transporter, as well as its repair costs. The introduction of monitoring systems along with the current communication techniques allow the development of new optimization methods in which, not only replacement dates are determined optimally but also, vehicle usage is changed accordingly, ensuring cost optimization, and continuously extending trucks remaining useful life. With today's technology, those optimization methods could be turned into services that help clients defining replacement dates, manage logistics to minimize degradation levels of the fleet, or even change vehicle software parameters to minimize the long-term costs.

This approach to maintenance, in which life is extend through a myriad of different actions encompassing several aspects of usage, is often referred to as prescriptive maintenance. Although prescriptive maintenance was from the beginning an important element of the research project that originated this work, its definition is rather controversial in the scientific literature. As a consequence, a conceptual effort is done in this document in order to clarify the scope of this kind of maintenance paradigm. With more precise definitions and a clear scope, prescriptive maintenance is applied in the context of heavy vehicles.

Prescriptive maintenance applications for heavy vehicles can be seen as original optimization problems in the realm of transportation science. Throughout the investigation of such problems, significant scientific contributions were made. First and foremost, prescriptive maintenance requires models that can realistically connect degradation and vehicle usage. Such models are hardly adapted for decision-making problems and require adaptation. In this document, such models are studied in detail.

More concretely, this document is divided in two main parts. The first part contains most of the conceptual relevant discussions around PsM and its application for vehicles. It is concerned with defining important concepts, visiting the scientific literature and clearly stating the class of problems that will be addressed in the second part. It contains 3 chapters, which are now detailed.

In Chapter 1, the motivation behind this research is discussed. It comes down to recent shifts on business models of vehicle manufacturers, which now tend to include aftermarket

services as part of their offers. However, the importance of this research goes beyond merely creating tools for future services development. In order to justify its relevance in a more broad sense, in Chapter 1, the social role of heavy vehicles is discussed. Furthermore, the state of art of maintenance management and aftermarket services is presented, showcasing possible improvement paths that may involve the concept of prescriptive maintenance. Finally, other relevant research initiatives are visited, in order to provide what are the new challenges addressed in this particular work.

In Chapter 2, a robust scientific treatment is given to the concept of prescriptive maintenance. In order to understand it in the scientific context, several important aspects of maintenance as a whole are discussed, providing the reader with a high level view of modern maintenance policies and strategies. Despite its recent popularity both in academia and among industrial practitioners, prescriptive maintenance is not well defined. This claim is supported by a review on the usage of the term in publication, highlighting common conceptual weaknesses. This chapter also proposes another definition of prescriptive maintenance, clarifying potential confusion points. It ends by a presenting a development framework designed to help the development of future solutions.

In Chapter 3, this framework is applied for this document subject of interest: heavy vehicle. It contains a description of the particularities of those vehicles in terms of usage management, presenting useful definitions and discussing technical limitations. Additionally, in this chapter, a general discussion on the concrete problems that can be addressed by prescriptive maintenance is held. It allows the reader to have a clear scope of relevant optimization problems, and through a brief literature review, show possible modeling approaches. Chapter 3 closes the first part of the document.

Chapter 4 opens part 2 by addressing solving a version of the prescriptive maintenance problem presented in Chapter 3. This version is built around a stochastic degradation model that can represent different vehicle components. Based on it, health management is defined as, controlling degradation through routing and deciding replacement dates in an opportunistic maintenance scenario. Chapter 4 presents a composed optimization model made from a variation of a classical Vehicle Routing Problem (VRP) and another Integer Programming (IP) problem representing maintenance decisions. The advantages of this model when compared to classical VRPs is shown through extensive numerical experiments that cover different hypothesis.

In Chapter 5, the focus shifts to electric vehicles. A degradation model is proposed for the Energy Storage System (ESS) which is seen as an ensemble of batteries. This model combines concepts used in battery degradation studies and logistical problems alike, representing a potentially useful tool to connect battery degradation and vehicle usage realistically. More precisely, it introduces a new state of charge model, that is better than the alternatives used by most Electric Vehicle Routing Problems (EVRPs) in the literature, since it considers the physics of battery cells. The advantages when compared to other models are proved through different numerical experiments. Finally, realistic state of charge estimation allows for more precise degradation prediction. As a consequence, the proposed model connect battery state of health to vehicle displacements, opening the doors for new approaches to health management

in electrical vehicles.

Chapter 6 showcases those new approaches by introducing variations of shortest paths and routing problems accounting for degradation. Those versions are significantly harder to solve than their original counterparts. As such, optimization algorithms are proposed based on the particularities of the proposed optimization models. They are used to perform numerical experiments that not only prove the benefits of considering battery degradation but also show their viability in terms of computation time.

Through this work, insights on vehicle usage and health optimization were obtained. Significant contributions were made on the realm of maintenance management definition and for the transportation science. Maintenance was included in routing problems through models that can be used to connect degradation and vehicle usage. In particular, for electric vehicles, a realistic state of charge/state of health was proposed and included in optimization problems. Those contributions can be used as the basis for new aftermarket services in which clients will have access to a set of different recommendations (maintenance, but also usage and operating modes) to keep the fleet operational to the maximum.

Resumé étendu

Avec la numérisation, l'internet des objets et la popularisation des services centrés sur les données, différents secteurs économiques ont connu des changements importants dans leur modèle d'entreprise. Pour le secteur automobile en particulier, ces changements concernent l'évolution vers des offres davantage axées sur les services. La vente d'un véhicule n'est plus le dernier contact avec le client, car les services après-vente représentent une part importante du chiffre d'affaires des constructeurs automobiles. Dans cette optique, le principal objectif de ce projet de recherche est de jeter les bases des futurs services pour les véhicules lourds.

Ce travail souligne l'importance de l'optimisation de la maintenance ainsi que sa relation avec l'utilisation du véhicule. Dans le passé, la maintenance se limitait à des remplacements correctifs de pièces défectueuses, ce qui entraînait de longues périodes d'inactivité. Cela avait un impact sur l'activité du transporteur, ainsi que sur ses coûts de réparation. L'introduction de systèmes de surveillance et les techniques de communication actuelles permettent de développer de nouvelles méthodes d'optimisation dans lesquelles, non seulement les dates de remplacement sont déterminées de manière optimale, mais aussi l'utilisation du véhicule est modifiée en conséquence, ce qui permet d'optimiser les coûts et d'allonger continuellement la durée de vie utile des camions. Grâce à la technologie actuelle, ces méthodes d'optimisation pourraient être transformées en services qui aident les clients à définir les dates de remplacement, à gérer la logistique pour minimiser les niveaux de dégradation de la flotte, ou même à modifier les paramètres du logiciel du véhicule pour minimiser les coûts à long terme.

Cette approche de la maintenance, dans laquelle la durée de vie est prolongée par une myriade d'actions différentes englobant plusieurs aspects de l'utilisation, est souvent appelée maintenance prescriptive. Bien que la maintenance prescriptive ait été dès le départ un élément important du projet de recherche à l'origine de ce travail, sa définition est assez controversée dans la littérature scientifique. Par conséquent, un effort conceptuel est fait dans ce document afin de clarifier la portée de ce type de paradigme de maintenance. Avec des définitions plus précises et un champ d'application clair, la maintenance prescriptive est appliquée dans le contexte des véhicules lourds.

Les applications de la maintenance prescriptive pour les véhicules lourds peuvent être considérées comme des problèmes d'optimisation originaux dans le domaine de la science des transports. L'étude de ces problèmes a permis d'apporter des contributions scientifiques significatives. Tout d'abord, la maintenance prescriptive nécessite des modèles qui peuvent relier de manière réaliste la dégradation et l'utilisation du véhicule. De tels modèles sont difficilement adaptés aux problèmes de prise de décision et nécessitent une adaptation. Dans ce document, de tels modèles sont étudiés en détail.

Plus concrètement, ce document est divisé en deux parties principales. La première partie contient la plupart des discussions conceptuelles pertinentes autour de la PSM et de son application aux véhicules. Elle s'attache à définir les concepts importants, à consulter la

littérature scientifique et à définir clairement la catégorie de problèmes qui seront abordés dans la deuxième partie. Il comprend trois chapitres, qui sont maintenant détaillés.

Dans Chapitre 1, la motivation de cette recherche est discutée. Il s'agit de l'évolution récente des modèles d'entreprise des constructeurs automobiles, qui tendent désormais à inclure des services après-vente dans leurs offres. Cependant, l'importance de cette recherche va au-delà de la simple création d'outils pour le développement de services futurs. Afin de justifier sa pertinence dans un sens plus large, le Chapitre 1 aborde le rôle social des véhicules lourds. En outre, l'état de l'art de la gestion de la maintenance et des services après-vente est présenté, mettant en évidence les voies d'amélioration possibles qui peuvent impliquer le concept de maintenance prescriptive. Enfin, d'autres initiatives de recherche pertinentes sont examinées, afin de présenter les nouveaux défis abordés dans ce travail particulier.

Dans le Chapitre 2, le concept de maintenance prescriptive fait l'objet d'un traitement scientifique solide. Afin de le comprendre dans le contexte scientifique, plusieurs aspects importants de la maintenance dans son ensemble sont examinés, offrant au lecteur une vue d'ensemble des politiques et stratégies de maintenance modernes. Malgré sa récente popularité, tant dans les milieux universitaires que parmi les praticiens industriels, la maintenance prescriptive n'est pas bien définie. Cette affirmation est étayée par un examen de l'utilisation du terme dans les publications, qui met en évidence les faiblesses conceptuelles communes. Ce chapitre propose également une autre définition de la maintenance prescriptive, qui clarifie les points de confusion potentiels. Il se termine par la présentation d'un cadre de développement conçu pour faciliter l'élaboration de solutions futures.

Dans le Chapitre 3, ce cadre est appliqué au sujet d'intérêt du présent document: les véhicules lourds. Il contient une description des particularités de ces véhicules en termes de gestion de l'utilisation, en présentant des définitions utiles et en discutant des limitations techniques. En outre, ce chapitre contient une discussion générale sur les problèmes concrets qui peuvent être traités par la maintenance prescriptive. Il permet au lecteur d'avoir une vision claire sur les problèmes d'optimisation pertinents et, par le biais d'une brève revue de la littérature, de montrer quelques approches de modélisation possibles. Le Chapitre 3 clôt la première partie du document.

Le Chapitre 4 ouvre la partie 2 en abordant la résolution d'une version du problème de maintenance prescriptive présenté au Chapitre 3. Cette version est construite autour d'un modèle de dégradation stochastique qui peut représenter différents composants du véhicule. Sur la base de ce modèle, la gestion de la santé est définie comme le contrôle de la dégradation par le biais de l'acheminement des véhicules et le choix des dates de remplacement dans un scénario de maintenance opportuniste. Le Chapitre 4 présente un modèle d'optimisation composé d'une variation d'un VRP classique et d'un autre ILP représentant les décisions de maintenance. Les avantages de ce modèle par rapport aux VRP classiques sont démontrés par des expériences numériques approfondies qui couvrent différentes hypothèses.

Le chapitre 6 présente ces nouvelles approches en introduisant des variantes des plus courts chemins et des problèmes d'acheminement des véhicules tenant compte de la dégradation. Ces versions sont nettement plus difficiles à résoudre que leurs homologues originaux.

Ainsi, des algorithmes d'optimisation sont proposés sur la base des particularités des modèles d'optimisation proposés. Ils sont utilisés pour réaliser des expériences numériques qui non seulement prouvent les avantages de la prise en compte de la dégradation de la batterie, mais démontrent également leur viabilité en termes de temps de calcul.

Ce travail a permis d'obtenir des informations sur l'utilisation des véhicules et l'optimisation de leur santé. Des contributions significatives ont été apportées à la définition de la gestion de la maintenance et à la science des transports. La maintenance a été incluse dans les problèmes de routage grâce à des modèles qui peuvent être utilisés pour relier la dégradation et l'utilisation des véhicules. En particulier, pour les véhicules électriques, un état de charge/état de santé réaliste a été proposé et inclus dans les problèmes d'optimisation. Ces contributions peuvent servir de base à de nouveaux services après-vente dans lesquels les clients auront accès à un ensemble de recommandations différentes (entretien, mais aussi modes d'utilisation et de fonctionnement) pour maintenir la flotte opérationnelle au maximum.

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Acronyms

Chapter 1

EVs Electric Vehicles

RUL Remaining Useful Life

IRU International Road Transport Union

ICE Internal Combustion Engine

TCO Total Cost of Ownership

IEA International Energy Agency

STEPS Stated Policies Scenario

APS Announced Pledged Scenario

CNR National Road Commission

CSR Customer Service Representative

GCW Gross Combined Weight

POC Powertrain Operating Condition

DTCs Diagnostic Trouble Codes

PsM Prescriptive Maintenance

DTCs Diagnostic Trouble Codes

Chapter 2

CMA Corrective Maintenance Actions

PMA Precautionary Maintenance Actions

CM Corrective Maintenance

PM Preventive Maintenance

TbM Time-based Maintenance

CbM Condition-based Maintenance

PdM Predictive Maintenance

KbM Knowledge based Maintenance

Chapter 3

ECU Electronic Control Units

CAN Controller Area Network

FHT First Hitting Time

SPP Shortest Path Problem

ILP Integer Linear Programming

VRP Vehicle Routing Problem

MILP Multi-Integer Linear Programming

BB Branch and Bounding

EVRP Electric Vehicle Routing problem

AGAN As Good As New

ESS Energy Storage System

Chapter 4

Chapter 5

VPs Vehicle Parameters

SoH State of Health

SEI Solid Electrolyte Interphase

SoC State of Charge

OCV Open Circuit Voltage

mSoC Mean SoC

DoD Depth of Discharge

ECM Equivalent Circuit Model

MSE Mean Squared Error

Chapter 6

GA Genetic Algorithm

Part I

Prescriptive maintenance for heavy vehicles: industrial need, development framework proposition and optimization tools

Chapter 1

Maintenance and services for heavy vehicles

Contents

1.1 Context and goals

In today's globalized world, economy has become extremely dynamic and markets are gradually more interconnected. As a consequence, new recent trends such as digitalization, the internet of things and data centricity have had a deep impact on several different sectors and businesses across the globe. As an active and important part of the economy, the automotive sector is not blind to those changes or to the opportunities arising because of them. As a consequence, important shifts on the business models of this sector can already be seen. For example, the importance of aftermarket services on vehicle manufacturer offers has grown and is believed to continue growing in the coming years [VDB99]; [CV10].

The aforementioned trends affect economy in general, however, an important technological shift has had a huge impact in the automotive sector in particular: the creation of new Electric Vehicles (EVs). Those vehicles are becoming increasingly popular and are expected to soon become the norm of transportation as their adoption is seen as one of the most important measures to reduce the negative environmental impacts of road transportation.

Considering those two groundbreaking paradigm changes, the shift towards service-oriented business models and the inclusion of EVs in the market, this research project, financed by the Volvo Group, was born with a very concrete goal: investigate and create techniques which can enable the development of services suitable for modern heavy vehicles owners. In particular, it focuses on maintenance-related services since maintenance has been considered an important factor for ensuring transport robustness and guaranteeing customer profit [HDL16]; [Hed20].

There are several challenges and opportunities when considering such services. Firstly, efficient maintenance requires a broad view, addressing and accounting for all the particularities of each customer [Hed20]. Furthermore, with the current technology, maintenance services can go beyond simply monitoring vehicle health indicators or recommending replacement dates. Since, most of the vehicles are now connected to internet and regularly log different kinds of data, it is possible, on a daily basis, to impact their Remaining Useful Life (RUL) by optimizing usage. Such a service could encompass, for example, remotely changing software parameters, optimizing logistics, defining recharging strategies in the case of EVs and so on.

During the development of this research, several relevant concepts related to maintenance and usage optimization were developed. Those concepts were applied in the context of heavy vehicles, leading to original scientific contributions on the realm of transportation science. This thesis report documents the main aspects of this investigation, providing insights on how to formalize and solve maintenance and usage related decision-making problems. The techniques created have been proved useful and can be used as the basis for new services in the automotive industry.

This first chapter provides a description of different aspects of the automotive world, including the impacts of recent technological shifts. To understand the potential and interest behind new maintenance and usage services, an overview on how maintenance is handled today is given, discussing its importance and illustrating how future services can be an improvement when compared to what heavy vehicle manufacturers offer today. A discussion on clients expectations is also held in order to define the most important elements of such a solution which have, in turn, guided most of this research.

1.2 Heavy vehicles: importance, trends and costs

The object of interest of this work are heavy vehicles. This term is used herein to designate different types of vehicles such as heavy and medium duty trucks or busses. Although, at times their importance is taken for granted, the society's most basic functions, such as food supply, rubbish handling and even passenger transportation, rely on heavy vehicles [Eng16].

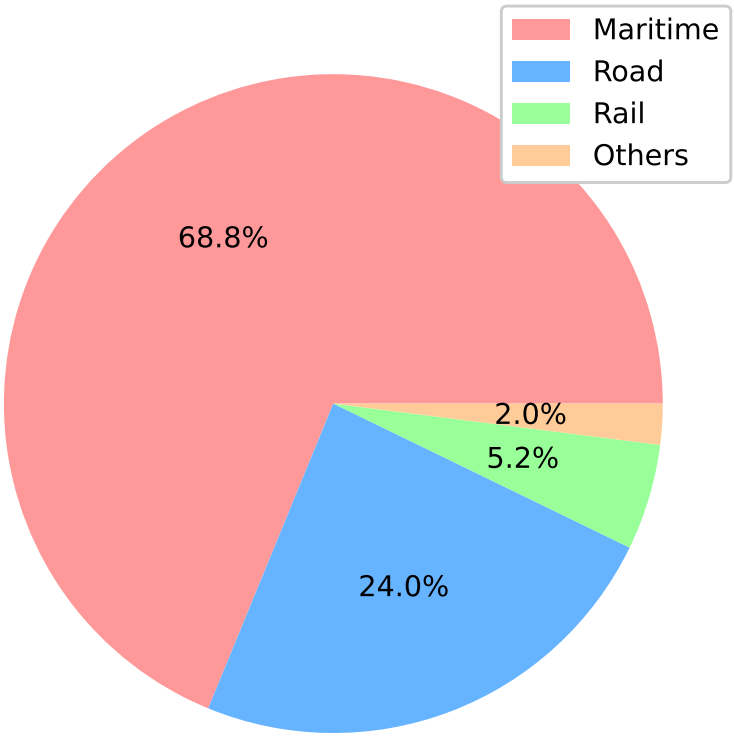

Figure 1.1: European modal distribution of freight transportation in 2020. [EUR22]

Heavy vehicles are also crucial for logistics since they are responsible for most of road freight transportation. Figure 1.1 shows the European modal distribution of the total freight transported in 2020 and Figure 1.2 shows inland freight modal distribution. As can be seen, road transportation accounted for 24% of the total freight and 77.3% of inland freight in terms of tonne-kilometers[1] in 2020. Besides its obvious importance terms of tonne-kilometers, road transportation has also a critical and unique role due to its flexibility [Eng16]. Roads are, in many countries, the only way of accessing several regions, making this freight mode crucial in terms of last mile transport [Rod20], being the basis of the logistic chain as a whole.

Heavy vehicles have also a significant impact from a sociological point of view. For example, as shown in Figure 1.3, this transportation mode is also the most important in terms of employments in Europe[2]. Furthermore, they also reduce geographical inequality. According to the International Road Transport Union (IRU), heavy vehicles link "producers, businesses and consumers, giving them the freedom to locate wherever they choose thanks to their

[1] In terms of percentages and tonne-kilometers both of those figures have been relatively steady in Europe in the past decade [EUR22]. However, in several countries of the emergent world, road transportation is on the rise. This is not surprising since, there is a strong correlation between GDP growth and road transportation importance in developing economies [Age17]. In India, for example, road freight activity has increased to around 290% in 25 years, from 0.4 trillion tonne-kilometers in 1990 to 1.4 in 2015 [Age17].

[2] Similar figures can be found for the United States [TS23] and the proportion grows when accounting for warehouse-related activities.

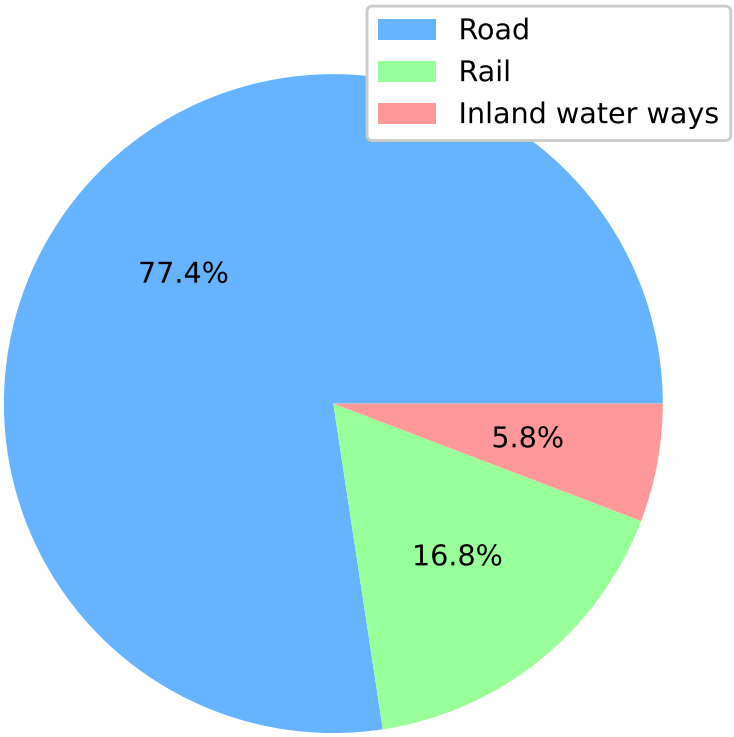

Figure 1.2: European modal distribution of inland freight transportation in 2020 [EUR22].

unparalleled flexibility. That freedom in turn helps to promote a fairer distribution of wealth and jobs between urban and rural areas" [Eng16].

Lately, however, society has become sensible to the dangers of climate change. Recognizing the urgency of the problem, reducing emissions is now a priority for several countries. Despite its undeniable importance, from 2000 to 2015, road transportation accounted for 75% of all freight transportation CO_2 emissions and has contributed to 8% of the overall growth of CO_2 emissions form fuel combustion [Age17]. Different initiatives were taken to address this environmental downside and, as a consequence, EVs have become a viable and important product. The history and particularities of EVs are now presented in more depth.

1.2.1 Electric mobility

Despite the hegemony of Internal Combustion Engine (ICE) vehicles, EVs were actually the first to be invented. They appeared in the years 1830 and by the end of the XIX century, functional versions of EVs could already be found [Sit09]. In fact, according to the number of vehicles registrations, by 1930, EVs outnumbered ICE vehicles in a three to one ratio [Sit09]. They were an important transportation mean, being widely used for short distance displacements [Sit09].

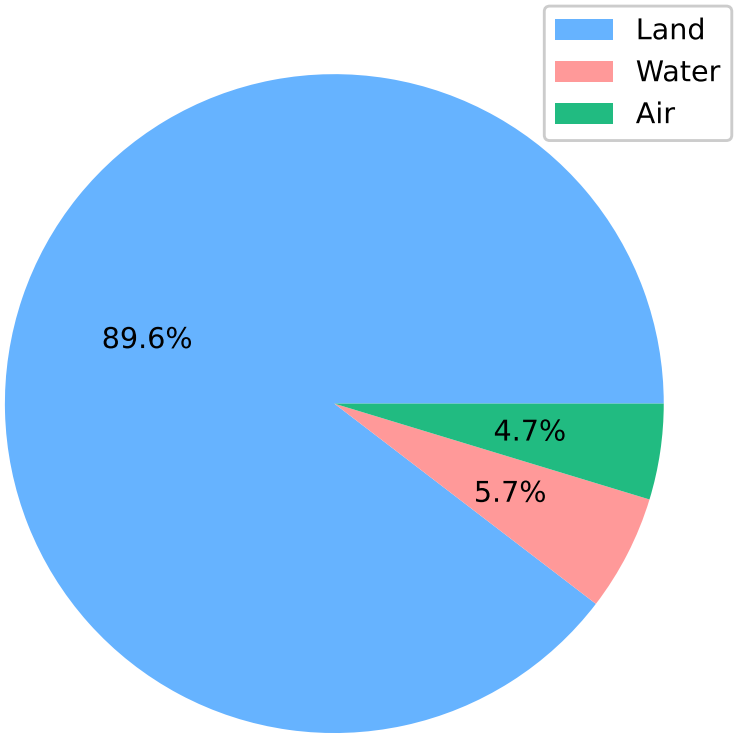

Figure 1.3: Employment generated by different transportation modes [EUR22].

However, in the years 1930, ICEs took over. The main reason for this change was the fact that industrialization made vehicles available for the general public, which became more interested in the ICE version since it was cheaper and energetically more efficient. From 1930 to 2010, road transportation remained dominated by ICE vehicles with occasional periods when EVs gained some interest, mainly due to the political tension between western countries and the OCEP [Sit09].

After the years 2010, with the increasing concern around climate change, EVs started to be regarded as a way to mitigate the environmental impacts of accelerated green-house effect and reduce petroleum dependency. As a consequence, private manufacturers and researchers addressed important challenges for their adoption. For example, to this day, the main challenge for EV adoption is the high purchase price when compared to ICE vehicles. This mainly comes from the battery cost which accounts for 30% [Mis+17] to 50% [Bag+16] of EVs production cost. However, substantial improvements in battery technologies have been made since 2013, constantly reducing this cost, as can be seen in Figure 1.4. This has deeply contributed for making EVs commercially viable [Mur+21].

Furthermore, several countries are creating, through legislation, conditions to popularize EVs. For example, in its green deal announcement [Com19], the European Union presented

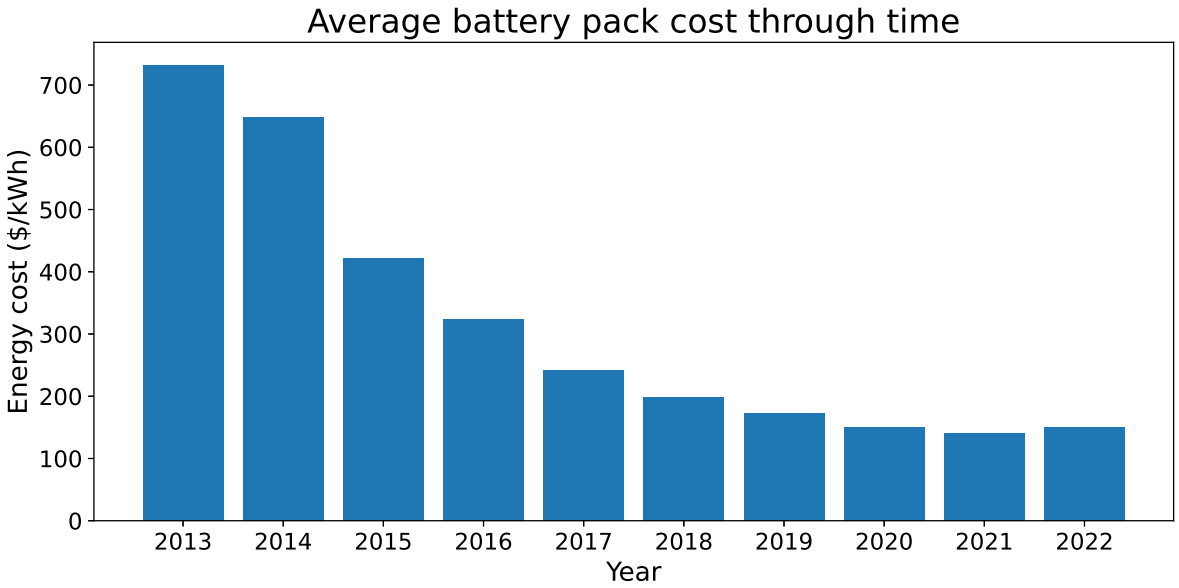

Figure 1.4: Battery pack cost evolution between 2013 and 2022 estimated in the latest Bloomberg's annual battery price survey [Blo22].

a plan for reaching carbon neutrality by 2050. In this document, they explicitly address the necessity of creating laws "to ensure a safe, circular and sustainable battery value chain for all batteries, including to supply the growing market of electric vehicles", which will contribute to the popularization of EVs. More concretely, in 2023, the European Parliament approved a law that effectively bans the sale of ICE vehicles by the year of 2035 [Par23]. The effects of those policies and fiscal incentives can already be seen in several countries. In [LDT17], a comparison between Total Cost of Ownership (TCO)[3] estimations of ICE vehicles and EVs is done. It shows that the legislation already in place in countries such as Norway, makes EVs less expensive than ICEs in the long term. This contributes to their adoption since there is a negative correlation between EVs market share and TCO [LDT17].

For the aforementioned reasons, it is safe to say that EVs are now well established and will soon enough become the status-quo in terms of transportation. This is confirmed by the market share and customer adoption trends observed worldwide. Figure 1.5 shows the evolution of EVs sales in the world. As can be seen, from 2015 onward, sells grew exponentially. Although this growth is mainly driven by China and the US, this phenomenon will probably be seen worldwide with estimations that, in 2030, 38% of vehicles will be EVs [IEA23].

Although EVs can indeed mitigate the consequences of global warning, they bring challenges for the transportation industry and logistic professionals alike. To quantify their future impact, assumptions around EV adoption must be made. The International Energy Agency (IEA) makes such estimations considering two different scenarios. The first scenario is called

[3]The differences between TCO and total exploitation cost, as used in this document, is that the first also considers the cost of acquiring a vehicle while the second only involves costs related to using it.

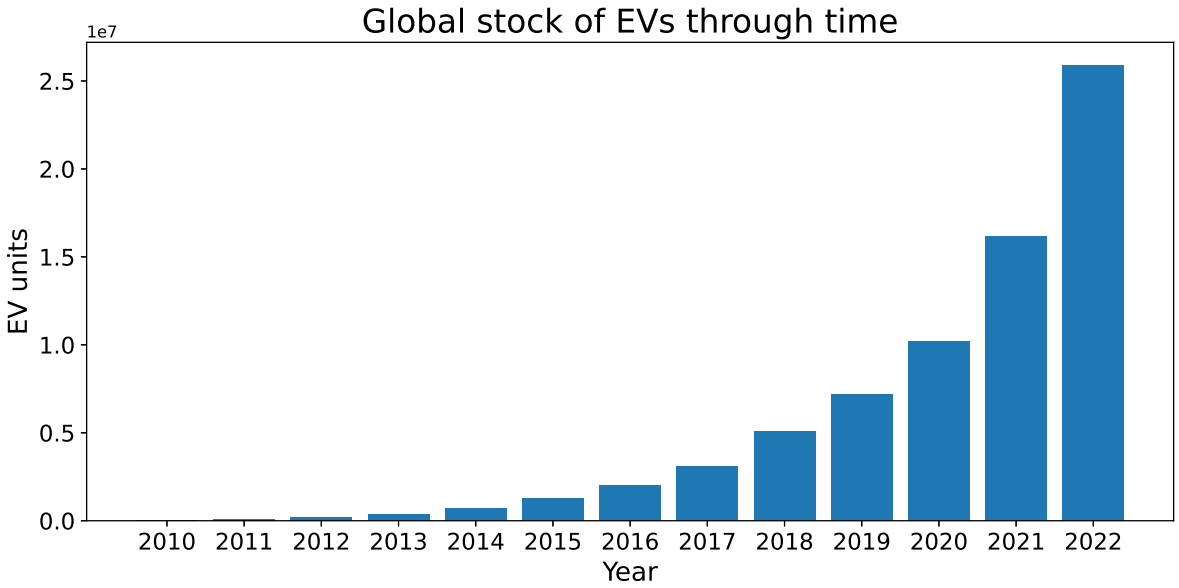

Figure 1.5: EVs stock evolution as estimated according to the public database [IEA23].

Stated Policies Scenario (STEPS) and it projects the future number of EVs conservatively, accounting only for existing government incentives already in place or under development [Age22]. The second scenario is called Announced Pledged Scenario (APS), in which EV adoption is projected more aggressively, considering that all government targets will be reached [Age22]. Figure 1.6 shows the historical and projected number of chargers, while Figure 1.7 shows historical energy consumption of EVs. In both, values for 2025 and 2030 are the projections in STEPS.

The impact in terms of chargers necessity is huge, being expected to increase in 10 times. In the APS scenario this number is even greater, increasing 14 times [Age22]. The implication is that, a significant infrastructural effort will be required in order to install all those stations. Looking at energy consumption, it can be seen that 104 TWh are reached in the STEPS scenario. The increase in even greater for APS, with EV related energy consumption reaching 880 TWh in 2030. The energy sector will be deeply impacted and, to ensure that EVs will really mitigate global warming effects, efficient electric energy generation must be guaranteed.

From a logistical point of view, EVs also require significant adaptation. ICE long-haul vehicles travel up to 1400 kilometers with a full tank [4] and take from 10 to 15 minutes to refill it. On the other hand, the average electric truck range is 300 km and a full recharge can take up to 9,5 hours in AC charging and 1,5 hours in DC charging [Truc] and recharge stations are still scarce. Developing services that improve maintenance and vehicle usage for EVs require that all those particularities are taken into account. Any service that addresses

[4] This estimation is based on the empirical fuel efficiency seen at [SM15], which observed fuel efficiencies of 32 L/100 km considering heavy duty trucks tanks of 450 liters. However the record range for commercial heavy duty-vehicles was established by the Mercedes Actros with impressive 12728 kilometers traveled with a full tank on a test track [Mer].

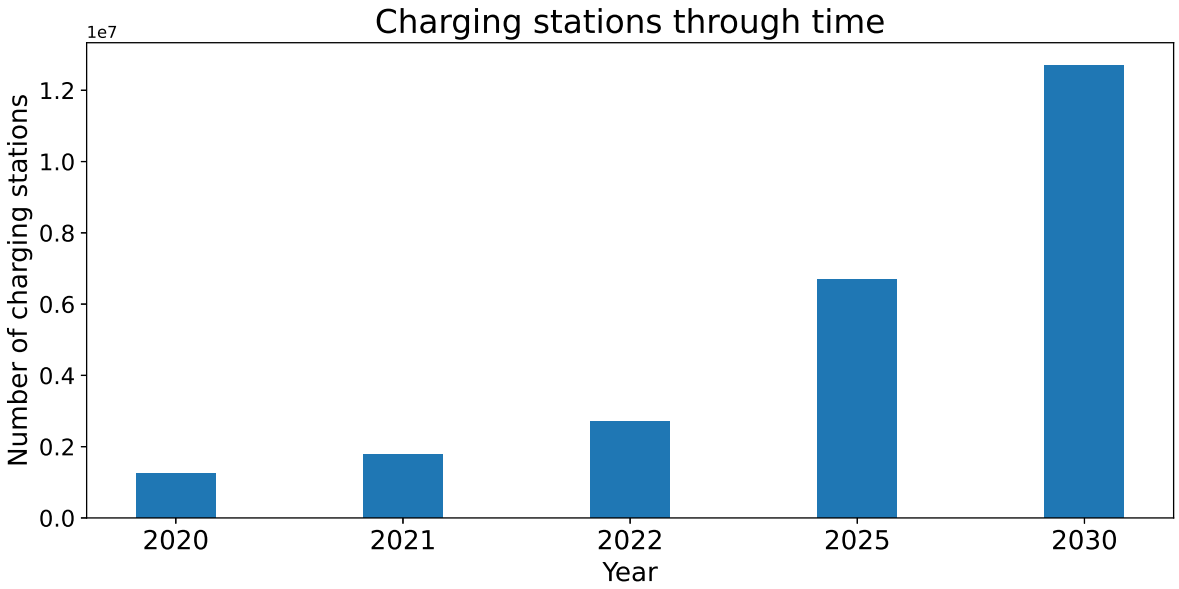

Figure 1.6: Number chargers evolution. The values for 2025 and 2030 are estimations made considering the STEPS scenario [IEA23].

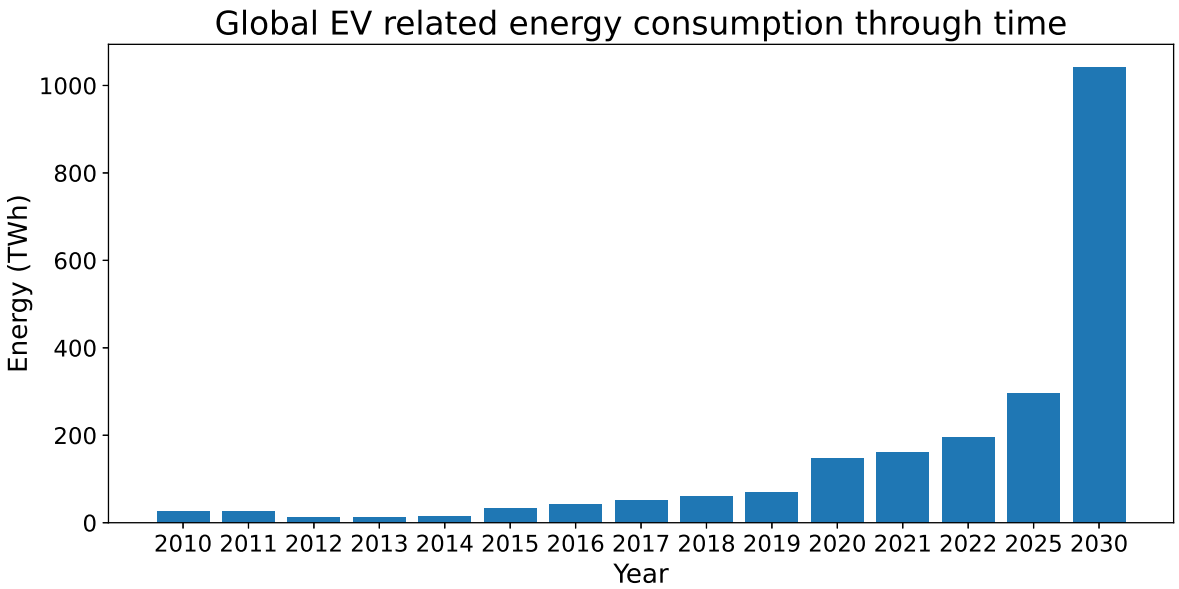

Figure 1.7: EVs energy consumption evolution. The values for 2025 and 2030 are estimations made considering the STEPS scenario [IEA23].

usage optimization and therefore affects logistics must consider the availability of recharge stations, energy consumption and other EVs particularities.

1.2.2 Exploitation cost and maintenance

To envision a useful service for customers, it is important to understand what composes the overall exploitation cost of managing a heavy vehicles fleet. With ICE vehicles or EVs, freight transportation is complex and different costs affect operation on a daily basis. Figure 1.8 shows those different types of expenses related to vehicle exploitation:

- **Driver:** The total cost of drivers, considering wage charges and other benefits imposed by legislation.
- **Fuel:** Fuel cost before taxes, taking into account various refuelling methods and the partial refunding of the French Energy Tax.
- **Overheads:** Structural costs and other indirect charges such as administrative staff costs.
- **Equipment:** Costs of possession, renewal, financing and insurance costs (for the vehicle and eventually for the payload).
- **Maintenance:** Maintenance and repair costs as well as tire replacement costs.
- **Infrastructures:** Costs of motorway tolls and the annual tax on heavy goods vehicles.
- **Travel expenses:** Costs of long distance missions, including meals and accommodation based on French Labour Agreement and the travel expenses protocol.

As can be seen, maintenance costs related to periodic operations and repairs are a relevant expense, being responsible for 8.2% of the total cost. Some of those costs are affected by French legislation elements. Similar statistics are not available on a continental or global level. However, it is reasonable to assume that, financially, maintenance is even more important in other European countries, since CNR data indicates that drivers and overheads costs are on average significantly lower in the rest of the continent when compared to France [Cnrb].

It is important to highlight though, that the financial impact of maintenance goes way beyond its cost. Related opportunity costs are hard to estimate but can be extremely impactful in the long-run. Maintenance operations imply vehicle immobilization and often represent a missed opportunity to generate revenue. However, if the vehicle is not well maintained and this leads to a breakdown, it can cause significant revenue loss. [PS23] estimate that breakdowns cost around 700 USD per day of immobilization. This estimation is very conservative since it does not consider repair costs and credibility losses related to potentially not making a delivery in due time.

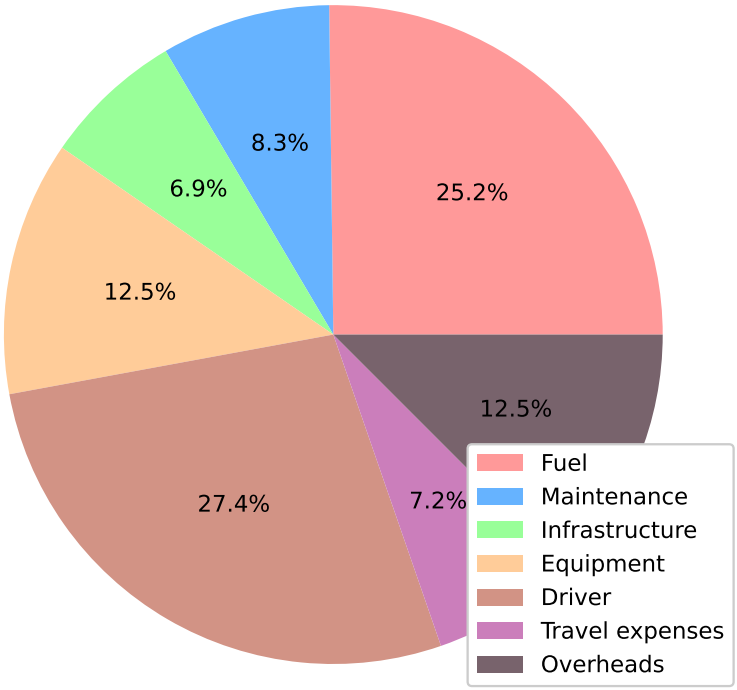

Figure 1.8: Exploitation cost estimation for long-haul vehicles in 2022 according to France's National Road Commission (CNR) [Cnra]

Therefore, maintenance is of key importance in road transportation and must be planned so that uptime is maximized without risking unplanned breakdowns while adapting to the reality of fleet managers and fleet owners [HDL16]; [Hed20]. It is also clear that, since other sources of expenses are relevant, health management and maintenance optimization must account for the complete operational context. In the next section, an overview on how maintenance for trucks works in practice is given in order to provide insights on possible improvements and opportunities to propose new services.

1.3 Maintenance management for heavy vehicles

To understand why services combining maintenance and vehicle usage would be potentially interesting for customers, it is necessary to understand some aspects of maintenance management and contracts in the context of road transportation. The first important aspect is the fact that there are several different actors involved in the process of maintaining a vehicle, such as:

- **Vehicle owner:** the person who owns the vehicle or provides the financial resources to acquire them. When considering to buy a vehicle from a particular brand, vehicle owners considers not only the purchase price but also the cost of maintaining it and the services offered by the manufacturer.

- **Fleet managers:** responsible for managing logistics. His goal is to ensure competitiveness, operational efficiency and optimize the fleet exploitation. In several cases, the fleet manager is also responsible for taking maintenance decisions, correctly following maintenance schedules to assure uptime.

- **Driver:** responsible for executing the mission plan established by the fleet manager. The way the driver handles the vehicle has huge impact. It impacts, for example, fuel consumption and vehicle degradation which in turn leads to the necessity of maintenance and can cause downtime. Therefore, a careless driver, can have a negative impact on the total exploitation cost.

- **Workshop:** responsible for performing maintenance operations. The workshop deals with unplanned immobilization due to breakdowns or accidents as well as scheduled maintenance operations such as oil changes.

- **Customer Service Representative (CSR):** responsible for acting as the interface between a customer and a workshop, acting as a single point of contact for the fleet manager, ensuring that customer expectations are managed at all times. In several cases, the CSR is constantly in contact with the fleet manager in order to provide maintenance insights and guarantee that all operations are carried out when necessary.

- **Spare part supplier:** responsible for delivering vehicle spare parts to the workshop enabling maintenance operations. Besides the recurrent restocking, urgent deliveries can also occur when a vehicle is subjected to unplanned stops.

- **Vehicle manufacturer:** responsible for selling vehicles to vehicle owners. As mentioned before, offering services that can improve transportation purchaser's experience is also an important goal of modern vehicle manufacturers.

Maintenance contracts connect all of them. The manufacturer (represented by dealers) proposes a maintenance contract as part of the offer. Fleet managers commit to respecting maintenance intervals and instruct drivers accordingly. Workshops and spare part suppliers organize themselves around those maintenance intervals to ensure that the required operations take place exactly when needed.

In the Volvo Group, maintenance contracts are usually proposed when a new vehicle is acquired. The exact terms of the contract are negotiated between manufacturers and vehicle owners but in general, its cost is based on the expected number of maintenance operations. This number is defined by vehicle configuration (number of axes, total weight, size, model, etc) as well as its expected usage, which is estimated through a survey aiming to find out the following information:

- **Transport cycle:** defined as the type of application for which the vehicle will be used. Vehicles used in construction site or long distance applications require maintenance operation more often than those performing city distribution.
- **Topography:** understood by Volvo as the slope of the road in which the vehicle will operate on average. Hillier roads imply maintenance operations to be performed more often.
- **Gross Combined Weight (GCW):** defined as the combination of the vehicle weight and its payload. Vehicles operating on average with more mass require maintenance more often.

After this survey is completed, the information gathered is used to compute the expected Powertrain Operating Condition (POC) of the vehicle. The POC is a quantity that is deeply related to fuel consumption and is used by the Volvo Group to quantify the severity of vehicle usage. Table 1.1 shows how it is estimated through this survey, where w_1 and w_2 are values of GCW while the remaining symbols are acronyms.The ones used for topography stand for:

- **PF:** Predominantly Flat
- **H:** Hilly
- **VH:** Very Hilly

while the ones used for POC stand for:

- **L:** Light
- **M:** Medium
- **H:** High
- **S:** Severe
- **VS:** Very Severe
- **VS+:** Extreme

Table 1.1: POC estimation rules for two different transport cycles: long distance driving and construction site.

Transport cycle	Long distance driving					Construction		
GCW	$\leq w_1$		$]w_1, w_2]$		$\geq w_2$	$\leq w_1$	$]w_1, w_2]$	-
Topography	PF	H	PF	H	-	H	H	VH
POC	**L**	**M**	**M**	**H**	**S**	**L**	**M**	**H**

Table 1.2 shows how POC is used to define operation intervals. More severe POC corresponds to tighter maintenance intervals. They can be defined in terms of mileage, months or operating hours thresholds and, whichever one is reached first defines the date of the next operation. For example, a vehicle with VS POC, must perform Operation 1 whenever it reaches 4000 engine hours since the last time this operation was performed. This must happen even if the vehicle has not yet travelled 200000 kilometers or reached 12 months of operation. Notice as well that Operation 1 is performed only once for L POC.

In reality, however, the estimated POC may not correspond to the actual one. The Volvo Group offers services that, among other things, allow CSRs and fleet managers to monitor the real value of POC, adapting maintenance intervals if needed. Some of those services are presented below.

1.4 Aftermarket services at Volvo

As mentioned before, services are a crucial part of vehicle manufacturer's offer as they are seen as a key client retention factor. For example, findings of a 2019 survey [Pow] that inquired heavy-duty truck owners, indicate that services are the second most important factor when it comes down to client satisfaction. It looses only to the quality of the vehicle itself and surpassing factors such as vehicle cost.

The Volvo Group has different services offers composed of different monitoring tools used to visualize relevant data. The most important data types will now be reviewed, however, since the group is composed of different brands (such as Volvo Trucks, Renault Trucks, Volvo Busses, etc), the exact scope of each service offer can vary.

1.4.1 Maintenance-related services content

As previously stated, maintenance is a very important factor when dealing with heavy vehicles and is seen by many researchers as an extremely important aspect to be explored in service offers [HDL16]. The services related to maintenance offered today are mainly used to monitor data split into three categories: usage monitoring, wear monitoring and breakdown prevention.

Usage monitoring data is related to several dimensions of vehicle usage such as yearly mileage, yearly fuel consumption, GCW and average fuel consumption. From the point of view of maintenance, this information is important because it allows users to obtain real POC which, as seen in Section 1.3, impacts maintenance operation intervals. Furthermore, intervals can be defined in terms of mileage and engine hours, which are also part of this data.

Fixed maintenance operation intervals do not account for the nuance of usage conditions. Several components have health indicators which physically represent the necessity of performing a maintenance operation. For example, brake-pads only need to be replaced when their thickness falls under a specific threshold. For those components, the wear monitoring data

Table 1.2: Examples of operation interval definition based on POC.

POC	L	M	H	S	VS	VS+
Mileage / months / hours						
Operation 1	**First interval only:** 200000/24/-		**First interval:** 20000/24/- **Subsequent intervals:** 400000/24/6		200000/12/4000	
Operation 2	500000/36/8000			400000/36/6600	300000/36/5000	200000/36/3300
Operation 3	300000/36/5000				200000/24/4000	
Operation 4	500000/-/-	375000/-/-	300000/-/4500	225000/-/4500	100000/-/4500	-/-/4500
Operation 5	-/24/-				-/12/4500	-/12/4000

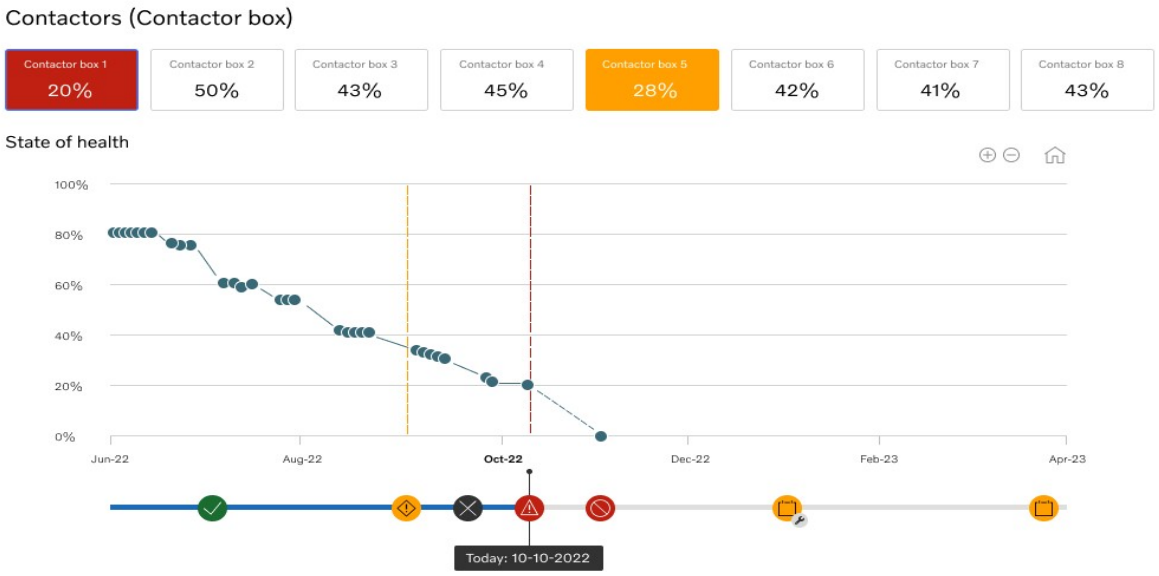

Figure 1.9: Health indicator visualization for a contactor. The graph shows data points collected from the vehicle until the present date. The dashed line seen after October is the predicted trajectory of this indicator, showing when this component is expected to reach a critical state

allows users to see the evolution of those indicators. It also enables predicting when thresholds will be reached. Figure 1.9 is an example of a data visualisation tool used to display wear monitoring data.

Breakdown prevention data revolves around the fact that some vehicle failure modes are not necessarily caused by the gradual deterioration of health indicators but can happen abruptly. Based on data related to those failure modes, such as Diagnostic Trouble Codes (DTCs) and variables such as mileage, health indicators and etc, detection models are created to identify any anomaly that can lead to an unplanned stop. Alerts can then be sent to drivers and fleet managers so that they can plan inspections and component replacements in advance, avoiding downtime.

Those three types of data are the core of maintenance-related services offered by the Volvo Group. They are part, for example of the "Predict" offer of Renault trucks [Trua] and "Uptime" offer of Volvo Trucks [True]. It is important to highlight that, although those services are offered to vehicle owners, the data is mainly displayed to CSRs, which in turn need to reach out to clients change the maintenance schedule if needed.

1.4.2 Vehicle-usage-related services content

Aftermarket services are not limited to maintenance. There are also services related to vehicle usage support, specially in terms of logistics. Once again, since the Volvo Group is composed

of different brands, the exact scope of those services may vary, however, the most important tools, from a fleet manager point of view, revolve around the following data:

- **Vehicle performance data:** Data related to vehicle performance such as fuel consumption, number of time brakes were used and time percentage in idle. It can be used to improve drivers performance and help fleet managers deciding to pay for driver coaching, for example.
- **Geo-mapping data:** Information related to vehicle location. It provide fleet managers with the current location of each truck as well as their travel history. It allows delivery confirmation, for example.
- **Driver legal data:** Driver information such as traffic violations, time lapse of driving sessions and so on. It is mainly used to ensure that vehicles are driven in accordance to the legislation.
- **Vehicle safety data:** Events related to a vehicle safety systems, such as how often the advanced emergency braking system is used, for example. It also helps detecting any excessive braking or acceleration or any driving behaviour that can be considered dangerous.
- **Vehicle health data:** Information related to warning alerts shown in vehicle clusters. It allows fleet managers to be informed of potential vehicle problems. Although, this overlaps with breakdown prevention data, it is important to highlight that data of usage-related services is consumed by fleet managers while maintenance services have their data used by the CSR.

This is the core of usage-related services offered by the Volvo Group and this data is part of Volvo Truck's Dynafleet service [Trud] and Renault trucks Opitfleet service [Trub], for example. However, it is important to highlight that services offered nowadays work as monitoring tools that provide insights through data visualization. All the decision-making process related to how to exploit the vehicles, how to perform deliveries must still be done by the fleet manager.

1.5 Prescriptive maintenance: bringing usage and maintenance together

Analyzing the content of nowadays offers, it is possible to identify some gaps that can be the base for future services improving the experience of vehicle owners and fleet managers alike. The main point to be stressed out is that usage and maintenance services are not integrated. This oversights the dual relationship between usage and maintenance. The way vehicles are used will impact their health state and at the same time, scheduling maintenance operations affects logistics which in turn forces adaptation on how vehicles are employed.

Furthermore, as indicated by the aforementioned 2019 survey [Pow], the majority of satisfied vehicle owners mention that they see the manufacturer as a logistic partner. This indicates that there is a desire for robust decision-making services. However, today, both maintenance and usage services only provide insights to the fleet managers, lacking a quantitative measure of how different choices can affect the overall exploitation cost of the fleet.

Such a solution would be extremely useful for fleet managers. They are not only interested in breakdown predictions or alerts but would rather prefer a set of recommendations of actions to keep vehicles operational as much as possible and reducing exploitation costs. Vehicle purchasers would be even more interested, since this service would not only contribute to performing maintenance operations without impacting operational availability but also increase productivity through usage optimization, ensuring maximum profit.

The basis of such a service would be the quantification of the relationship between usage, system health and exploitation cost. When investigating contemporary maintenance trends, the expression ***Prescriptive Maintenance*** (PsM) frequently appears as a new maintenance paradigm that is capable of concealing all those different things identifying the best course of action in terms of system exploitation [5]. This thesis is then mainly dedicated to studying and developing the techniques to create PsM solutions for heavy vehicles in order to lay solid foundations for future service offers.

1.6 Previous research projects

This research project is not the first one conducted at Volvo's addressing maintenance services. Since 2010, three other PhDs were conducted within the aftermarket services area, each one dealing with different aspects of maintenance management and optimization. The first one was [Bou10]. It revolved around the fact that the fixed intervals defined by maintenance contracts (Section 1.3) do not consider the evolution of health indicators. The goal was to create a dynamic data driven maintenance plan. To do so, the proposed methodology was based on three steps:

- Infer probability models for the failure of different critical components. By analyzing time series of health indicators, a degradation model capable of giving a failure probability in a specific time horizon was conceived.
- Define the best replacement date for each component. This process is done for each vehicle component individually through an optimization process.
- Use an heuristic to group the different replacement operations together as close as possible to their optimal replacement date. This leads to a maintenance plan that involves

[5] PsM has in the last years became a buzzword often used to describe holistic maintenance solutions. The term got so popular that it was included in the original proposition of this research project. For those reasons, it deserves careful attention as will be seen in Chapter 2

less workshop visits and therefore reduces downtime. Whenever new degradation information becomes available, this maintenance plan can be updated.

This method has improved the fixed schedule maintenance approach. By relying on data collection, stochastic models can be employed and conditioned on health indicators measures, which allows for the variance of failure predictions to gradually decrease. Those models also naturally capture the uncertainty related to degradation and are useful in the decision-making context. Furthermore, the grouping strategy allows for the maintenance schedule to be condensed, avoiding excessive downtime. However, this work has some shortcomings.

The first shortcoming is related to the fact that each component failure date is estimated independently and that the operation grouping process does not account for the system functionality. Components of the same subsystem should be replaced together since their impact on the vehicle is correlated. The second one is that, the maintenance plan considers exclusively health indicator evolution and failure probabilities. This is unpractical in real applications since it disregards fleet managers operational constraints, maintenance plans of other vehicles in the same fleet and so on. To address some of those issues, a second research project [Les15] was carried out.

In this project, the operation grouping principle is improved by considering subsystems, ensuring that components that relate to the same functionality of the vehicle are replaced together, based on failure probabilities of the whole subsystem and not each individual component. This work also accounted for operational constraints, defining time windows in which maintenance operations could not occur, ensuring vehicle availability in moments when demand is more intense and the fleet manager is expected to have more deliveries to plan for. Finally, the notion of vehicle usage is introduced by considering "normal" operation and "stressed" operation modes. In the first one, vehicle health indicators degrade slowly compared to the second and vehicles are assumed to be able to change from one mode to the other between time windows.

Both in [Bou10] and [Les15], vehicle usage was either indirectly observed through the randomness of the degradation process considered, in the first case or just as input as in the second one. No explicit consideration for how vehicles are used was made and usage optimization was not included in those works. To close this gap, a third research project [Rob19] proposed a maintenance optimization combined with delivery scheduling.

This work accounts for vehicle usage by considering the scenario where a fleet of vehicles has a set of missions (a delivery or a set of deliveries) to perform. Each mission has a fixed particular deadline and duration. A stochastic process is used to model vehicle degradation and each mission can have different probabilistic parameters, contributing differently to degradation evolution. Maintenance operations can be scheduled after missions are performed and both missions and the maintenance operations are jointly scheduled. As such, this work introduces vehicle usage as an output of an optimization method, stressing its importance in terms of maintenance planning. However, improvements can still be done.

The first axis of improvement is the fact that vehicle usage was simplified and some as-

pects of their definition of mission are not realistic, ignoring important spatial considerations. [Rob19] considered, for example, that the order of missions did not impact the cost function used in the optimization algorithm. However, in practical cases, this order impacts due dates, fuel consumption and even degradation. In fact, the cost function ignored some of those important operational expenses. Furthermore, this work does not address the differences regarding the time scale of maintenance and mission scheduling. As the optimization criteria rely on failure probabilities, they ignore the fact that throughout most of vehicle life, degradation levels are so far from criticality that those probabilities are neglectable. However even at this stage, usage-related decisions may impact the long-term outcome of failures.

Some of those improvement axes are explored in this current research project. A deeper consideration of the particularities of vehicle usage and the importance of long-term strategies are present in all the modeling choices made. Furthermore, with the recent interest in electrical heavy vehicles, in this work the particularities of EVs are also accounted for, creating consumption and degradation models adapted for those.

1.7 Thesis contributions

This thesis sums up the research work done in a collaboration between the Volvo Group and the lab GIPSA-Lab, a joint research unit of the CNRS, Université Grenoble Alpes and Grenoble INP. It aims to investigate and provide methodological contributions, as well as practical tools to move towards maintenance services that account for and impact system usage in the context of heavy vehicles applications.

From Volvo's point of view, the main contributions are the development of usage and maintenance optimization techniques and the proposition of realistic vehicle usage models. Furthermore, particularities of EVs are considered, laying down the basis for possible services adapted to the current technologies of the automotive sector. Scientifically speaking, the contributions of this research project can be divided into two main categories: conceptual contributions and practical implementations

1.7.1 Conceptual contributions: Prescriptive maintenance definition, development framework and implementation for heavy vehicles

As stated before, the original research scope proposed by the Volvo Group was built around the concept of PsM. Despite its relative recent popularity among researchers [AGN19]; [Nem+18] and industrial practitioners [Tra]; [IBM] alike, PsM has, at best, an immature definition. The first significant contribution is a scrutiny of PsM as an idea, performing a critic bibliography review and discussing it in the context of maintenance science.

Through the insights and fragilities identified in the review process, a more robust definition of PsM is proposed. Based on this definition, a systematic development framework for PsM solutions is presented, in order to help researchers to conceptualize such solutions. Finally,

this framework is applied to heavy vehicles and leading to a high level view of PsM problem in this context. The second category of contributions arise from the scientific efforts required to solve such problem in practice.

1.7.2 Methodological tools for practical implementation of prescritive maintenance for heavy vehicles

When solving a PsM problem for vehicles, several challenges arise and, as a consequence, in order to achieve the goal of reducing the exploitation cost of a fleet of heavy vehicles through maintenance and usage optimization the following contributions were made.

1.7.2.1 Vehicle usage based degradation models

In order to develop post-prognostic decision-making methods for optimal management of vehicles subjected to degradation, it is necessary to employ models capable of connecting usage and vehicle health. This can be achieved by employing degradation models which are sensible to different usage conditions, however, those models are rarely used for transportation applications.

Furthermore, in order for those models to be useful in the context of decision-making, they must be capable of being incorporated into optimization frameworks, correlating degradation to decision variables. Different alternatives for creating such models are explored in this manuscript. Concrete models are proposed for different kinds of vehicle components and the advantage of using them when compared to more classical alternatives is illustrated through numerical experiments.

1.7.2.2 Optimization formulation for PsM problems

Employing the aforementioned degradation models in practical decision-making context often requires original formulations of classical problems such as shortest paths, vehicle routing and electric vehicle routing. Non-trivial considerations must be made when formulating those PsM optimization problems.

In this manuscript, several different original formulations of optimization problems are proposed. Through a set of numerical experiments, it is shown that those formulations lead to different exploitation strategies when compared to classical routing approaches. This proves the value of combining usage and degradation optimization, and leads to valuable insights when it comes down to fleet management.

1.7.2.3 Optimization algorithms

PsM optimization problems can be seen as a more complex variation of classical decision-making problems as mentioned in Section 1.7.2.2. As a consequence, finding solutions can become computationally challenging as traditional optimization methods are not always suitable.

To solve those problems, new optimization algorithms are proposed. Their performance is examined and compared to classical algorithms when this is relevant. Discussions on the properties of PsM problems are discussed and explored to justify the creation of those algorithms, highlighting the mechanisms employed to enhance computational performance.

1.7.3 Publications

Throughout almost 4 years of work, the following articles were published:

- Dias Longhitano, P., Tidriri, K., Bérenguer, C., Echard, B. Proposition of a Generic Decision Framework for Prescriptive Maintenance. In: Pinto, J.O.P., Kimpara, M.L.M., Reis, R.R., Seecharan, T., Upadhyaya, B.R., Amadi-Echendu, J. (eds) 15th WCEAM Proceedings. WCEAM 2021.
- Pedro Dias Longhitano, Khaoula Tidriri, Christophe Bérenguer, Benjamin Echard. A closed-loop prescriptive maintenance approach for an usage dependent deteriorating item - Application to a critical vehicle component. ESREL 2021 - 31st European Safety and Reliability Conference, Sep 2021, Angers, France.
- Pedro Dias Longhitano, Khaoula Tidriri, Christophe Bérenguer, Benjamin Echard. Joint optimization of routes and driving parameters for battery degradation management in electric vehicles. SAFEPROCESS 2022 - 11th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes, IFAC; University of Cyprus, Jun 2022, Pafos, Cyprus. pp.6, ⟨10.1016/j.ifacol.2022.07.187⟩. ⟨hal-03717814⟩
- Pedro Dias Longhitano, Benjamin Echard, Khaoula Tidriri, Christophe Bérenguer. Battery degradation model for mission assignment in a fleet of electric vehicles. ENBIS Spring Metting 2022, European Network for Business and Industrial Statistics, May 2022, Grenoble, France.
- Dias Longhitano, P., Bérenguer, C., Echard, B. Battery degradation incorporated on fleet management optimization. Mimar 2023 - 12th IMA International Conference on Modelling in Industrial Maintenance and Reliability, July 2023, Nottinghan, United Kingdom.

With the last one been granted the "IMechE Safety and Reliability Group prize for Best Contribution by Young Professional at the 12th MIMAR, June – 6 July, 2023". The following journal article is under review:

- Dias Longhitano, P., Bérenguer, C., Echard, B. Joint Electric Vehicle Routing and Battery Health Management Integrating a Realistic State of Charge Model. In the journal: Computers & Industrial Engineering.

Additionally, a patent request on the models proposed in Chapter 5 is under review.

1.8 Thesis outline

This document is divided in two main parts. Part I contains most of the conceptual relevant discussions around PsM and its application for vehicles. Besides this first introductory chapter, it also contains:

- **Chapter 2:** In this chapter, the concept of PsM is deeply investigated. In order to understand it in the scientific context, several important aspects of maintenance as a whole are discussed in order to provide the reader with the state of art of maintenance policies and strategies. A critical review on the most popular attempts of defining PsM is given, highlighting common conceptual weaknesses. A more precise definition for PsM is given at the end of the chapter, followed by a proposition of a development framework designed to clarify the path for building PsM solutions.
- **Chapter 3:** In this chapter, the development framework proposed in Chapter 2 is applied for this document subject of interest: heavy vehicle. Relevant concepts particular to those vehicles are described and the clear scope of the developments made during this research is presented. Useful topics, such as optimization problems related to transportation science, degradation models and decision-making algorithms are reviewed.

While Part I contains most of the conceptual contributions made in this research, Part II revolves around the results arising from applying the aforementioned concepts in practice. It is composed of the following chapters:

- **Chapter 4:** In this chapter a PsM solution is proposed by considering a generic vehicle component. It is modeled by a degradation process that can be applied for components such as brake-pads, air filters, starter batteries and many other important components for ICEs and EVs alike. An optimization problem related to this application is proposed and solved in different contexts, displaying, through numerical experiments, that the proposed approach for usage and maintenance optimization can lead to significant exploitation cost reduction.
- **Chapter 5:** In this chapter, PsM degradation model is proposed for the Energy Storage System (ESS) which is one of the most important EV components. This model combines concepts used in battery degradation studies and logistical problems alike, representing a potentially useful tool to connect battery degradation and vehicle usage

realistically. Numerical experiments illustrate the potential improvement of this model when compared to common alternatives used in transportation science.

- **Chapter 6:** In this chapter, the model developed in the previous chapter is employed in the context of decision-making. It is included in several different optimization models related to classical logistical problems such as shortest paths and vehicle routing. All of those problems are solved through algorithms capable of dealing with the computational complexity arising from combining ESS degradation and vehicle usage. Numerical experiments are once again presented in order to validate the proposed approach.
- **Chapter 7:** Finally, in this chapter, an overview of the work done is presented, discussing limitations and proposing possible improvement directions for future research.

Chapter 2

Prescriptive maintenance: critical review and framework proposition

Contents

2.1 Introduction

This thesis is mainly dedicated to studying and developing techniques to create PsM solutions for heavy vehicles. Since PsM it is treated as the pinnacle of maintenance by some authors

[AGN19], it is first necessary to understand what this term really means. Despite its recent popularity among researchers and industrial practitioners alike, some weaknesses regarding its definition deserve to be addressed. Therefore, this chapter studies the concept of PsM attempting to provide an useful definition that really characterizes it as a different alternative to most classical maintenance paradigms.

To justify this conceptual effort, in this chapter, a review of the history of maintenance is done as well as the definition of key terms for understanding maintenance as a science in a large sense. A critical systematic review of the usage of PsM in the literature is presented, discussing how the term is used in the scientific community and critically debating some theoretical shortcomings.

Finally, a PsM definition is given, with an explicit list of its required features. This definition is followed by a generic framework for PsM development, idealized in order to guide the implementation of such solutions. It is an improved version of the one presented in [DL+21]. The chapter ends by discussing possible limitations of the framework and the new definition presented in order to suggest future perspectives for contributions aiming to conceptualize maintenance solutions.

2.2 Maintenance history

According to the European standard EN-13306 [En1], maintenance can be defined as the "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to a state in which it can perform the required function". Since every machine, device or tool is subjected to wear and can, therefore, enter into a state where it no longer properly performs its functions, maintenance has always been necessary. For example, Egyptian documents from 600 B.C mention maintenance operations in boats [PŽB19]. The consequences of poor maintenance management are also known by mankind for a longtime. For instance, the negative impacts of poor road maintenance in medieval England led to critical logistical limitations with sensible social consequences in 1406 [Bla57].

Until the years 1870, maintenance was mainly reduced to replacing or repairing defective parts after a breakdown occurred [PŽB19]. However, after the second industrial revolution, electrification led to more complex machines which enabled the creation of large scale assembly lines. In this scenario, unplanned downtime had severe financial consequences and was harder to address. This led to the adoption of planned maintenance operations [PŽB19]. Those operations consisted of repairs and replacements done preemptively before machines entered a defective state.

The importance of breakdown prevention was not limited to assembly line machines however. As the general public gradually started to gain access to complex devices, the view of preventive actions as necessary to ensure up-time started to spread. This can be seen, for example, in this extract from the Ford Manual for Owners and Operators of Ford Cars of

1915:

"Frequently inspect the running gear. See that no unnecessary play exists in either front or rear wheels and that all bolts and nuts are tight. Make a practice of taking care of every repair or adjustment as soon as its necessity is discovered. This attention requires but little time and may avoid delay or possible accident on the road" [Com15].

Therefore, according to [PŽB19], from the second industrial revolution on, maintenance actions gradually started to be scheduled based on regular intervals. However, at first, the criteria for defining those intervals were qualitative since little was known about failure modes [KM+08]. As a consequence, maintenance was at best sub-optimal, being possibly detrimental. For example, in 1940, C.H Waddington noted that regular maintenance interventions carried out carelessly led to extra breakdowns in military airships [Ign10].

A more rigorous and systematic study of maintenance cost effectiveness was only made possible with the development of reliability engineering [KM+08]. This discipline applies "scientific know-how to a component, product, plant, or process in order to ensure that it performs its intended function" [Kir17]. According to [SM06], reliability engineering was founded by Walter Shewhart, gained relevance during the World War II and consolidated itself as a recognized discipline in 1957 [SM06]. With the application of probability to assess equipment survival promoted by reliability engineering, maintenance operations could be scheduled in more systematic ways, based, for example, on mean time to failure and other statistics. That way, quantitative parameters for establishing maintenance intervals were employed, reducing excessive expenses and downtime.

Even when based on mathematically valid probabilistic models, scheduling operations based on operating time has its limitations. For example, maintenance intervals are based on probability distributions, and therefore, specific devices may fail or be replaced prematurely. Furthermore, with the complexification of devices, failure modes of subparts started to superpose, leading to no dominant time-related failure modes [KM+08]. To avoid those problems, and with the development of sensors, computers and other technological enablers, maintenance actions can, nowadays, be carried out based on the measured health condition of the equipment. This leads to more assertive interventions and reduces waste caused by premature replacements.

Now, in the modern economy, maintenance occupies a critical role and is of strategical importance for most companies [Als07]. As a consequence, maintenance research works from different areas such as history [Bla57], management [HDL16] and even sociology [JP19]; [DMP15] can be found.

2.3 Maintenance policies

To contextualize and establish what PsM is it is important to define key maintenance concepts that are useful to understand and investigate other maintenance policies. However, before

starting, some considerations are necessary. The first one is that, as stated before, different scientific communities investigate maintenance. As a consequence, it has been studied through different prisms and a myriad of concepts and classifications exist. In this thesis, maintenance is mainly approached from a quantitative point of view, following the tradition of reliability engineering and operational research which limits the discussion around its typology to this point of view.

The second consideration is that, because research on maintenance is extremely relevant and dynamic, several articles are published everyday. Therefore, presenting and defining all maintenance types is impossible. In this section, the most popular maintenance policies found in literature are analyzed as well as those relevant for discussing PsM.

As a consequence of maintenance research dynamism, a lot of concepts and definitions that will be presented are not completely agreed upon by the whole scientific community. For that reason, only the most general and agreed upon definitions are presented, favouring those found in technical standards such as [En1]. Whenever necessary, discussions on the disagreements and confusion revolving those terms will be held.

2.3.1 Actions and policies

According to [KM+08], part of the disagreement related to maintenance terminology comes from the confusion around some key terms such as maintenance action and maintenance policy which they define as:

- **Maintenance action:** Basic maintenance intervention, elementary task carried out by a technician. [KM+08]
- **Maintenance policy:** Rule or set of rules describing the triggering mechanism for the different maintenance actions. [KM+08]

Therefore, maintenance actions refer to what must be concretely done while maintenance policies relate to the criteria used to decide when to apply those actions. Actions can be split into two categories [KM+08]. The first one is corrective maintenance actions and the second, precautionary maintenance actions, defined as:

- **Corrective Maintenance Actions (CMA):** actions aiming to restore the system to a functional state *after* a breakdown occurs. For example, repairs or defective component replacements [KM+08].
- **Precautionary (or Preventive) Maintenance Actions (PMA):** Any maintenance action applied to the system when it is still in a functional state. Those actions aim to reduce failure probability or diminish the consequences of breakdowns. For example, preventive repairs and replacements, inspections, monitoring through sensors, etc [KM+08].

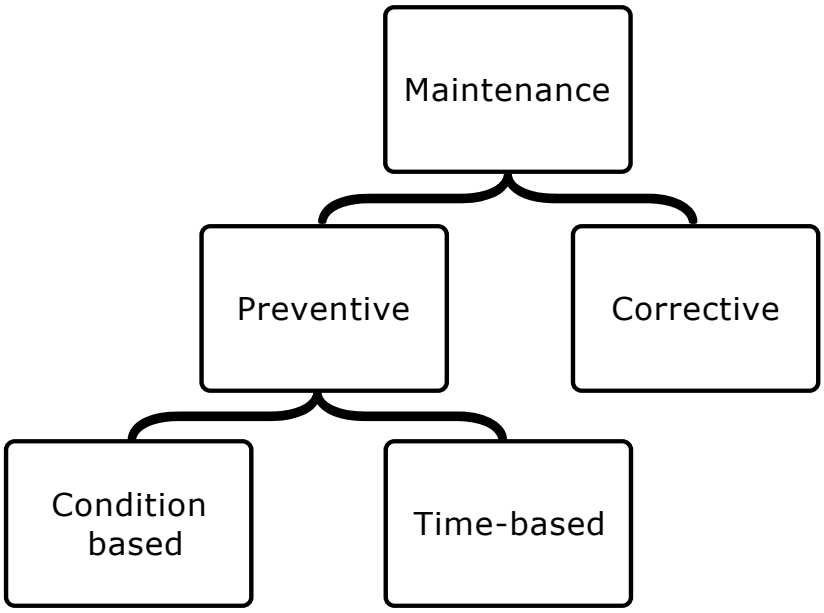

Figure 2.1: Maintenance according to the technical standard [En1]

Notice that, in general, due to downtime related costs, CMAs are considered more expensive than PMAs however, in practice, failures can happen unpredictably and any maintenance policy may require CMAs [KM+08].

2.3.2 Types of policies

Several maintenance policies can be found in the literature. For the sake of robustness and clarity, definitions and terms presented in technical standards are preferred, as stated before. Figure 2.1 shows the most common maintenance policies listed in the EN 13306 standard [En1]. The first important typology maintenance differentiation, according to it relates to the following two categories:

- **Corrective (run-to-failure, failure based) Maintenance (CM):** maintenance policy where no PMAs are taken, implying that maintenance operations are made only reactively after a failure.
- **Preventive Maintenance (PM):** maintenance policy that combines PMAs and CMAs.

Notice however that there are several different ways to decide when to apply PMAs. PM is therefore an umbrella term that encapsulates different policies and it can also be split into two different categories which are:

- **Time-based (predetermined) maintenance (TbM):** maintenance operations are

scheduled in intervals based on the operation time.

- **Condition-based Maintenance (CbM):** maintenance operations are performed based on measurements of the system which represent its operating condition.

Figure 2.2 illustrates this difference for the simplest forms of TbM and CbM. In the TbM policy, maintenance operations occurs in regular fixed intervals. As can be seen this can lead to premature replacements or even worst, create down time. In the CbM policy, components can be replaced based on health indicators monitored through sensors, reducing breakdown risk while ensuring that no unnecessary replacement will be performed.

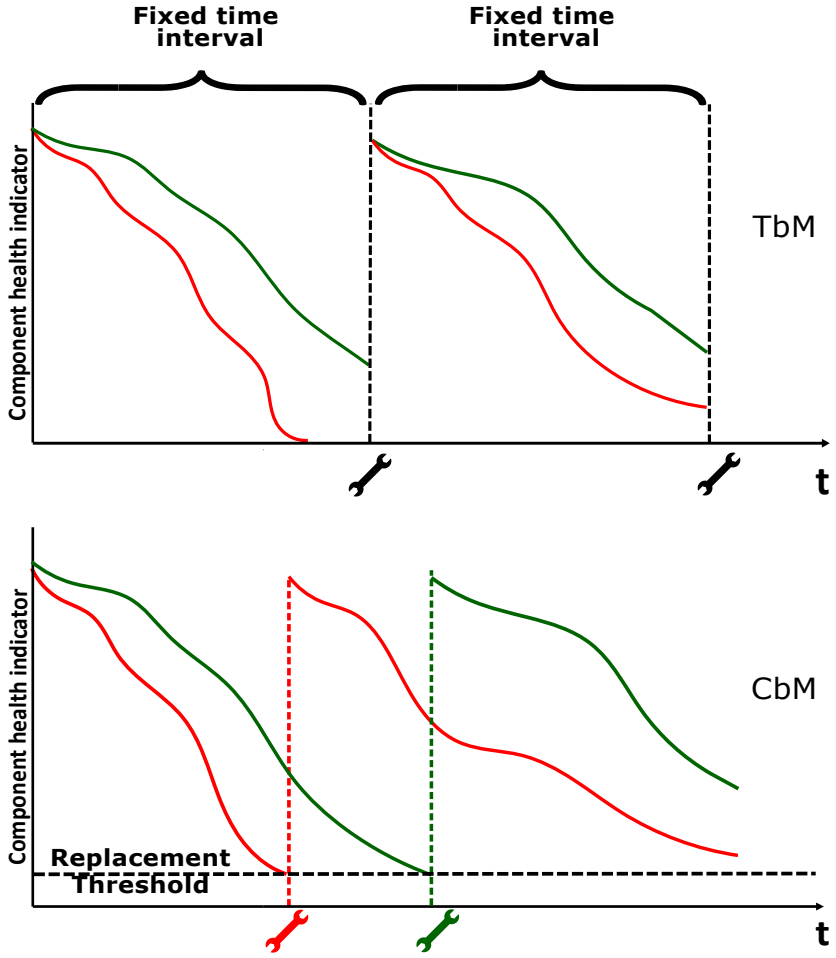

Figure 2.2: Illustration of the difference between the simplest forms of TbM and CbM. Dashed lines represent maintenance operations that restore each component to a as good as new state. Notice that in CbM each component has a different maintenance date while in TbM both are maintained at the same moment. As a consequence, Component 1 - health state represented by the red line - is change too late in the first maintenance interval while component 2 - health state represented by the green line - is replaced too early in the second intervention.

In TbM, "time" may represent different quantities related to how much the system has been used. For example, as seen in Chapter 1, for several heavy vehicle components, PMAs

intervals are defined based on vehicle mileage. It is also important to notice that some authors use the term Preventive Maintenance to refer to TbM. This is probably a by-product of the fact most of PM policies adopted in the industry are still TbM. However, the distinction is important and from an etymological point view, the PM definition provided by [En1] is more natural.

Between CbM and TbM, there is no intrinsic hierarchy. To decide when to implement those different policies it is necessary to consider the particularities of the system that will be maintained [KM+08]. As CbM is usually more expensive to implement due to the necessity of sensors, if failure modes are very "time" dependent or the system is not critical, TbM should probably be preferred.

Despite not being included in the most recent versions of European maintenance terminology standards, a very popular term used in the literature to define policies is Predictive Maintenance (PdM). The idea behind PdM is to use data gathered from different sensors to predict failure dates and schedule PMAs based on those predictions.

At first glace, the definitions of PdM and CbM may seen different, however, when putting the scientific literature of CbM into a historical perspective, the differences start to fade. From the beginning, most of the works on CbM revolved around using data and stochastic models to perform prognostics, finding the RUL distribution which can easily be translated to a failure prediction date. In fact, RUL distributions are more useful from a decision-making point of view allowing for uncertainty quantification around predictions.

In fact, some consider prognostics to be a key feature of CbM as can be seen in [TL01], a technical standard from 2001 used to guide the implementation of CbM software by the US army. Therefore, since CbM addressed failure predictions way before the term PdM appeared in the literature it is hard to differentiate those things and several authors treat them as synonyms [GS04].

Finally, with the most common maintenance policies defined, it is now possible to compare them with the definitions of PsM found in the literature. As will be seen, in most cases, although PsM is often treated as an improvement with respect to CbM, the diffrenences are often not well defined.

2.4 PsM in the literature: an empty jargon?

The term PsM has gained some traction in the scientific literature in recent years. Figure 2.3 shows the number of articles published per years in which the term PsM appears in the scientific database of *Scopus*. As can be seen, PsM popularity is on the rise. Its occurrence has exponentially evolved from 2016 on and has been used in 346 scientific articles so far.

In those recent appearances, the word "prescriptive" in PsM was probably borrowed from "Prescriptive analytics" which is seen as the extension of predictive analytics [Lep+20]. While the second uses data to predict outcomes, the first uses those predictions to provide a set of

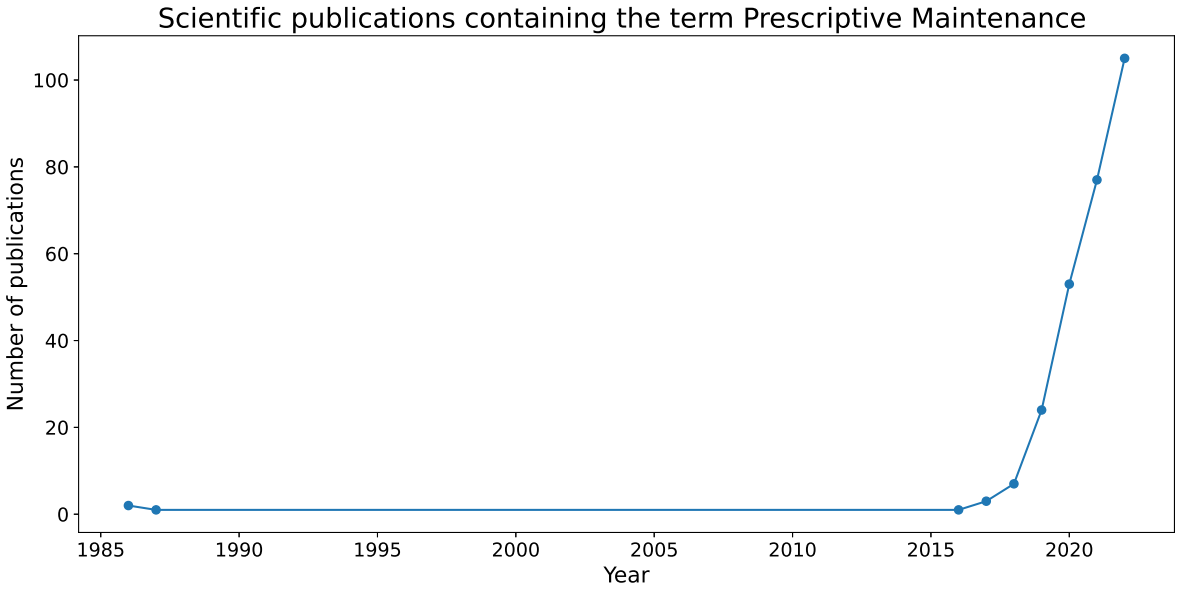

Figure 2.3: Occurrences of PsM in the scientific literature through time

recommend actions (prescriptions) to control an outcome, obtaining a the most desirable result [Lep+20].

However, the natural definition of PsM as prescriptive analytics applied to maintenance is unsatisfactory, since, by definition, maintenance always presupposes some sort of action (Section 2.2). Using sensor data to find the best replacement opportunity is referred to as CbM could also be seen as prescriptive analytics applied to maintenance.

In this section the bibliography of PsM is analyzed to shed some light on the maturity of its definition and how different authors use it. The methodology used in this review is as follows: from the 346 articles in which PsM appears, 88 in which this term appeared on the title, abstract or keywords were selected to filter those in which authors consider PsM to be a crucial part of their contributions. Each of those articles was analyzed and a review of the works which presented a explicit definition of PsM was performed. In the following sections, the most relevant ones are investigated and criticized, providing a systematic review of how PsM is understood in the literature.

2.4.1 PsM as taking actions

The most extensive discussion around the definition of PsM is found in [AGN19] (and similar works from the same authors such as [Nem+18] and [AGS20]). In this work, authors aim to present a conceptual framework for developing PsM and thus discuss what are the needed features to characterize such maintenance strategy. Their view on PsM leans on the concept of *Knowledge based Maintenance* (KbM), which according to them "takes into account long-term effects of maintenance policies and decisions on economic terms, as a non-isolated sub-domain

of production systems, which influences on organisational value creation" [AGN19]. They proceed to state that KbM has four stages which are:

- **Descriptive maintenance:** "answers the question 'What happened?' by providing information about previous maintenance operations. Thus, it supports information collection and analysis and increases the level of information visibility."[AGN19]
- **Diagnostic maintenance** "answers the question 'Why did it happen?' by analyzing cause-effect relations, reasoning, and providing further technical details about former maintenance operations. Therefore, it supports knowledge generation and increases the level of knowledge transparency."[AGN19]
- **Predictive maintenance:** "answers the question 'What will happen when?' by learning from historical maintenance data, possibly in real-time, and predicting future events. Thus, it supports knowledge discovery and enhances the level of (semi-) supervised or unsupervised prognostic capabilities. Notably, this is often referred to as 'Smart Maintenance','Data-Driven Maintenance' and 'Maintenance 4.0', not only in scientific but also in commercial contexts".[AGN19]
- **Prescriptive maintenance:** "answers the question 'How can we control the occurrence of a specific event?' (How should it happen?) by providing actionable recommendations for decision-making and improving and/or optimising forth-coming maintenance processes. It also refers to the recent advances in enhancing self-organisation and self-direction capabilities of cyber-physical production systems, which ideally aim at machine self-diagnosis and self-scheduled maintenance. Hence, prescriptive maintenance may reach the highest degree of maturity which involves complex methods to produce and reinforce adaptation and optimisation capabilities." [AGN19]

Based on those concepts, they propose a general PsM model composed of four layers called PriMa. The first layer consists of a data warehouse where all relevant data, such as system health indicators, production plans and so on, is stored. The second layer is composed of data analysis algorithms which will generate insights from the inputs stored in the aforementioned data warehouse. In the third layer, the outputs of those algorithms are cleaned, treated and fed to a set of decision making support tools that will indicate the best course of action based on a "if and else" set of rules. Finally, the forth layer consists of a knowledge based model that will improve the action recommendation of the third layer through time as more data is gathered, by identifying the root cause of failures.

Although [AGN19], provides a rich discussion around PsM, their definition presents some problems. First of all, for them, PsM is an improvement of descriptive, diagnostic and predictive maintenance. However, based on how those terms are defined, they do not respect the definition of maintenance presented in most technical standards (Section 2.2). For example, in their definition of PdM, they seem to assume that it is simply predicting a failure date for a component. Since maintenance implies that concrete actions are applied to the system in order keep it or restore it to a functional state, that would not be considered maintenance.

Furthermore, this PdM concept makes no practical sense and could never be applied in a concrete case. Making failure predictions would inevitably imply that actions are taken. A factory manager, when receiving the information that a machine will fail in the coming days, could not ignore it and would instead schedule a maintenance action.

If this interpretation of their definition of PdM is incorrect and they implicitly consider that predictions would be somehow used to update maintenance schedules, another problem arises. Their definition of PsM contains the notion of controlling "the occurrence of a specific event" [AGN19] (implied to be a failure) through "optimising forth-coming maintenance processes" [AGN19] which seems to imply that, for them, prescriptive maintenance is the optimisation of maintenance schedule based on failure predictions. However, they do not describe how this optimisation must take place and what criteria should be used to define optimality. They also refer mainly to decisions related to performing replacements. Therefore, there is no significant conceptual difference between this definition of PsM and CbM that also has addressed maintenance interval optimisation based on data.

At the second part of their work, they propose a practical application of their model with a concrete usecase to illustrate their understanding of PsM. The application happens in the context of a factory. The proposed solution gathers data related to the performance and health state of a particular type of machine in the production line and proceeds to use it to compute numerical indicators related to production quality and degradation. Those indicators are extrapolated in order to predict the instant when they will reach predefined thresholds that indicate critical failure risk. This is only possible because the production plan is known in advance and they have modelled how each operation contributes to the deterioration of health state and quality indicators. Based on those predictions, a decision-support consisting of an interface used by maintenance operators suggests some operations to be performed earlier than planned.

Those suggestions seem to be limited to replacements and repairs, although they emphasise the importance of holistic considerations about the system, there is no explicit discussion on how the logical rules to send those alerts are defined. In fact, by holistic considerations, they seem to refer to the fact that they account for spare part availability and for the production plan which is an input of the prediction layer.

[Mat+17] is also a relevant work since it is one of the most cited articles used to define PsM. According to it, "Prescriptive maintenance means moving from planned preventive maintenance to proactive and smart maintenance planning" [Mat+17]. It is hard to know if authors consider PsM as a synonym of proactive maintenance [1] or what they mean by smart maintenance.

In this definition, they probably use PM to refer to TbM and mean to differentiate it from policies that account for component condition. That again makes PsM indistinguishable from CbM. Furthermore, the notion of what kind of prescriptions should be recommended, which criteria should be used to perform prescribed actions and other elements that could be

[1] Proactive maintenance usually refers to considering root cause analysis to prevent future failures due to equipment misuse [KM+08], although some authors use it as a synonym of PM [CAC20].

expected to define PsM are left out of the discussion.

They proceed to propose a concrete application to illustrate their understanding of PsM which is a more detailed version of the one presented in [AGN19]. Once again, in a production line context, machines are analyzed, production quality is measured and wear sensors are put in place. Historical failure data is gathered to establish correlations between failure modes and production quality issues. Based on this study, a set of if and else's rules are established to, based on the extrapolation of performance and quality indicators computed in real-time, suggest maintenance replacements. They refer to "prescriptive maintenance decision module" as the part of their application that presents those suggestions to the user, combining maintenance actions that would affect the same machine component. Once again, although this solution led to significant cost reduction, it is hard to see conceptual differences from CbM.

Several other contributions refer to [Mat+17] and [AGN19] (or [AGS20] and [Nem+18]) to discuss and define prescriptive maintenance and therefore, present the same problems [CBJ19]; [Liu+19]; [Pad+21]; [PL22]; [Tzi+23]. Although [PL22]and [Kar+16] do not refer to [AGN19] they use similar concepts and can also be submitted to similar criticism. [2]

Another limit of defining PsM by the presence of a decision-making element appears in [Iun19]. In this work, authors recognize that decisions are taken in PdM (or CbM) strategies, however, they mention that automated and optimal decisions would configure a PsM solution. According to them, the previous example of a factory manager that schedules a replacement when receiving a failure prediction would be considered PdM since there is no optimization and no quantitative metric to justify choosing a particular date for the replacement. However, this definition ignores the fact that optimizing maintenance interventions has been addressed from the beginnings of reliability and is often also included in problems explored by researchers interested in PdM [PM21].

In all the aforementioned contributions, the differences between CbM and PsM remain unclear as both of them will lead to, in some sense, a decision-making support based on data. Other definitions stress different aspects of the policy, mentioning more complex decision making criteria as will be seen now.

2.4.2 PsM as different criteria for taking actions

To differentiate between PsM and CbM, authors often refer to a "holistic view of the system", indicating that PsM would indeed be an improvement in comparison to other policies because of a richer optimisation criteria. However, as most of those works do not discuss what holistic means, a clear difference between PsM and CbM remains unattainable.

For example, in [MG19], it is said that "the prescriptive maintenance philosophy is a step ahead (of PdM) providing real-time adaptive recommendations, using artificial intelligence, about the tasks that should be done and keep updating as the operation continues. In other

[2] Notice that [Kar+16] uses the term *"Maintenance Prescriptive analytics"* which is seen as equivalent to PsM for the authors.

words, the prescriptive maintenance not only is based on the failures' prediction accordingly to the analysis of data patterns and trends, but also taking the specific company's maintenance process into consideration to provide detailed recommendations, and supports the solution-finding process."

As can be seen, for them, the distinction revolves around considering the "specific company's maintenance process". Further discussion is necessary to establish PsM. For example, considerations about operational constraints, spare parts availability and so on have been already extensively investigated with or without condition monitoring [WZ21]. They also attempt to explicitly differentiate CbM [3] from PsM: "In terms of maintenance planning, while the CbM approach looks to the "when" and "why" to maintain, the prescriptive maintenance looks to the "what" and "where", defining the place and order of the maintenance tasks to accomplish and "who" should be engaged to execute each one." [MG19]. As it is laid out, the distinction is problematic. Firstly, the "what to maintain" is by definition considered by CbM as data is always acquired for a specific known component.

The remaining features are even more controversial. The "where to maintain" is hard to interpret. In the case production lines, for example, machines remain in the same place throughout most of their useful life and most maintenance operations happen *in loco*. This spatial decision would only makes sense in very specific applications such as vehicles that can be maintained in different workshops. Finally, without further clarification, the "who will perform the operation" can be seen as an availability constraint similar to those studied in maintenance problems considering operational constraints as seen in [PM21].

Another attempt of defining PsM based on what criteria is used to prescribe actions is found in [Kou+22]. They refer to PsM as "a type of data analytics that supports making better judgments by analyzing raw data. It takes into account information about potential conditions or scenarios, available resources, previous and present performance, and recommends a plan of action that optimizes equipment maintenance." [Kou+22] Once again, since constraints related to maintenance opportunities and resources have been addressed by multiple research works in different maintenance strategies, accounting for available resources is not a distinctive feature. As for "potential conditions or scenarios" and "previous and present performance", those are also accounted for in CbM which presupposes prognostics and often predicts degradation evolution under uncertainty.

They also propose a framework for PsM development and detail what kind of prescriptions they intend to propose. For example, in the case of a fridge that is not cold enough, a possible prescription could be to check the compressor and clean the dust [Kou+22]. Since this could probably be modeled as an imperfect maintenance operation or an inspection, this example would be similar to others that have been extensively addressed in the literature [MC19].

One of the most concrete attempts to differentiate PsM from PdM in terms of criteria to apply maintenance action is found in [MRW21]. Although they refer to [AGN19] as their main source for defining PdM and PsM, they present very different definitions:

[3] Notice that they employ the terms CbM and PdM but a discussion on what is the difference is never carried out

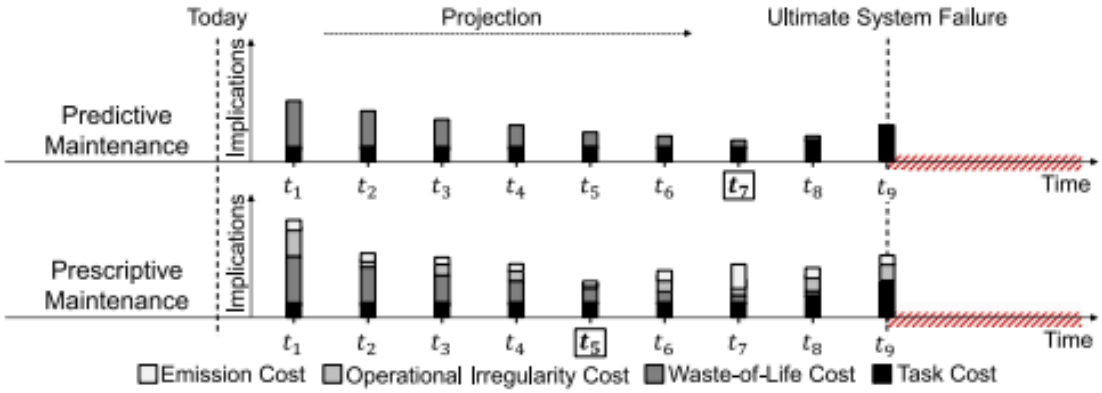

Figure 2.4: Difference maintenance plans created by PdM and PsM strategies, taken from [MRW21]

- **Predictive Maintenance:** "As arguably the most discussed maintenance strategy in recent years, the focus here is on extending the knowledge about degradation mechanisms and extending the degradation propagation into the future to project system failures. Subsequently, this approach utilizes the knowledge discovery process and combines insights into the experienced degradation in the past with anticipated operating loads in the future in order to support a maintenance decision making process." [MRW21]
- **Prescriptive Maintenance:** "This approach will utilize the information about degradation projections and extend the scope of the maintenance decision making process beyond the asset itself, e.g. the aircraft. Thus, by consideration of the surrounding ecosystem, a prescriptive maintenance strategy will allow a holistic analysis and optimization of maintenance measures." [MRW21]

It is interesting to notice that, by explicitly considering that PdM supports decision-making, they make it coherent with the technical standards definitions of maintenance [En1]. In their PsM definition they employ the term "optimization of maintenance measures" considering "the surrounding ecosystem". As seen before, this vague notion of holistic considerations is not enough to characterize PsM, however, in this case, authors proceed to illustrate the differences between it and PdM concretely.

To understand this distinction, more context about their contribution is required. It revolves around maintenance schedule optimization for a fleet of airplanes. In this application, maintenance operations can only happen in a predefined time interval and maintenance opportunities are scarce. The problem comes down to, among the set of maintenance opportunities (which are known in advance), choose the best one. To do so, they use a simulation based optimization method. They solve the problem twice with different optimization criteria which correspond, according to them, to a PdM and a PsM solution. The two maintenance schedules can be seen in Figure 2.4.

Time instants t_i represent maintenance opportunities. When using PsM, maintenance

took place in t_5 while in the PdM solution, maintenance happened at t_7. The difference is related to the optimization criteria. PdM only considered costs related to breakdowns where the "waste-of-life cost" represents the expenses related to replacing a component too early and "task cost" represents the expenses related to the operation itself which increases with system degradation since, in their case, systems close to failure required more complex maintenance operations.

On the other hand, PsM also accounts for costs such as "operational irregularity costs" which represent the expense related to the flight delays caused by maintenance operations therefore depending on mechanics availability and flight schedule, and "emission costs" which are related to extra emissions caused by maintenance operations. With this practical example, it is clear what authors mean by holistic considerations. While for them PdM is mainly asset-centric and consider only the operational cost related to equipment unavailability, PsM considers the full exploitation cost of the system, accounting for every cost source and leading to better maintenance schedules.

2.4.3 PsM as extending the notion of maintenance actions

As seen in [KM+08], maintenance actions are mainly thought of as repairs, replacements and inspections. A possible way of defining PsM would be to consider different actions as part of the maintenance policy. For example in [Gor+20] PsM is defined as a policy that "builds upon predictive maintenance by using predictions to recommend operating and maintenance decisions to counteract future equipment degradation and failure" [Gor+20]. They consider that PsM extends PdM by also considering operating decisions to minimize future degradation. This implies that PsM goes beyond classical maintenance decision such as when to perform replacements, inspections, etc. They proceed to propose a solution that simultaneously optimizes the maintenance schedule and the production schedule of a factory reducing operational costs.

Similarly, in [SEM21] authors mention that "prescriptive maintenance recommendations allow for the power of machine learning to be applied in a more holistic way in an organization or enterprise's physical operations" and they proceed to compare PdM and PsM: "Where predictive maintenance allows for delivering data regarding binary decisions, like an option to defer or perform asset maintenance, it suggests a series of options and results from which to choose from. For instance, a production full stop may be circumvented by running a compressor at an inferior pressure or a plant maintains the speed of a machine below a specific threshold, thus delaying the planned downtime for the purpose of overlapping with the delivery of new equipment." [SEM21]

Authors reduce PdM to deferring "pre-scheduled maintenance operations" which is unreasonable and there is no discussion around which kind of "series of options" could characterize PsM. However, they provide a concrete example of prescription that goes beyond classical maintenance decisions as they consider affecting the operation mode of machines to ensure uptime and control degradation evolution as part of the policy. Since this is not classically con-

sidered in most maintenance problems, it could indeed be a defining feature of a maintenance strategy that goes beyond what most researchers refer to as PdM.

Another similar definition is found in [Fra+19] in the context of PsM for vehicles: "the implementation of prescriptive maintenance first of all means the scheduling of an initial optimal maintenance plan on the basis of assumptions about the operation of the target vehicle. Those assumptions can be experiences of the operator, but also historical data, for example from condition monitoring systems.

An essential difference to previously known strategies is then based on the interpretation of the vehicle in operation. While only the condition of individual components is investigated in predictive approaches, the prescriptive approach interprets the vehicle as a proactive maintenance control element. If the objectives of the initial maintenance planning are not met, the system autonomously initiates corrective actions. Corrective actions may be to reduce the average speed or to harmonize acceleration and braking operations, and technically to manipulate the drive train."

They employ the term corrective actions in a different way than most authors but their interpretation is clear. PsM actions can be any change in system usage to ensure that the original maintenance plan is respected, extending the notion of action beyond replacements, repairs and etc.

2.4.4 A systematic summary of the literature review

Since there are several research papers that somehow define PsM, reviewing all of them in detail is unfeasible. Therefore, a more systematic review of the definitions of PsM presented in the literature is given in Table 2.1.

Notice that column "decision-making definition" refers to those works in which PsM is characterized by a maintenance solution in which actions are taken based on data or any kind of information such as in [AGN19]. Column "Action criteria definition" indicates that PsM was defined mostly based on what specific criteria must be applied to the system such as [MRW21]. Column "type of action definition" refers to those in which the definition used revolves mostly around actions that go beyond replacements, inspections and repairs, such as [SEM21]. Finally, "distinguishes PsM from other policies" considers the robustness of the definitions presented classifying them based on the capacity to distinguish PsM from other maintenance paradigms.

Most of the works reviewed do not present a definition of PsM that clearly differentiates it from other maintenance policies suffering from the problems mentioned before. Most either failing to recognize that decision-making is a mandatory part of any maintenance policy, use vague notions of "holistic considerations".

Definition on paper	Decision-making definition	Action criteria definition	Type of action definition	Distinguishes PsM from other policies
[AGS20]	X			No
[AGN19]	X			No
[Nem+18]	X			No
[Mat+17]	X			No
[Tzi+23]	X			No
[CBJ19]	X			No
[Liu+19]	X			No
[Pad+21]	X			No
[PL22]	X			No
[MRW21]		X		Yes
[SEM21]			X	Yes
[Gor+20]			X	Yes
[Kou+22]		X		No
[MG19]		X		No
[Iun19]	X			No
[Fra+19]			X	Yes

Table 2.1: Prescriptive maintenance literature review summary

2.5 The problem with PsM and why it matters

As discussed in previous sections, PsM has gained some popularity lately. By reviewing its use in the literature, it can be seen that most authors use it in an ambiguous way which could be considered extremely similar to what is understood in practice by CbM or PdM. This is a problem when, in most of those works, PsM is treated as an improvement with respect to what exists so far [AGN19]; [Kou+22]. Without proper definition, this use of PsM could be seen as another instance of a hype problem [Wei17]; [Hop+20], which would be corroborated by the insistence in using umbrella terms such as "big data", "data analytics", "machine learning" in PsM definitions such as the one presented in [Kou+22].

This problem has also practical implications. The usage of this term leads to noise and can hinder the development of new maintenance solutions as well as scientific communication. For example, among the different works reviewed, most of those that present practical contributions propose policies that are conceptually indistinguishable from other consolidated policies. Employing the term PsM in this case only causes confusion and undermines the valuable contributions made.

However, this is not the case in all examined contributions. Some works deal with criteria and actions which are not commonly explored in the literature and could be used as an inspiration for establishing PsM in a clear way. For example, [SEM21]; [Gor+20]; [Fra+19] extend the concept of maintenance and [MRW21] gave practical insights on what holistic decision criteria should look like. Based on those, in the next section, a new PsM definition

is proposed.

2.6 Defining PsM

To characterize PsM as a distinct maintenance policy, it is necessary to define it in a clear and technical way. Based on the findings of the literature review, we extend the notion of PsM we originally introduced in [DL+21] [4] and propose the following definition:

Prescriptive Maintenance: Maintenance policy based on decision making algorithms with ***closed-loop structure*** that minimize a ***metric related to the overall exploitation cost*** of the system through actions that affect ***all system functionalities***.

There are three distinctive features of PsM. The most important is that prescriptions must go beyond classical maintenance actions such as replacements, inspections or repairs. PsM prescriptions should consider all aspects of system usage that may impact its RUL. If this is not the case, the distinction between CbM and PsM becomes fuzzy.

As a consequence of this extended notion of maintenance action, PsM solutions account for the whole exploitation cost of the system, which is the second defining feature of the definition. This means that PsM requires a quantitative model for the impact of each action both in terms of system performance and RUL. For example, in several cases, in terms of RUL extension, the best prescription is to not use the system at all. This is unsatisfactory from a practical point of view and the only way to ensure that such meaningless prescriptions are avoided is to define optimization criteria and constraints considering the whole system operation.

Finally, the last defining feature is a closed-loop structure. This is required to ensure that those solutions are useful in practical applications. Due to the fact that PsM prescribes different actions that are applied in the system in very different time scales (for some systems, maintenance happens every year while prescriptions related to system usage can happen every second) the close-loop structure ensure that the natural randomness surrounding real applications is accounted for in the long term, correcting for any disturbance.

It is important to highlight that, although some elements of the discussion about different actions are presented in [Fra+19], this definition of PsM is slightly different from the one defended by them. In their case, actions are mainly applied to ensure that a pre-established maintenance plan will be respected and in this new definition, the criteria to prescribe any change in usage is the overall exploitation cost. Therefore, usage can be changed to respect maintenance schedules but also to postpone operations. In some cases, it could even be changed to accelerate degradation if that represented performance increase.

[4] It is important to highlight that other authors have used our original publication in their work when defining PsM, therefore, those are not extensively explored in this review since we believe those authors share our view on PsM [ECG+23]; [Esp23]

2.6.1 PsM generic Structure

Based on the proposed definition, it is reasonable to assume that all PsM applications will present some common elements. Figure 2.5 synthesises a generic PsM structure and its elements. It is composed of several sub parts which are described below.

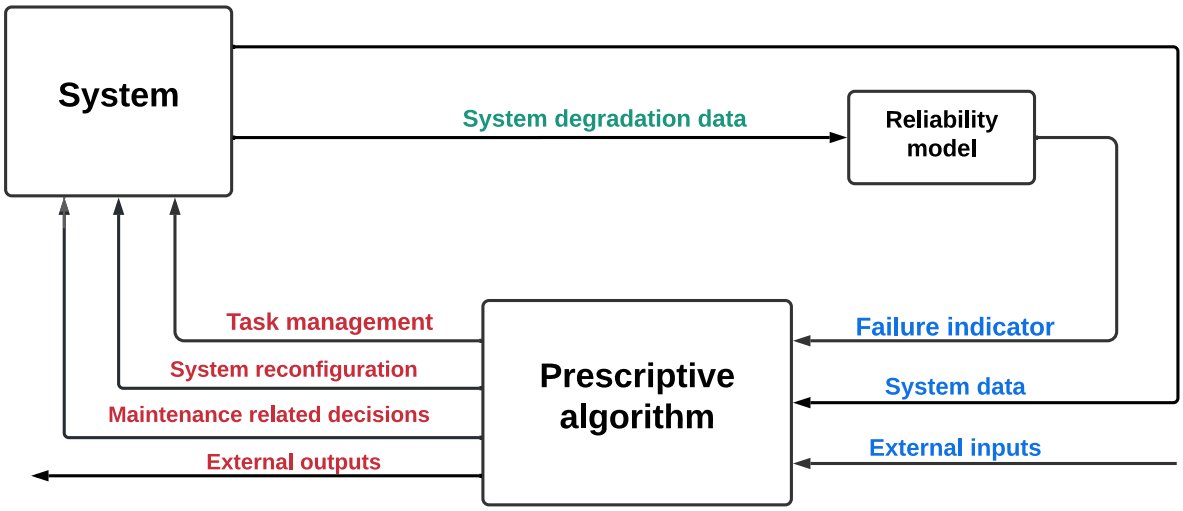

Figure 2.5: Generic structure of PsM solutions

2.6.1.1 System

The first entity on this generic PsM solution is referred to as system. It is an abstraction of the physical entity PsM will be applied to, which depending on the application can represent different things.

Very important design choices revolve around how to define the system. More complex systems, composed of several sub machines and components, will often lead to more complex solution spaces, there is a clear trade-off between having more degrees of freedom to impact the overall exploitation cost and being able to solve the optimization problem that represents the PsM decision-making process. Therefore, the most important consideration when modeling a PsM system is that it must capture the different possible actions without leading to unsolvable optimization problems.

2.6.1.2 Reliability model

The PsM reliability model plays an important part on the PsM loop, providing a health indicator that will be accounted for by the Prescriptive algorithm. This model must be flexible and capable of accounting for all usage patterns that may arise from the system following different prescriptions. It gives quantitative measures that can be used by the prescription algorithm to understand how actions affect system health.

It is also important to highlight that its output, the health indicator, can represent different quantities depending on how the system was defined. It could be the RUL of the whole system, its degradation level, a vector containing either one of those quantities for each machine in a factory and etc.

2.6.1.3 Prescriptive algorithm

The PsM algorithm is responsible for combining the different inputs and providing prescriptions to affect the system as an output. It represents an optimization model whose decision variables translate to prescriptions and whose constraints and cost function will reflect the different inputs and the behaviour of the reliability model chosen.

To satisfy the definition of PsM this optimization model must have a cost function that takes into account the whole exploitation cost of the system and include the impact of each prescription on it.

2.6.2 Prescriptions

The four different classes of actions to be prescribed, presented in Figure 2.5 are now detailed with concrete examples. It is important to highlight though that this list is not exhaustive, as it merely captures some of the most common types of PsM actions.

2.6.2.1 Task management

This class of actions relates to the order in which system tasks are performed. In a single component system, for example, a machine in a production line, it comes down to the classical single machine scheduling problem [GK87]; [SN10]. In systems such as a fleet of vehicles, it comes down to choosing which one will perform different deliveries, in a set-up such as of a vehicle routing problem [TV02].

This type of prescription is important in the PsM context because for most systems, different tasks will affect degradation differently. In the example of single machine scheduling, this could mean, for example, that very damaging tasks must be postponed when possible to complete as much as possible before having a breakdown. In the example of a fleet of vehicles, it could mean that more degraded vehicles should be used to perform less severe displacements. Task management considering degradation information can be found in [Rob+19], where the delivery plan of a fleet of trucks is decided based on the expected severity of each displacement and the current health state of each vehicle.

2.6.2.2 System reconfiguration

This class of actions relates to the different ways a system can perform a particular task. For example, a machine can be reconfigured, restricting its power or, in the case of a fleet of vehicles, speeds can be limited to reduce degradation.

System configuration can also be useful not only for minimizing degradation but also to ensure operational improvements. If, for example a maintenance operation is already scheduled and will soon be performed, tasks can be carried out in a more 'aggressive' way to improve system performance.

A concrete example of parameter reconfiguration considering degradation can be found in [RMB21], where wind turbine control parameters are changed in order to positively impact degradation trajectory. In this example, the wind turbine may move away from the operational point that maximizes power generation but this is compensated by the fact that its useful life is extended, implying that long-term considerations are important.

2.6.2.3 Maintenance related decisions

PsM solutions often also account for classical maintenance actions, such as inspections, replacements and repairs. The vast majority of literature on decision-making for maintenance focuses on how to take those actions in different cases such as perfect and imperfect maintenance operations [MC19], perfect and imperfect information [GYO07], etc.

In the context of PsM, maintenance decisions must be made accounting not only for health indicators but also for the whole context of system usage. For example, periods when demands are less urgent and downtime is not as deterring should probably be preferred.

2.6.2.4 External outputs

This class of actions encapsulates everything that will neither impact system degradation or operation directly but is important in terms of the overall exploitation cost. A concrete example would be inventory control, which can be seen in [WZ21] where deterioration information and operational demand are used to decide inventory level, providing insight on the best spare part management strategy, ensuring uptime without wasting resources.

2.6.3 Inputs

As with the prescription outputs, the three different classes of inputs listed in Figure 2.5 are now detailed.

2.6.3.1 Health indicator

The health indicator is the output of the PsM reliability model, which gives a measure of the system health. This measure is used by the prescriptive algorithm to establish what is the best course of action from that point on. As mentioned before, health indicators can be different depending on the kind of system and reliability model choice. It can be a RUL, a degradation level, a vector containing both, etc.

2.6.3.2 System data

This class of inputs encapsulates any system information that can be monitored and contains information related to its health state and usage. This data will be used by the reliability model to estimate health indicators and by the prescription algorithm so that it can have an image of its operation such as what tasks remain to be performed, its current performance and etc. For example, in a fleet of vehicles, it could represent the position of each vehicle, how much fuel each one has and so on.

2.6.3.3 External inputs

This class of inputs refers to those which are not obtained directly through the system. If, for example the system represents a vehicle, external inputs could represent the delivery addresses it needs visit, their deadlines and so on.

The distinction between external inputs and system data depends on the design choice of how to model the system as discussed before. In this example transport applications, if a system was defined to be a single vehicle in a fleet, information about what deliveries still remain to be done could be seen as external inputs. However, if the system was defined as the whole fleet of vehicles, this information could be seen as system data since they would be defined through task managements prescriptions.

2.7 A framework for PsM solutions development

To guide the conception of PsM solutions in the sense of the presented definition, a development framework is presented. It is conceived to be as generic as possible, keeping the defining features of PsM while being applicable to different systems. It is important to highlight though, that its application to particular cases can lead to very unique scientific challenges that must be addressed accordingly, as will be seen later when it is used in the context of heavy vehicles. This framework is composed of four parts: system abstraction, reliability modeling, system modeling and optimization modeling. Throughout this section, they are detailed.

2.7.1 System abstraction

The first step, referred to as System abstraction, consists in understanding and refining the definition of system. This implies in establishing the scope of what will be addressed by the PsM solution and listing all possibly relevant actions to be applied as prescriptions.

As stated before, this design choice is impactful for PsM applications as it will define what actions can be applied to the system. In the example of transport applications, as mentioned before, considering a single vehicle as a system has practical implications as the next delivery to be performed will be seen as an external input. In contrast, considering the whole fleet as a system would make delivery planning part of the prescriptions.

When defining the system, there is a trade-off between the potential impact of the solution and its complexity. A system composed of several sub components can be impacted by several possible actions, which can deeply reduce the overall exploitation cost. However, it will also be hard to model and may require input information that can not be monitored in reality.

Therefore, this trade-off must be addressed in the light of the available resources both in terms of data acquisition and the computational power required to solve the resulting optimization problem. In general, system definitions that lead to simpler optimization problems are preferable. Those considerations about simplicity and performance are hard to be made at this stage and will only become clearer throughout the next steps, therefore, this framework must be applied through multiple iterations.

By the end of this step, the definition of system must be clear as well as what are all the different actions that can be prescribed and the relevant system information that can be monitored.

2.7.2 System modeling

Once the system and relevant actions are defined, it is necessary to model them explicitly. This model needs to capture the impact of all its inputs *i.e.* actions that could be prescribed on the system data *i.e.* the data available that contains information on usage. The exact model choice will depend on the complexity of the system and actions. This will be illustrated throughout this work when applying the framework to different vehicle components which led to radically different system models.

2.7.3 Reliability modeling

In order to optimize maintenance and system usage, it is necessary to employ an explicit reliability model. It must be built considering the outputs of the system model and the physical mechanisms underlying the most relevant failure modes. Naturally this implies that once again, the choice of reliability model will depend on the system definition.

Several different classes of models can be used such as stochastic degradation models, conditional reliability distributions, physics-based models and data-driven models, for example. The choice must be guided by availability of degradation data and the understanding of degradation mechanisms. The most important thing is that the reliability model connects system degradation with the different actions to be prescribed.

2.7.4 Optimization modeling

The last step of the framework is to formalize one or more optimization models that will be solved through the prescription algorithm. Optimization models are composed of three parts: the cost function, the constraints and decision variables.

In a PsM application, the decision variables must be translatable to the actions listed in the system abstraction step discussed in Section 2.7.1. Those will therefore represent the best course of actions when the optimization model is solved.

The cost function is the metric that must be minimized in the optimization defining the best set of prescriptions. It has to, following the PsM definition, consider the overall exploitation cost of the system and capture all relevant trade-offs between degradation and system usage. For example, reducing machine power can postpone maintenance operations but it can also reduce productivity. The cost function has to be defined such that it is possible to balance out those effects. The solution will then decide when and how to reduce machine power to minimize exploitation cost.

The constraints of the optimization model represent conditions that must be respected by the found solution. In the context of PsM they need to represent system and reliability models. They must also ensure that the found solution can indeed be translated to meaningful prescriptions. For example, when solving routing problems for vehicles, constraints are employed to ensure that sub-tours are eliminated, as will be seen in Chapter 3.

After defining the optimization model, it is necessary to choose an algorithm to solve it. Different techniques can be employed and this choice will mainly depend on complexity of the problem and the requirements related to computation time of the PsM solution. In cases of non-linear optimization models, or in cases of huge decision variables spaces heuristics methods can be practically useful even if they are not guaranteed to find the best solution whereas in cases where the problem can be solved in reasonable time, exact methods must be chosen.

2.8 Self criticism

This section is dedicated to justify some aspects of the critics to some reviewed works that, at first glance, may seem unfair, clarifying why, even though several of them contain rich discussions on maintenance concepts, they are indeed incapable of delimiting the perimeters of PsM. It also acknowledges and displays possible critics to the PsM definition presented in

this work.

It was seen that several publications define PsM by referring to a "more holistic" view of maintenance. When that holistic aspect was vaguely defined, those were considered as incapable of differentiating PsM from other policies. It could be argued, that in those cases, although authors were not explicit, they could have a similar understanding of PsM than the one presented in Section 2.6). However, very often, when those works provide examples of practical maintenance solutions, authors present methods conceptually similar to what is understood as PdM and CbM [Mat+17]; [Kou+22].

It is important to highlight that some of the reviewed works that were considered incapable of defining PsM present solutions including usage optimization. However, in those cases, usage optimization was not considered to be intrinsically part of PsM as a concept. For example, in [Elb+22] they address production schedule combined with maintenance optimization but they explicitly consider PsM to be limited at choosing when to replace items. Usage optimization for them is not an integral part of PsM definition. Similarly, [AGN19] acknowledge that their maintenance solution could generate insights on how to manage the production but do not see that as integral part of the concept of PsM.

One could argue that the definition of PsM presented is also incapable of differentiating it from other maintenance strategies due to the fact that joint optimization of maintenance and usage was already investigated by authors which refer to their policies as PdM or CbM [PM21]; [LN13]. However, none of those authors seem to consider system usage optimization to be a defining characteristic of any type of maintenance policy and do not present any conceptual discussion regarding maintenance.

It is necessary to acknowledge, though, that the presented definition of PsM is very similar to the concept of Prognostics and Health Management (PHM) defended by authors such as [Ata+17], and in the end, PsM can be seen as the application of PHM to define a maintenance policy.

2.9 Conclusion

In this chapter, our main conceptual contribution is presented as a clear definition of PsM. It was designed to justify the use of this term as a distinct maintenance policy and was proposed after reviewing the history of maintenance, investigating the most common policies in the literature and reviewing different works that discuss PsM. Although this definition is inspired by the concept of PHM, it is sufficient to differentiate PsM from other forms of CbM and can be clearly understood by researchers.

Finally, to encourage the adoption of PsM, a step-by step conceptual development framework is proposed. Although the particularities of each application may lead to original scientific problems, at least this framework showcases the most important features of a PsM solution.

To move towards concrete implementations of those concepts, in the next chapter, the proposed development framework is applied to the object of interest of this work: heavy vehicles. The main challenges of this application are discussed, as well as some promising modeling approaches and possible optimization methods for such problems. It will close Part I, providing the reader with an overview of the scientific challenges addressed in Part II.

Chapter 3

PsM for heavy vehicles : specific issues, tools and methods

Contents

3.1 Introduction

In the previous chapter the definition of PsM used through the rest of this document was presented. As the goal of this research project is to investigate and develop methods that can be used to create services for vehicle usage and health optimization, the PsM framework introduced in Chapter 2 is now applied to heavy vehicles. As a result, a general PsM structure for transportation applications is obtained.

This PsM structure is presented and its details are explored in this chapter. All actions and inputs are detailed as well as possible choices for reliability models. The aim is to give

the reader a general view of the PsM problem for vehicles, understanding scope limitations, reasonable modeling assumptions and notation choices adopted throughout the rest of this document.

At the end of this chapter, an overview of optimization models used in similar problems is given in order to present concepts and modelling assumptions that will be used in Part 2, as well as the most common algorithms used to solve them. A final section discusses and highlights the complexities arising from the combination of degradation and usage optimization and the challenges that must be addressed in the rest of this document.

3.2 PsM for heavy vehicles: considerations and system abstraction

Before discussing the results of the development framework application to heavy vehicles, it is useful to briefly recall some elements discussed in Chapter 1. Furthermore, some technical aspects of modern vehicles must be described since they are important for understanding some of the modeling assumptions made later. Those elements are addressed in this section.

3.2.1 Service perspective

The goal of this research project, as stated before, is to create tools that can be used as the foundation of services that will be part of vehicle manufacturer service offers. Those services will be used for decision-making support. Therefore, at this stage, it is useful to recall what the fleet managers' and vehicle owners' needs are, since the later is responsible for service subscription and the former will be its day to day user.

For a service to be attractive for vehicle owners, it must lead to significant cost reduction in the long-term while respecting the particularities of their businesses. The fleet exploitation cost is composed of the different expenses seen in Figure 1.8. Maintenance and fuel consumption are together responsible for 33.5% of the total cost, furthermore efficient health management leads to less downtime, guaranteeing that deliveries are performed. This importance justifies why PsM, as previously defined, is attractive for vehicle owners and stresses the fact that those expenses must be minimized by this potential service.

Even if the decision of subscribing to PsM services is ultimately taken by vehicle owners, such solutions would be mainly used by fleet managers. This consideration is important when delimiting the scope of PsM actions. As a general hypothesis, in this work, it is considered that fleet managers work based on a list of addresses that must be visited (deliveries, garbage collection points and etc). Those addresses are referred to, from now on, as *missions*. Therefore, fleet manager's daily decision-making mainly consists on deciding which fleet vehicle must be used to perform a particular mission.

In that perspective, those decisions must be the base of all actions considered. For example,

even if changing software parameters to limit acceleration reduces degradation, this limitation must be made in a way that does not cause significant delays. This is crucial to ensure customer satisfaction and avoid solutions that reduce the exploitation cost at the expense of damaging the business of the user.

3.2.2 Mobile assets particularities

In Chapter 2, a class of PsM actions referred to as task management was discussed. Since those actions encapsulate deciding the order of missions to be performed which is the most important logistical decision as discussed in Section 3.2.1. Although task management for vehicles has been previously addressed similarly to how task management in production lines is classically approached [Rob+19], this ignores the spatial particularities of transportation applications. The first problem with this approach is considering that missions effect are independent of the order in which they are performed. This order impacts traveled distances, fuel consumption and therefore, even degradation. Furthermore, in a dynamic mission planning problem, where new missions can appear while others are being performed, assigning vehicles to them depends on their current positions. Finally, in the context of maintenance, this spatial dimension is also relevant. Vehicles perform maintenance in several different workshops, which means that choosing a workshop can also be included in the decision-making process.

The fact vehicles are mobile units is relevant and impacts optimization model choices. It forces PsM applications to move away from common maintenance and production line optimization approaches and to consider models similar to those used in transportation science, where spatial considerations are always part of problem formulations. Those models are typically used in routing and shortest path problems as will be seen later.

3.2.3 Vehicle subsystems and components

So far, in this work, the term *component* has been used to designate a sub-part of a machine. In order to better understand future modeling assumptions, it is important to, at this point, provide a more precise definition of this term as well as discuss some relevant hardware aspects of modern heavy vehicles.

In general, heavy vehicles are composed of sub-systems responsible for different vehicle functions (*e.g:* braking system, heating system, etc). Each sub-system can in turn have its own subsystems. Figure 3.1 illustrates this, through an exploded truck view. In the context of vehicles, through this work, the term component is used to describe parts of those sub-systems that can be replaced in maintenance operations, such as the brake-pad, which is part of the braking sub-system.

As sub-systems are responsible for specific functions, each one can contain Electronic Control Units (ECUs). They are embedded numerical controllers responsible for processing

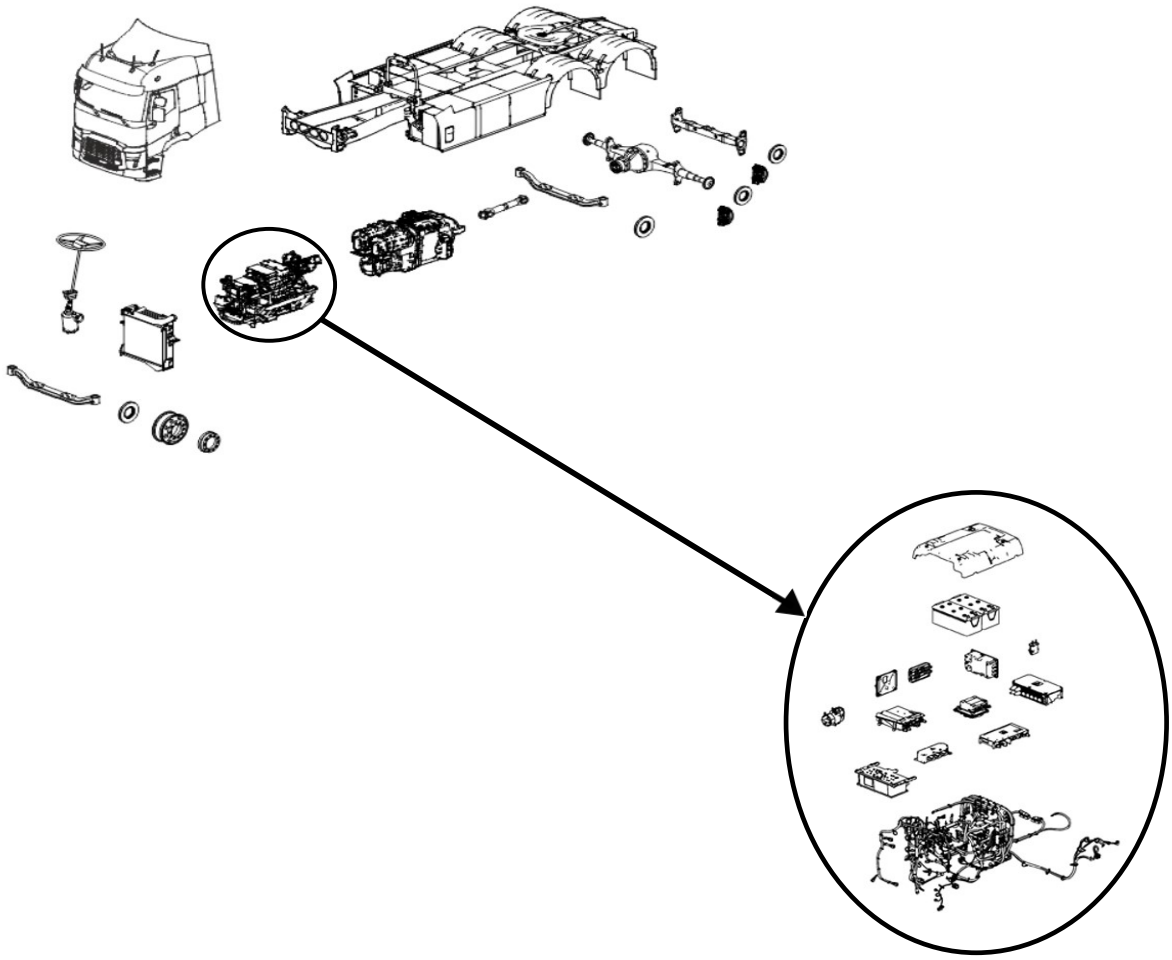

Figure 3.1: Exploded view of a truck highlighting some of its subsystems. Each of those systems can have several sub-parts composed of different component and containing ECUs.

sensor data and coordinate relevant actuators. Vehicle functions are not independent[1] hence, ECUs must communicate among themselves in an efficient and robust way. The most popular communication protocol used is called Controller Area Network (CAN) [LP01]. CAN works based on a particular hardware configuration in which each ECU is connected to a common BUS. ECU data is then sent through this BUS propagating to the other concerned ECUs. Some of CAN main advantages are [LP01]:

- High robustness.
- Efficient transfer of relatively short messages.
- Known maximum latency time of messages.
- Low implementation costs.

[1]For example, when the braking system is used, braking lights, must also be activated

As discussed in Section 1.4, nowadays vehicle data can already be used for several services. This data comes from different sub-systems managed by different ECUs, however, in order for it to be exploited outside the vehicle, it needs to go through a particular ECU that is responsible for sending data to the cloud, in a process called vehicle connectivity. This implies that only data passing through the CAN BUS can be used in a service. As a consequence, data acquisition is limited to the CAN BUS frequency. Furthermore, logging data to the cloud in real time is expensive. The most common approach in terms of storing vehicle data is to log only the most important signals periodically with low frequencies. The exact frequency can vary but it is reasonable to assume that degradation data can be logged at least daily.

This relatively low logging frequency limits modeling assumptions on PsM prescriptions. For example, since parameter reconfiguration related actions also depend on vehicle connectivity, real time software updates can not be included in the scope of this work as well as dynamic mission planning based on real time vehicle usage data.

3.2.4 System abstraction for heavy vehicle applications

With all those consideration around the particularities of heavy vehicles, system abstraction, the first step of the development framework proposed in Section 2.7, can be done. Figure 3.2 shows the arising PsM problem structure for heavy vehicles. The first important consideration is that the PsM system represents the whole fleet of vehicles, considering the different interactions between them. This choice is made since the fleet manager assigns missions to vehicles accounting for their availability and particularities. Considering a single vehicle within the fleet as a system has less cost reduction potential. It also requires restricting hypothesis on how mission plans are defined, since those would be considered as external inputs. In the following sections, all actions listed are detailed.

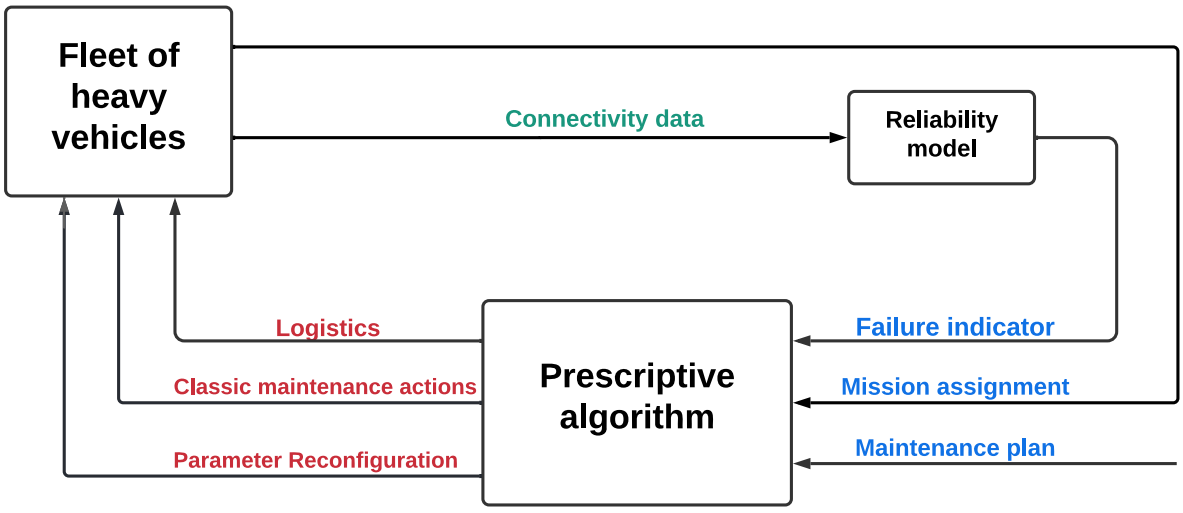

Figure 3.2: PsM problem structure for heavy vehicles

3.2.5 PsM actions scope in the context of vehicles

The actions listed in Figure 3.2 are split into three categories: logistics, which revolves around most of the decisions the fleet managers already makes today; classic maintenance actions, related to deciding when replacing a component; and parameter reconfiguration which relates to software updates through connectivity.

3.2.5.1 Logistics

Most of the day to day work of fleet managers revolves around logistics. It encapsulates everything related to assigning missions to vehicles. In the context of this work, logistics is divided into three categories that are now defined.

- **Path selection:** when performing a mission, there can be many different paths to arrive at a destination. This logistical decision has a clear impact in terms of performance and operational costs since it affects arrival time and fuel consumption. It can also impact the degradation level of some vehicle components such as air filters [DB21] and batteries [PA20], which makes this decision suitable from a PsM action point of view.
- **Routing:** the most important logistic decision is defining which vehicle will perform each mission and in which order. In transportation science, this is referred to as *routing*. It directly impacts traveled distance and, as a consequence, fuel consumption and different components degradation.
- **Charging:** in the particular case of EVs, planning charges is important, since, as seen in Chapter 1 those vehicles present limited range when compared to ICE vehicles. Deciding when to charge and either to use fast charging or not can impact the degradation of different components and must be included for EV PsM applications.

The combination of those three decisions composes the general logistical problem of PsM for heavy vehicles. Figure 3.3 provides a visual representation of it. Notice, however that not all logistical decisions affect component health in the same way. Therefore, the exact optimization problem formulation depends on the components considered for defining vehicle reliability.

Making logistical decisions requires the set M composed of missions m_j that can be represented as:

$$m_j = \begin{bmatrix} a_j \\ l_j \end{bmatrix} \tag{3.1}$$

where a_j is mission m_j address, composed of space coordinates $[x_j, y_j]$ and l_j is its deadline. Several different hypotheses about how M is obtained can be made. One of the most natural

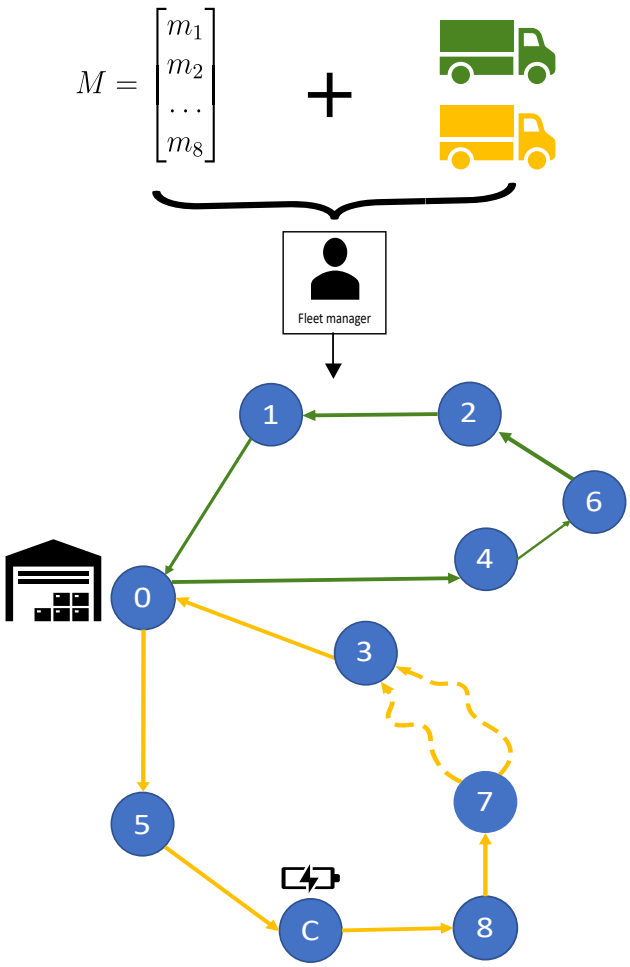

Figure 3.3: Representation of the logistics problems addressed by the fleet manager. The decision consists in, based on a list of missions M, define how the fleet will perform them. This means defining routes for each vehicle, planning eventual visits to recharge stations (represented by C) and choosing, when relevant, different paths as represented between point 7 and 3.

is to consider it as static. In this case, all logistic decisions are taken at once at the beginning of a *working session* that lasts until all missions are performed and vehicles return to the headquarters. However, there are also problems in transportation science that consider that, while vehicles perform missions, new ones can arrive, requiring dynamic re-planning such as seen in [Rio+21].

3.2.5.2 Classic maintenance actions

classic maintenance actions encapsulate defining when to replace a component, perform an inspection or perform a repair. As discussed in Chapter 2, there is no intrinsic hierarchy between maintenance policies. The choice of when using PsM, CbM, TbM is a result of

a careful cost effectiveness analyses. As such, it is reasonable to assume that less critical components will not be covered by PsM and accounted for in the reliability model, specially since it is expensive to collect data for all of them with vehicle connectivity.

Therefore, since not all vehicle components are considered, TbM will be, at some level, still required. Routine visits to workshops will still happen for any maintenance operation on components not included in the reliability model. As a consequence, maintenance actions for heavy vehicles will be prescribed in an opportunistic maintenance set-up [TLI08]; [MRW21], meaning that they should preferably happen in already scheduled workshop visits in order to reduce downtime.

A direct consequence of the opportunistic set-up is that the list of predefined maintenance operations dates must be known in advance. Several hypotheses are reasonable for defining how this maintenance schedule is built. A valid assumption is to consider that those operations are based on calendar time and will occur at periodic regular intervals. However, as seen in Chapter 1, some operations can be triggered by usage intervals.

It is also important to highlight that, some vehicle components are not expected to be replaced throughout the life of a vehicle. Nevertheless, their degradation levels can impact vehicle performance and they are often so expensive that they *define* the duration of vehicle useful life. For those components, PsM works through usage optimization to ensure total exploitation cost reduction which, in general, leads to RUL extension.

3.2.6 Parameters reconfiguration

As previously discussed, with the current technology, several different software parameters can be updated remotely through connectivity. As such, it is possible to affect the way vehicles are driven and positively impact their useful life duration. For example, as will be seen in Chapter 6, limiting maximum vehicle speed and acceleration, can be beneficial for EVs.

It is important to highlight however, that affecting those kinds of parameters can have impacts on how missions are performed. If updates are carelessly made, deadlines may not be respected. As such, parameter reconfiguration must always happen within the context of missions, requiring the same inputs as logistical decisions.

3.3 A review on useful mathematical models for heavy vehicle applications

With a general view of the decision-making problems included in PsM solutions for heavy vehicles, it is possible to investigate modeling alternatives for reliability and optimization models. It is important to highlight that as stated before, the reliability model has a huge impact on how actions will affect the health of a component. Some components are sensible to path selection while others are not. Some components are often replaced and some are not.

The reliability model must capture those aspects and in turn affect the choice of optimization models.

3.3.1 Reliability models for vehicles

PsM requires a model capable of quantifying how different actions will affect the health of the system. A possible approach for vehicle applications would be to directly employ probabilistic models for time to failure such as done in [Jbi+18]. This method is simple but not suitable for PsM since, throughout most of the useful life of vehicles, failure probabilities are neglectable but usage can be optimized at any time since it always has an impact on vehicle health or degradation.

A more natural choice is to use a reliability model based on degradation. For example, a possible approach is to use a First Hitting Time (FHT) model which considers that a quantity $W(t)$ representing degradation evolves through time. When $W(t)$ reaches a threshold L_w, it causes a breakdown. The failure time T_{fail} can then be defined as:

$$T_{fail} = \inf\{t : W(t) \geq L_w \mid W(0) \leq L_w\} \tag{3.2}$$

The advantage of such models is that, even when T_{fail} is expected to be too far in the future, the impact of PsM actions on $W(t)$ can be modeled and usage can be optimized at any point of vehicle life. Furthermore, even for components which are periodically replaced to avoid reaching a defective state, $W(t)$ can impact vehicle performance as will be seen in Chapter 5. Additionally, in many cases $W(t)$ is a measurable physical quantity (*i.e.* brake-pad thickness, battery capacity and etc), which leads to a very natural way of closing the PsM loop.

Different alternatives on how to employ FHT models for vehicles exist. For example in [Rob+19], vehicles were modeled, as a single component, with $W(t)$ representing an abstract health measure of the whole vehicle. In reality, heavy vehicles are extremely complex with different failure modes and, from a PsM point of view, it is better to consider those components individually since they can behave differently. There are several alternatives to model $W(t)$. The most common options are now reviewed.

3.3.1.1 Deterministic degradation models

Some approaches to model degradation rely on deterministic models which are usually based on empirical relationships between different parameters of the system and physical degradation quantities that can be measured. For chemical-induced or temperature sensible degradation processes the Arrhenius model is commonly used. It is based on the empirical relationship:

$$\dot{W}(t) = Ae^{\frac{-E}{RT}} \tag{3.3}$$

where $\dot{W}(t)$ can be seen as the degradation rate, E is the reaction energy, R the gas constant, T the absolute temperature, and A is a constant that must be empirically determined. This approach has been successfully used to model homogeneous aging processes in polymers [Zag+20], however, this model is not valid for all temperature ranges. Some alternative relationships have been proposed to deal with this limitations such as the Eyring model, which has been used in electronic applications [McP86].

Degradation phenomena of different nature are modeled in other ways. For example, in the case of degradation related to crack growth, the Paris' law model [PE63] is commonly employed. It is based on Paris' identity which is the following empirical relationship:

$$\dot{W}(t) = C\Delta K^m \tag{3.4}$$

where $\dot{W}(t)$ is now seen as the crack growth ratio per fatigue cycle. ΔK is the critical crack length and m and C are empirically determined constants. In this case, the degradation quantity $W(t)$ is precisely the length of the crack. This relationship holds true in specific crack length intervals and other relationships have been proposed to describe crack growth outside of them, such as [Bap+12].

Deterministic degradation models have also been used in vehicle applications. For example, in the context of lithium batteries, variations of the Arrhenius model have been employed [JKG18]. Although deterministic models are easy to interpret and implement, they fail to capture the intrinsic uncertainty surrounding degradation. This randomness comes from the variability among components, use modes and etc. For that reason, depending on the component, other alternatives may be preferred.

3.3.1.2 Stochastic degradation models

To account for uncertainties, either the parameters of deterministic models can be treated as random variables or $W(t)$ can be modeled directly as a stochastic process [Noo09]. In this case, the choice of which stochastic process to use depends on the underlying characteristics of the degradation phenomena. Some of the most commons alternatives are:

- **Poisson process:** Often used to model degradation phenomena that can be interpreted as a consequence of shocks. In this process, each increment of $W(t)$ is random, considered to be Identical and Independently Distributed (IID) and occurs following a Poisson process, as a consequence, $W(t)$ often resembles an irregular staircase. Variations of this process have been used in several different applications such as structural degradation [Wan22] and pit corrosion [Cab+15].

- **Gamma process:** Often used when the physical degradation process is monotonic, meaning that $W(t)$ can only increase. In the gamma process, each increment of $W(t)$ is IID and follows a gamma distribution [Noo09]. As a consequence, the expected degradation process is linear with respect to time. Variations of gamma processes have been used, for example, for modeling degradation in pipes [HBP22] and carbon films [WXM15].
- **Wiener process:** Often used when the physical degradation process is not monotonic, *i.e.* $W(t)$ can increase or decrease at any given t. In the Wiener process, each degradation increment is IID and normally distributed. Wiener processes are usually combined with a linear component to obtain a linear expected behaviour as in the gamma process. Variations of those models have been used, for example, in the context of battery degradation [TYG14] and LED lamps [Wan+14].

In the context of PsM, it is important to have models that reflect the impact of different usage conditions on degradation. In their basic form, the aforementioned stochastic processes do not explicitly account for usage changes. However, there are alternatives that can be used to model usage effects on the degradation. A common approach, for example, is to consider that the parameters of the increment distributions are dynamic and depend on covariates such as in [Wan+21] and [JZV21]. Regarding vehicle components examples, one can mention the use of Gamma process for brake-pad degradation [Zha+21].

3.3.1.3 Black-box degradation models

Another popular approach is to derive, through machine-learning like methods, regression models for $W(t)$. In this case, no explicit model structure is required and data sets containing several degradation measures are processed leading to future degradation estimations that can be used for prognostics. Several examples for different applications can be found in the literature. [Lu+22] employ neural networks to estimate future battery degradation and perform RUL prediction. [Geb+04] propose a general approach to process vibration data and apply neural networks for bearing degradation estimation.

Those models are useful in cases where little is known about the physical degradation mechanisms of the system. However, they have the drawback of requiring large data sets. Furthermore, those models can also be hard to interpret or explain. In the context of PsM, this problem is even more critical since several data points would be required in different usage conditions and gathering such data is a challenge.

3.3.2 Relevant optimization models

With the general structure of the decision-making problem of PsM applications presented in Section 3.2.4, it is possible to investigate similar problems previously addressed in the literature. Some common optimization models for logistics, maintenance and software parameter changes, are now reviewed.

3.3.2.1 Shortest paths

Deciding which path to take in order to go from point A to point B is an example of a Shortest Path Problem (SPP). Due to its universal importance and simplicity, its formal statement and consequential mathematical development started relatively late [Sch12], with the first SPP algorithms being developed in the years 1950. SPP can be described as an Integer Linear Programming (ILP) problem. Considering a weighted graph $G = (N, E)$, a target node t, a source node s and binary decision variables x_{ij} that are equal to 1 if the edge connecting nodes i and j is part of the shortest path, the problem can be described as finding:

$$P^*_{s,t} = \arg\min \quad \sum_{i,j \in N} c_{ij} x_{ij} \tag{3.5}$$

Subjected to:

$$\sum_{i \in N} x_{ij} - \sum_{i \in N} x_{ji} = \begin{cases} 1, & \text{if } j = t \\ -1, & \text{if } = s \\ 0 & \text{otherwise} \end{cases} \quad \forall i, j \in N \tag{3.6}$$

$$x_{ij} \in \{0, 1\} \quad \forall i, j \in N \tag{3.7}$$

where $P^*_{s,t}$ is the optimal path between s and t and c_{ij} represent the weight of each edge $e \in E$ and are often seen as the distance between nodes i to j. Constraint 3.6 guarantees that every path considered starts at node s and ends at node t. It also ensures path continuity. Constraint 3.7 imposes the support of variables x_{ij}. The SPP has several solutions in polynomial time. One of the most famous algorithms is Dijkstra's algorithm [Sni06], shown below.

Dijkstra's algorithm is based on the principle of optimality, which in the case of the SPP implies that, if node $n' \in P^*_{s,t}$ then $P^*_{n',t} \subset P^*_{s,t}$. On other words, if node n' is in the optimal path between s and t then the subset of this path connecting n' and t is the optimal path between n' and t. As a consequence, it is possible to evaluate paths recursively, finding the shortest paths to intermediate nodes, storing their optimal distances and restarting the process from them, gradually reducing the number of paths to be considered. This is illustrated by Figure 3.4, that shows each iteration of the algorithm for a small graph.

It is also important to highlight that several variations of the SPP exist. For example:

- **K-SPP**: SPP versions in which the goal is to find the k-best paths connecting source and target node.
- **Multi-objective SPP:** SPP versions in which the optimization objective involves minimizing different cost functions simultaneously.

Algorithm 1 Dijkstra's algorithm

```
Initialization:
for all n ∈ N do
    if n == s then
        dist(n) ← 0
    else
        dist(n) ← inf
        prev(n) ← None
        add n to N'
    end if
end for
Solving SPP:
while N' is not empty do
    n_min ← element of N' with min dist(u)
    for each neighbor node of n_min in N' do
        alt ← dist(u) + c_uv
        if alt < dist(v) then
            dist(v) ← alt
            prev(v) ← u
        end if
    end for
    remove n_min from N'
end while
```

- **Stochastic SPP:** SPP versions in which different characteristics of Graph G are random. For example, each c_{ij} can be seen as a random variable of known probability distribution with different parameters. There are also versions in which each edge corresponds to a probability distribution of reach a particular node. The problem then becomes establishing a policy for choosing the next node, starting from node s to reach node t with probability 1.

One particularly important variation for this work is the constrained SPP. In this version, in addition to c_{ij}, scalars w_{ij} are introduced to represent resource consumption (energy in the case of EVs or fuel in ICE vehicles, for example) between i and j and a constraint to impose maximum resource consumption is included in the optimization model. This variation, is NP-hard [LM13] and no polynomial time algorithm exists. Exact methods exist [PG13] but meta-heuristics are also commonly used in this case [Kai+18].

3.3.2.2 Vehicle routing problems

The problem of choosing which vehicle must perform each mission is an example of a Vehicle Routing Problem (VRP). VRPs are typically formulated as Multi-Integer Linear Programming (MILP) problems, but in their simplest version, they can be described as an ILP. Considering a

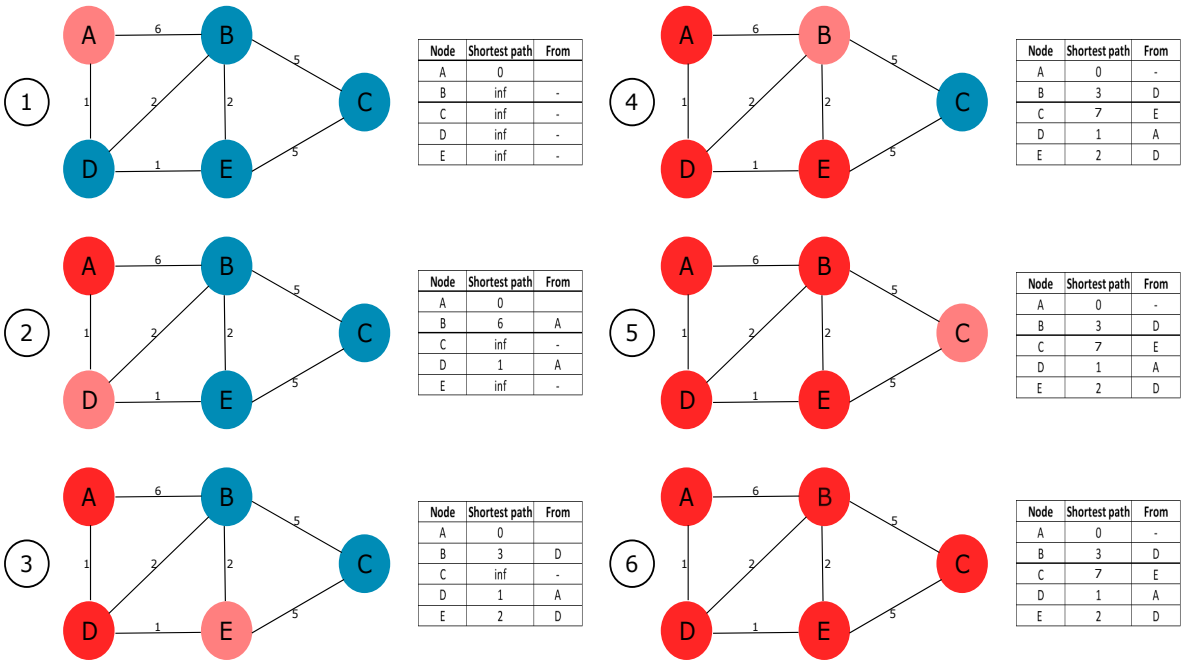

Figure 3.4: Djikstra's algorithm to find the shortest path between A and C in a small graph. In step one, the algorithm is initialized. the distance to each node is marked as ∞ with the exception of source node A. After the distance for reaching each neighbor of A is computed, it is removed from $N^{'}$ (red). The process is repeated for the node with the shortest distance, at each iteration. The algorithm ends once every node is evaluated.

weighed graph $G = (N, E)$, a set Z of vehicles with a node 0 which denotes the depot, where vehicles start and to where they must return at the end of the route, and binary decision variables x_{ijz} which are equal to 1 if the edge connecting nodes i and j is part of the route of vehicle z and 0 otherwise, the VRP can be written as:

$$\min \sum_{z \in Z} \sum_{i \in C} \sum_{j \in C} c_{ij} x_{ijz} \tag{3.8}$$

Subjected to:

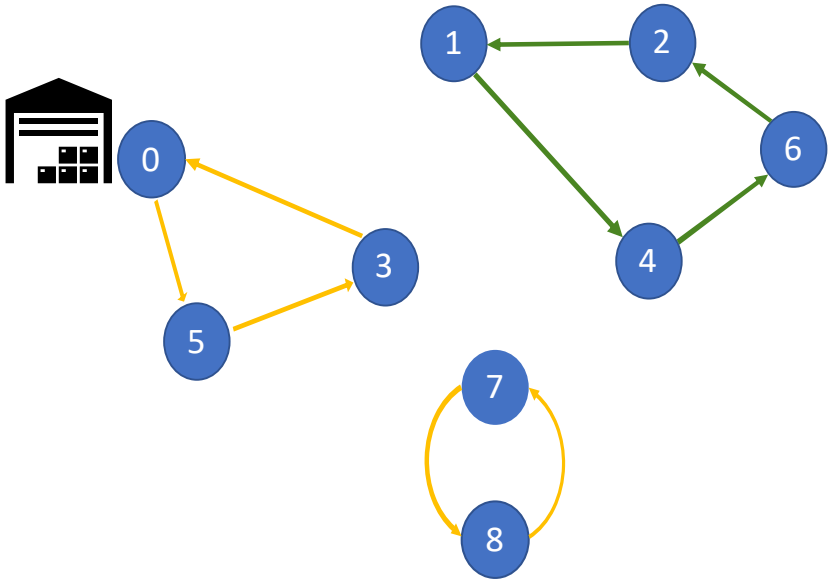

Figure 3.5: Example of solutions obtained when not including sub-tour constraints such as Constraint 3.12 in the VRP optimization model.

$$\sum_{z \in Z} \sum_{j \in C} x_{ijz} = 1 \quad \forall i \in N - \{0\} \tag{3.9}$$

$$\sum_{i \in N} x_{ijz} - \sum_{i \in N} x_{jiz} = 0 \quad \forall i \in N, \forall z \in K \tag{3.10}$$

$$\sum_{z \in Z} \sum_{j \in N} q_j x_{ijz} \leq Q \quad \forall i \in N - \{0\} \tag{3.11}$$

$$\sum_{i \in S, j \notin S} x_{ijz} \geq 2 \quad \forall S \in E \mid 2 \leq |S| \leq |N| - 2 \tag{3.12}$$

$$x_{ijz} \in \{0, 1\} \tag{3.13}$$

Where Q represents the maximum vehicle payload, assumed to be the same for the fleet and q_j is the capacity demand of node j. Constraint 3.9 ensures that every node, except 0, is visited exactly once. Constraint 3.10 ensures flux continuity, *i.e.* whenever a vehicle arrives at a node, it must leave this node in its next displacement. Constraint 3.11 ensures that the maximum payload is never exceeded. Constraint 3.12 is responsible for eliminating sub-tour solutions such as those shown in Figure 3.5. Constraint 3.13 determines the support of the decision variables.

VRPs gained popularity after 1981 when the first practical exact solution algorithms were proposed [LTV13] and have remained popular ever since, enabling substantial improvements in logistics. Those exact algorithms are, in general, based on Branch and Bounding (BB) approaches. BB is a search method that consists of exploring the solution space by recursively splitting it in sub spaces (branches) and computing lower bounds (in minimization problems)

for the cost function [Mor+16]. Whenever a branch with a lower bound bigger than previously explored solutions is found, it can be pruned, reducing the number of required computations. Algorithm 2 presents the generic structure for BB-like methods.

Algorithm 2 BB general structure

```
1: create a set L of sub-problems (branches) and initialize the best bound x*
2: while L ≠ ∅ do
3:     Select a sub-problem S from L
4:     if a solution x'* ∈ {x ∈ S|c(x) < c(x'*)} is found then
5:         x* ← x'*
6:     end if
7:     if S cannot be pruned then
8:         Partition S into regions S1,S2...Sn
9:         Insert S1,S2...Sn into L
10:    elseRemoveS from L
11:    end if
12: end while
```

The performance of BB depends on the quality of lower bounds and on the branching method used. One of the most common methods for BBs is to relax integrality constraints, obtaining a Linear-Programming (LP) problem. This LP is then solved and its optimal cost function value bounds the original ILP. The LP solution is rounded, leading to different branches. The process is repeated in each one of those branches. Constraints are relaxed, LP are solved to obtain bounds that are used to prone them if possible. Figure 3.6 illustrates this process concretely for the following maximization problem:

$$\max 45x_1 + 48x_2 + 35x_3 \tag{3.14}$$

Subjected to:

$$5x_1 + 8x_2 + 3x_3 \leq 10 \tag{3.15}$$

$$x_1, x_3, x_3 \in \{0, 1\} \tag{3.16}$$

Even though exact VRP solutions can be obtained through BB, solving instances with several nodes is a challenge. As a consequence, several heuristics were proposed for solving VRPs, one of the most important is Clarke-Wright savings algorithm due to its simplicity, and relative good performance [LTV13]. This algorithm can be used to enhance meta-heuristics, significantly closing the optimality gap while still ensuring reasonable computation time [PK12]. Several variations of VRPs have been studied, representing different scenarios which translate to different constraints and cost functions. Some of the most common are:

- **Capacitated VRPs:** as the original VRP, this version of the problem addresses vehicle

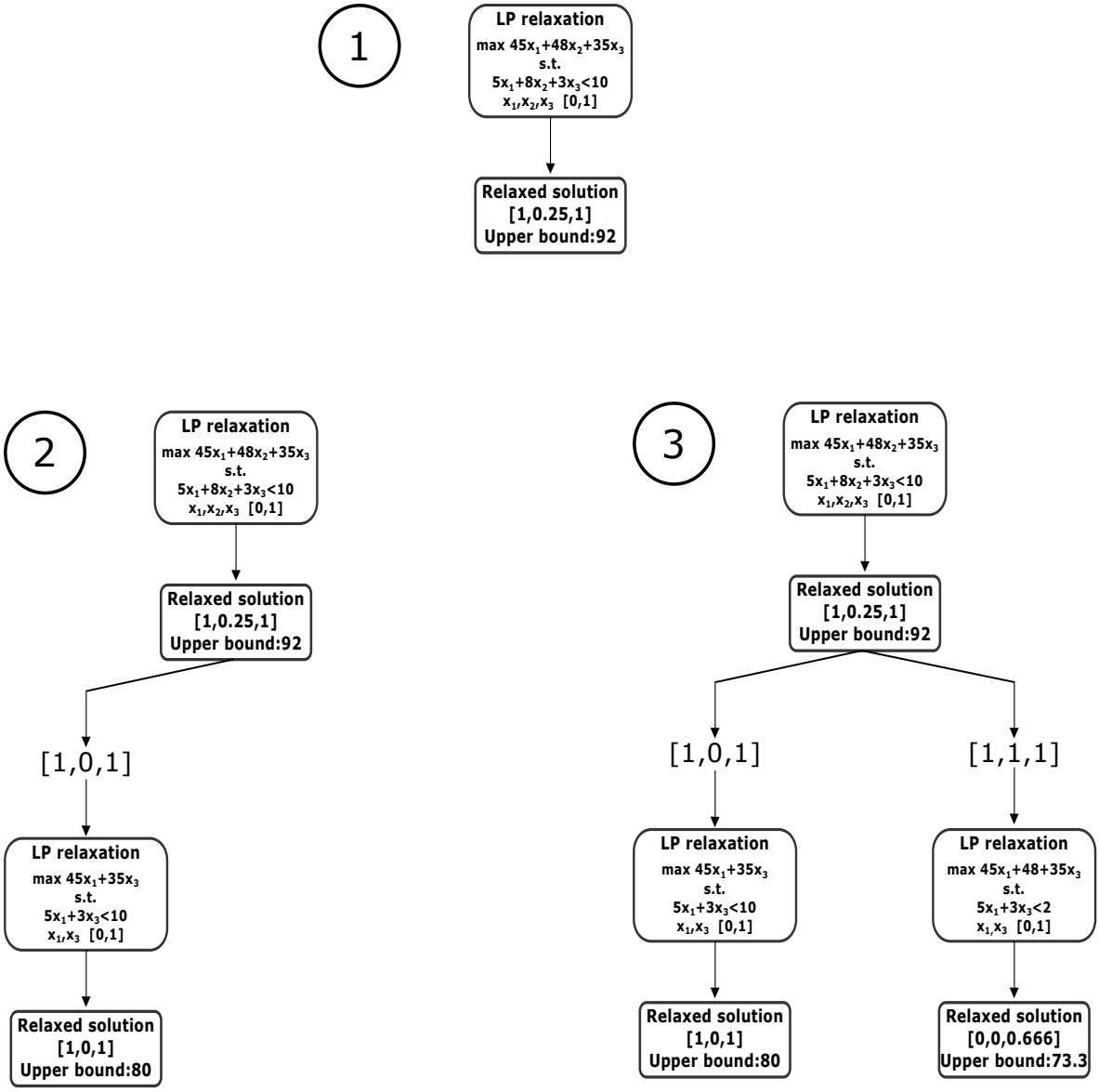

Figure 3.6: BB method for a simple ILP. At step 1, the original problem is relaxed and transformed into a LP. It is then solved, obtaining an upper-bound of 92 for the original problem. The LP solution is not made from integers, therefore, it is rounded creating two branches. In step 2 the first branch is analyzed. Once again, constraints are relaxed and the corresponding LP is solved. This time, the solution corresponds to integers and therefore, the best possible solution on this branch is found. In the third step, the second branch is analyzed. After solving the corresponding LP, it can be seen that the new upper-bound is inferior to the previously found solution and, therefore, this branch is pruned and the algorithm ends

capacity restriction, imposing limits to the amount of cargo that can be carried at once. Some examples can be found in [Akh+17] and [LDAU06].

- **VRP with Time Window:** in this variations, constraints impose rules for when nodes must be visited, establishing the earliest and latest acceptable instant for vehicle arrival. In those variations, service time (the amount of time required to unload the truck and finish the delivery) is considered, impacting deliveries and deadlines. Some examples can be found in [BG05]; [Tan+01].
- **VRP with Multi Depots:** in this variations, logistics topology are complexified, including multiple depots in which vehicle may reload throughout missions. Some examples can be found in [Ho+08]; [CCL07].
- **Stochastic VRP:** those variations encapsulate any version of VRPs in which parameters of the problem as distributed according to probabilistic models. For example, some stochastic VRPs consider that traveling times are random variables (in order to model traffic effects, for example). Other variations consider that delivery points are random and can change as vehicles move, introducing the need to dynamically adapt the mission schedule. Some examples can be found in [YMB00]; [LLM92].

One of the most relevant variations for this work is the Electric Vehicle Routing Problem (EVRP), in which the particularities of EVs are considered [KDC21]. Those particularities are mainly related to limited range (when compared to diesel trucks), the necessity of charging (which requires much more time than fueling a diesel tank), and the scarcity of charging stations (when compared to gas stations). The problem of defining what is the best moment to charge an EV, mentioned in Section 3.2.5.1, is therefore included as part for the EVRP. Variations of EVRPs include realistic charging profiles [Mon+17], energy consumption uncertainty [PJL19]; [BKSD21] and incorporating battery swap strategies to deal with long charging times [ZMO22]. For more detailed reviews, readers may refer to [KDC21].

3.3.2.3 Maintenance models

Different models for classic maintenance actions optimization exist in the literature [HR09]. Each one of them is adapted to different hypotheses related to how maintenance actions affect the system, the structure of the maintenance policy and the monitoring conditions. One of the most well known models for maintenance optimization arises in the case where maintenance actions are considered to take the system back to a As Good As New (AGAN) state (*i.e.* identical to its initial condition). Under this hypothesis, considering degradation to be stochastic in a TbM policy with maintenance interval T_0, establishes a renewal process with cycles determined by maintenance actions. Therefore, based on Blackwell's theorem [Bla48], the asymptotic maintenance cost per unit of time, C_{MC}, can be written as:

$$C_{MC} = \frac{E[C_{cycle}(T_{cycle})]}{E[T_{cycle}]} = \frac{c + k(1 - R(T_0))}{\int_0^{T_0} R(t)dt} \tag{3.17}$$

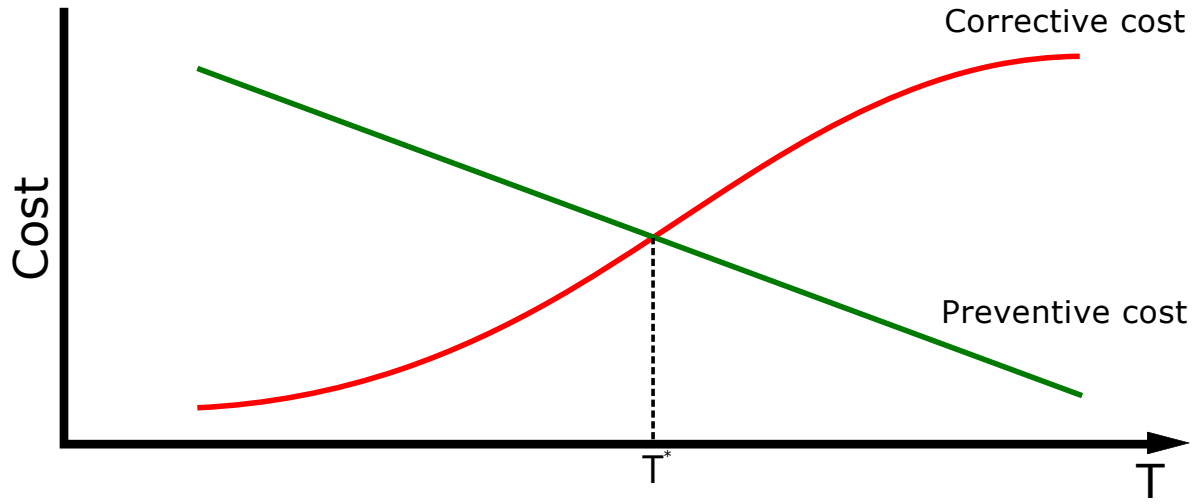

Figure 3.7: Comparison of preventive and corrective costs as a function of the preventive maintenance interval. T^* represents the length of the optimal interval.

where $E[.]$ denotes the expectation operator, $C_{cycle}(T_{cycle})$ is the cost of a cycle, which depends on its duration T_{cycle}. If it lasts less than T_0, it means a breakdown has occurred and corrective maintenance actions took place. Constants c and k are the costs of preventive and corrective maintenance actions, respectively. $R(t)$ is the reliability function which can be easily computed for lifetime models or degradation processes such as those listed in Section 3.3.1.2. In this simple case, maintenance optimization comes down to finding T^* such that:

$$T^* = \underset{T_0}{\operatorname{argmin}} \quad C_{MC} \tag{3.18}$$

which in several cases, has analytical solutions and can be seen as finding the optimal balance between the expected failure cost and preventive maintenance costs, as shown in Figure 3.7.

Considering operations to bring the system to AGAN is a strong hypothesis. Alternative models consider imperfect maintenance actions. For example, [Nak79] uses a maintenance models in which actions take the system back to an AGAN state with probability p but does not affect degradation levels at all with probability q. Other alternatives are based on the concept of virtual age [MC19]; [DG04] which consider that operations partially reduce the degradation accumulated since the last repair.

In opportunistic maintenance set-ups, which is the case for heavy vehicle PsM as discussed in Section 3.2.5.2, even with deterministic degradation models, more complex optimization maintenance models are required. In those cases, a common approach is to formulate the problem as an ILP, in which integer decision variables represent the choice among the possible maintenance dates. Such approach is seen in [MRW21] and [PM21].

3.3.2.4 Parameter reconfiguration models

Parameter reconfiguration encapsulate decisions that affect how missions are performed. With that in mind, it is natural to consider decision making on ECU level, which consists in managing actuators outputs. This is deeply related to the discipline of control engineering, concerned with problems such as determining the output of actuators in order to obtain a desired behaviour. For example, in [Kam+13], a model predictive controller is used to ensure stability while reducing fuel consumption for vehicles is proposed. Another example, closer to PsM since degradation is accounted for, can be found in [CZJ19], where control strategies for power distribution on photovoltaic systems are proposed not only for energetic efficiency but also for RUL extension.

However, due to the aforementioned discussed limits of vehicle connectivity, parameter-reconfiguration-related decision cannot occur based on real time updates of control laws. One example of considering degradation for parameter optimization, but not necessarily in real time, is seen in [LGB13]; [RMB21], where the gains of a linear quadratic regulator are updated periodically based on RUL estimations. Furthermore, as stressed before, parameter reconfiguration decisions affect mission performance. Therefore, a more suitable approach is to optimize them within the context of logistical decisions, considering that parameters changes can impact mission deadlines. An example can be found in [Ma+21]. Authors extend a VRP-like optimization model by including continuous decision variables representing vehicle speeds on different road segments.

3.4 Challenges for practical implementation

Looking at the complete picture of a PsM solution for heavy vehicles and relevant aspects of the state of the art, some practical implementation challenges become clear. Those are briefly explored in this section. The second part of this manuscript is dedicated to addressing them, creating tools to enable practical optimization solution.

3.4.1 Degradation and usage models

Formulating PsM optimization models as an extension of the classic optimization models seen in 3.3.2, although natural, yields to very complex problems. For example, VRP's are, in their simplest form, NP-hard and including degradation models can significantly complicate them. For instance, as will be seen in Chapter 5, deriving a PsM solution for the Energy Storage System (ESS) requires a non-linear degradation model which translates to a non-linear cost function which makes traditional BB methods harder to be applied.

Furthermore, some complex components are affected by different usage conditions in complex ways. Usage metrics used to feed the reliability/degradation model are often described by differential equations. Including them in the optimization problems requires numerical

integration to evaluate possible solutions which further complexifies the problem from a computational point of view. Even simpler logistical decisions described as SPP variations may become impractical to solve since the aforementioned differential equations compromise the principle of optimality. This is a consequence of the fact that, since the internal state of the vehicle is dynamic, the costs related to each edge of the graph depend on the previously visited nodes. A more in depth discussion on those complications is given in Chapter 5.

3.4.2 Decision impact in different time scales

PsM for heavy vehicles involve logistics, maintenance and parameters optimizations. However, the nature of those decisions is extremely different from a time scale point of view. While logistical and parameter actions are applied on a daily basis, maintenance happens only few times through the life of the vehicle. To ensure exploitation cost minimization, it is necessary to consider the joint effect of those actions when defining the best course of action for the system. Implementing a PsM solution requires an ingenious formulation of optimization problems that can account for those different time scales.

3.4.3 Long-term evaluation

Finally, PsM is a long-term cost reduction strategy by nature. In order to validate and estimate the effectiveness of the proposed solutions, it is necessary to simulate vehicle usage through long-time horizons. As the optimization problems arising from the PsM problem are computationally challenging, solving several sequential instances of them to capture long-term effects require the development of adequate computational solution methods.

3.5 Conclusion

This chapter concluded the first part of this thesis, closing the discussion on PsM and presenting a general problem structure for heavy vehicles. As previously stated, the exact hypotheses and optimization formulation of those problems require specific choices of degradation/reliability models to represent the vehicle components considered in this solution.

The computational complications arising from accounting for degradation, applying actions that will affect the system in different time scales and the long-term nature of the PsM solutions create the necessity of specific algorithm design and optimization models. In the second part of the manuscript, practical examples are given with different vehicle components that lead to original scientific problems which are then solved.

Part II is composed of three chapters containing two complementary PsM applications. The first one, presented in Chapter 4, is a PsM application that arises by defining vehicle reliability with a generic degradation model. This degradation model is flexible and can

represent several different vehicle components. However, due to its simplicity, it can not be used to correlate vehicle health with some of the actions described in Section 3.2.5. Therefore, this application revolves mainly around routing and maintenance.

To explore more complex components, address all possible PsM actions for heavy vehicles and consider EVs specifics, a second PsM application is presented. It arises from defining reliability in terms of the energy storage system (ESS). The results of this application are split among Chapters 5 and 6. Due to the complexity of this component, the first discusses how to model it while the second addresses optimization formulation and solution methods.

Part II

Prescriptive maintenance for heavy vehicles: problem formalization and solution methods development

Chapter 4

Prescriptive maintenance for generic replaceable vehicle components

Contents

4.1 Introduction

Although in Chapter 3 the general structure of a PsM solution for heavy vehicles was presented, as discussed, the concrete scope of actions depends on how vehicle reliability is defined. In this chapter, a generic PsM degradation model capable of representing different components is used. In this second part of this manuscript, the concepts developed in Part I are used to address concrete vehicle maintenance challenges. While Chapters 5 and 6 are concerned with an EV-exclusive application with a complex component, this chapter introduces a generic degradation model that can be used to represent different vehicle components. As a consequence, the scopes of actions in those two PsM applications are different but complementary.

The trade-off for the generic degradation model flexibility is the fact that it cannot be used to optimize some decisions such as path selection and vehicle parameters since, as will be seen in Section 4.2, it depends only on the total traveled distance. As a consequence,

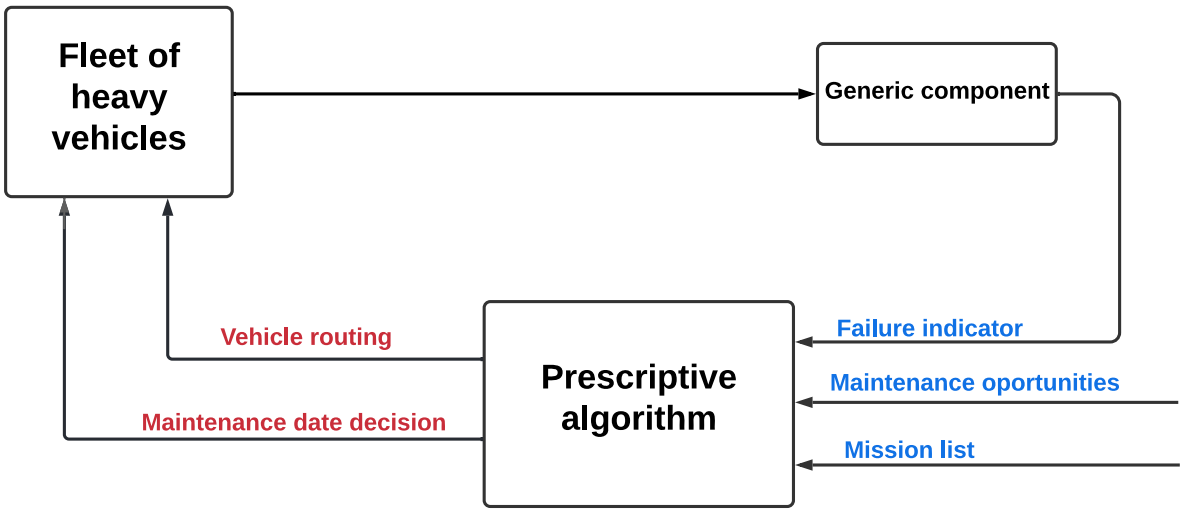

Figure 4.1: PsM solution structure for the generic component application.

in this application, the scope of the PsM actions is reduced as shown in Figure 4.1. Only classical maintenance actions and routing are considered. However, those two actions are extremely important in terms of exploitation cost minimization. Furthermore, the problem of jointly optimizing maintenance and missions has never been addressed in the transportation literature through a long-term perspective.

In this chapter, this scientific problem is addressed. An original contribution for solving a similar problem was presented in [Lon+21]. In this chapter, that work is improved with a more general problem formulation and solution method. A new optimization model is proposed to simultaneously account for maintenance and routing. The performance of this model is compared to traditional approaches and the benefits of PsM are quantified in several numerical experiments. Furthermore, algorithms are proposed to solve the PsM optimization model efficiently, since it is an extended form of VRPs and is computationally demanding.

4.2 Generic degradation model for vehicle components

The FHT approach discussed in Section 3.3.1 is suitable for modeling most components. A natural choice for a generic model is to use stochastic processes to describe degradation evolution. This is a way of circumventing the necessity of detailing the physical nature of wear mechanisms. The model randomness can be seen as a manifestation of specific component degradation phenomena that are not explicitly modeled.

Several vehicle components such as brake-pads, air-filters and oil present degradation behaviours strongly correlated to the traveled distance. It is common to modeled vehicle component degradation by either a gamma or a wiener process [Yan+22]; [Gué+10]; [Dai+22]. To be also applicable for components whose degradation process is not monotonic, the later is preferred leading to the following degradation model:

$$W(d) = W_0 + \lambda d + \sigma_b B(d) \tag{4.1}$$

where W represents the component health indicator, d is the traveled distance, W_0, λ and σ_b are constants and $B(d)$ is the standard Brownian motion. Thanks to vehicle connectivity, those parameters can be estimated directly through data, using for example, maximum likelihood techniques such as done in [TYG14]. Model parameters will be chosen so that the component must be replaced several times through vehicles life, forcing this PsM solution to address routing and maintenance decisions together.

4.3 The prescriptive maintenance problem

The proposed degradation model, although simple, correlates degradation to traveled distance and therefore can be used to connect classical maintenance actions and routing. Routing and maintenance have an interconnected nature that must be addressed. For example, sending vehicles that are more degraded to do less severe missions - those which are less likely to cause significant degradation increase - can postpone maintenance operations. This particular PsM problem becomes defining mission plans and choosing maintenance dates in a way that this relationship is exploited to reduce long-term costs. The following assumptions made are:

- Long-term optimization happens over a finite time horizon H, which is composed of different working sessions t.
- At each working session t, a set of missions must be performed. Each mission has a known address and deadline. All relevant addresses can be represented by a graph $G_t = (N_t, E_t)$ with $N_t = C_t \cup 0$. C_t represent mission addresses while 0 is the headquarters, where vehicles start and to where they must return by the end of t. The edges E_t represent the shortest paths between those addresses.
- The set of mission addresses does not change during a working session.
- Each vehicle in the fleet, represented by a set Z, has constant known degradation parameters λ_z and σ_z.
- At the end of each working session t, degradation levels W_z can be measured through connectivity and the health state of each vehicle z becomes known.
- Maintenance is treated in an opportunistic set-up. It can only take place after specific working sessions which define a set V of maintenance opportunities with $V \subset H$.
- Each maintenance operation takes the component back to an AGAN state. If W_z crosses a predefined critical threshold, a failure occurs.

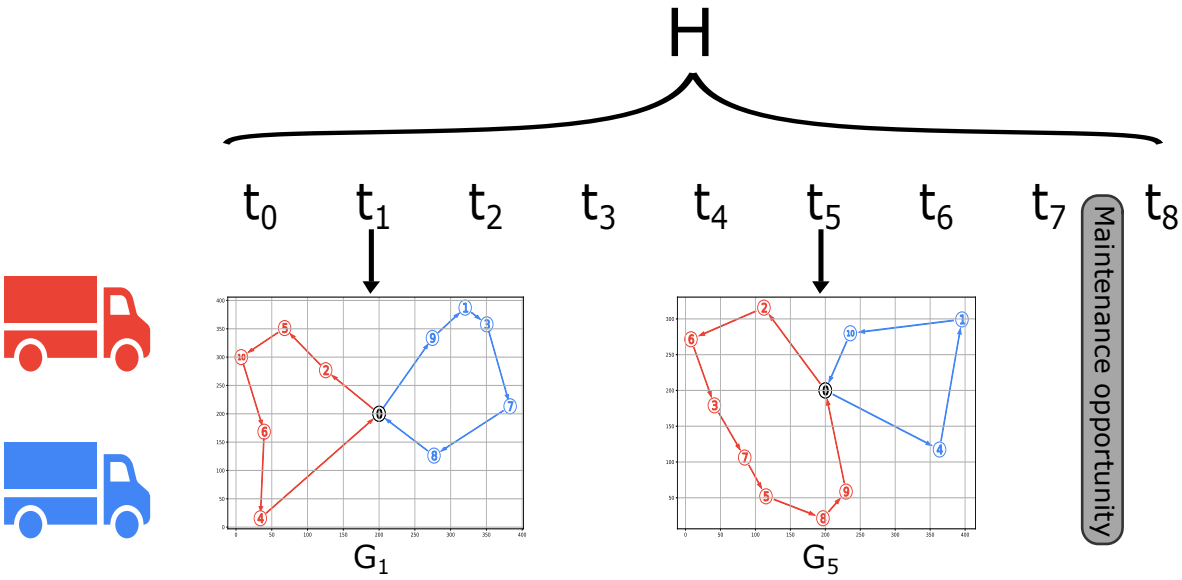

Figure 4.2: Visual representation of the PsM optimization problem for a generic vehicle component. Each working session t is indexed in this Figure for the sake of clarity. At each working session, a graph G_t is used to define routes, as explicitly shown for t_1 and t_5. In this case, $V = [7]$, meaning maintenance operations can occur between t_7 and t_8.

Figure 4.2 represents this decision-making problem which comes down to minimizing the exploitation cost over H. However, every routing process must be made ensuring that operational constraints such as mission deadlines, are respected. Furthermore, it is also important to keep failure probabilities under a maximum acceptable threshold to avoid downtime.

4.3.1 Optimization model

As in any PsM application, the cost function of this model is designed to minimize the exploitation cost, which, in the scope of this application, is equivalent to reducing maintenance and fuel consumption costs. Considering that all missions over H are known, each graph $G_t = (N_t, E_t) \forall t \in H$ can be seen as an input for the optimization model. Therefore, with the following decision variables:

$$x_{tzij} = \begin{cases} 1, & \text{if vehicle } z \text{ goes from node } i \text{ to node } j \text{ with } i, j \in N_t,\ z \in Z \text{ and } t \in H \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

$$m_{vz} = \begin{cases} 1, & \text{if vehicle } z \text{ performs a component replacement at } v \text{ with } v \in V \text{ and } z \in Z \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

the cost function of the optimization problem becomes:

$$\min \quad C_{psm} = \sum_{t\in H}\sum_{z\in Z}\sum_{j\in N_t}\sum_{i\in N_t} c_{km}x_{tzij}d_{tij} + \sum_{v\in V}\sum_{z\in Z} c_{maint}m_{vz} \tag{4.4}$$

where c_{km} is a constant related to the fuel cost and average vehicle fuel consumption while d_{tij} is the distance between each node i and $j \in N_t$. c_{maint} is the cost of preventive maintenance operations. In order to obtain solutions that represent valid routes, x_{tzij} must respect classical VRP constraints in each working session:

$$\sum_{z\in Z}\sum_{j\in N_t} x_{tzij} = 1 \quad \forall i \in N_t - \{0\}, t \in H \tag{4.5}$$

$$\sum_{i\in N} x_{tzij} - \sum_{i\in N_t} x_{tzji} = 0 \quad \forall i \in N_t, z \in Z, t \in H \tag{4.6}$$

$$\sum_{t\in H}\sum_{z\in Z}\sum_{j\in C_t} x_{tz0j} \leq |Z| \quad \forall i \in N_t - \{0\}, t \in H \tag{4.7}$$

$$x_{tijz} \quad \in \{0,1\} \tag{4.8}$$

$$m_{tz} \quad \in \{0,1\} \tag{4.9}$$

Constraint 4.5 ensures that every mission address is visited once. Constraint 4.6 ensures flux continuity and constraint 4.7 limits the number of vehicles used to the fleet size. Constraints 4.8 and 4.9 determine decision variables support. However, those constraints are not sufficient since they do not guarantee solutions without sub-tours and do not address operational constraints. Both problems can be fixed by adding decision variables y_{tzij} in the formulation. They are continuous variables representing the arrival time of vehicle z at node j coming from node i in a working session t. The following constraints are then required:

$$\sum_{j\in N_t} y_{tzij} - \sum_{j\in N_t} y_{tzji} \geq \Delta y_{tij}x_{tzji} \quad \forall i \in N_t, \forall z \in Z \forall t \in H \tag{4.10}$$

$$y_{tzij} \geq t_{0j}x_{tz0j} \quad \forall j \in N_t \forall z \in Z \tag{4.11}$$

$$y_{tzij} \leq l_j \quad \forall i \in N_t, j \in N_t, z \in Z, t \in H \tag{4.12}$$

$$y_{tzij} \quad \in [0, \infty[\tag{4.13}$$

with Δy_{tij} representing the time necessary to go from node i to j at t $\forall i, j \in N_t$ and $t \in H$. Constraint 4.10 makes y_{tzij} coherent with displacements duration when $x_{tzji} = 1$ and force them to 0 otherwise. It also acts as a sub-tour elimination constraint. Constraint 4.11 establishes the first arrival time of each vehicle while 4.12 ensures that mission deadlines are respected. Constraint 4.13 defines the correct support for variables y_{tzij}.

PsM optimization models must account for degradation and its effects. As previously stated, it is necessary to incorporate, for example, limitations on the acceptable failure probabilities. The first step to do so is to define a failure distance D_{fail} as:

$$D_{fail} = \inf\{D : W(d) \geq w_{crit} \mid W(0) \leq w_{crit}\} \tag{4.14}$$

with w_{crit} representing a failure threshold. Since $W(d)$ is modeled as a Wiener process with linear drift, D_{fail} is a random variable following an inverse Gaussian distribution with density:

$$f_{D_{fail}}(d) = \frac{w_{crit} - W(0)}{\sqrt{2\pi d^3 \sigma_B^2}} \exp \frac{-(w_{crit} - W(0) - \lambda d)^2}{2\sigma_B^2 d} \tag{4.15}$$

Including constraints on the failure probability directly through the correspondent cumulative distribution function is inconvenient. It would introduce non-linearities that would needlessly complicate the model from a computational point of view. It is possible to limit failure probabilities indirectly through the quantiles of D_{fail}. For example, imposing an acceptable failure probability q, is equivalent to limiting traveled distances to D^q_{max} where:

$$D^q_{max} = d : P(D_{fail} \leq d) = q \tag{4.16}$$

as shown in Figure 4.3.

Therefore, acceptable failure probabilities can be guaranteed by ensuring that, between every maintenance operation, vehicle z does not travel more than D_{max_z}. This is achieved by introducing decision variables $D_{vz} \forall v \in V, z \in Z$ and the following constraint, referred to as *safety constraint*:

$$D_{vz} + \sum_{v}^{t} \sum_{i \in N_t} \sum_{j \in N_t} x_{tzji} d_{tij} \leq D_{max_z} \quad \forall v \in V, t > v \tag{4.17}$$

In order for Constraint 4.17 to work as intended, it is necessary that $D_{vz} = 0$ if a replacement happens at v or that $D_{vz} = D_{v-1z} + \sum_{v-1}^{t-1} \sum_{j \in N_t} \sum_{i \in N_t} x_{tzji} d_{tij}$, otherwise. This conditional logic is achieved through the following constraints:

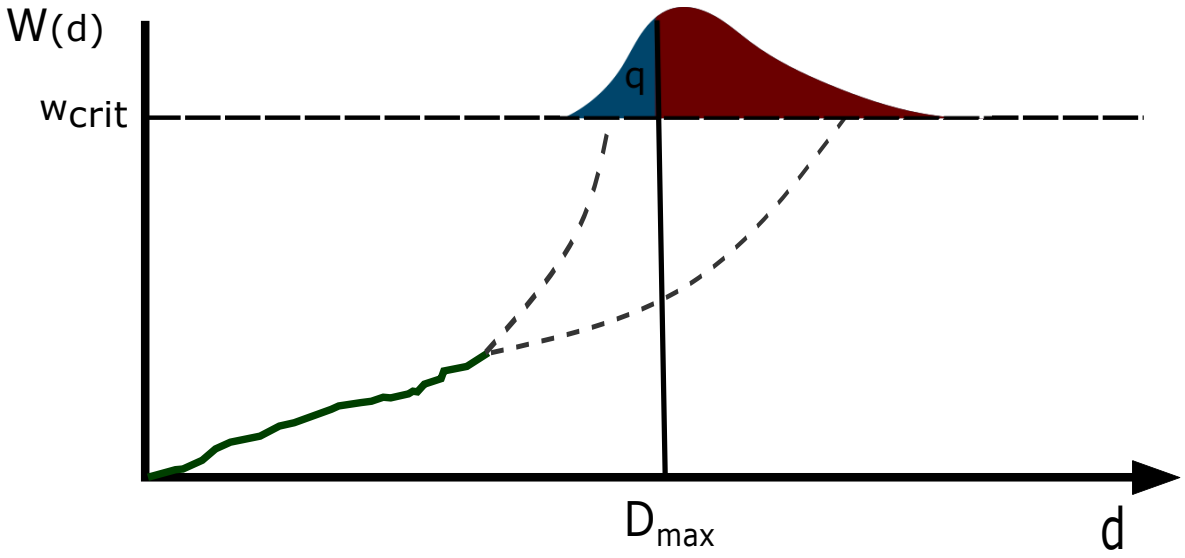

Figure 4.3: Illustration of the principle behind using quantiles to minimize failure probabilities.

$$D_{vz} \geq D_{v-1z} + \sum_{t-1}^{v-1} \sum_{j \in N_t} \sum_{i \in N_t} x_{tzji} d_{tij} - m_{tz} * K \quad \forall v, v-1 \in V z \in Z \tag{4.18}$$

$$D_{0z} = 0 \quad \forall z \in Z \tag{4.19}$$

$$D_{vz} \quad \in [0, \infty] \tag{4.20}$$

Constraint 4.20 establishes the support for D_{vz}. Constraint 4.18 is used to establish the conditional logic previously discussed. If constant K is large enough and a maintenance operation is performed at t, the right hand side of the inequality becomes negative, forcing D_{vz} to zero. Otherwise, D_{vz} becomes the accumulated distance until the last maintenance opportunity. It is also necessary to add $t = 0$ to the set V so that constraint 4.18 can be computed at the first maintenance opportunity. Additionally, it is required that $D_{0z} = 0 \forall z \in Z$ which is guaranteed by Constraint 4.19. Constraint 4.20 defines the range of D_{tz}.

This formulation leads to a method for combining maintenance and routes, reducing long term costs. Since this MILP is linear, classical BB methods can be used to solve it. Through a set of numerical experiments, different aspects of this formulation are shown, discussing its characteristics and potential benefits.

4.3.2 Numerical experiments

4.3.2.1 General setup and benchmark model

To assess the performance of the proposed optimization model, it is important to have a benchmark model representing standard fleet-managers which do not consider degradation

when dealing with logistics. The chosen benchmark model assigns routes to vehicles, at each working session t, according to the following VRP:

$$\min \quad \sum_{z\in Z}\sum_{j\in N_t}\sum_{i\in N_t} c_{km}d_{tij}x_{tzji} \tag{4.21}$$

Subjected to:

$$\sum_{z\in Z}\sum_{j\in C_t} x_{tzij} = 1 \quad \forall i \in N_t - \{0\} \tag{4.22}$$

$$\sum_{i\in N_t} x_{tzij} - \sum_{i\in N_t} x_{tzji} = 0 \quad \forall j \in N_t, z \in Z \tag{4.23}$$

$$\sum_{z\in Z}\sum_{j\in C_t} x_{z0j} \leq |Z| \quad \forall i \in N_t - \{0\} \tag{4.24}$$

$$x_{tijz} \in \{0,1\} \tag{4.25}$$

$$\sum_{j\in N} y_{tzij} - \sum_{j\in N_t} y_{tzji} \geq \Delta y_{tij}x_{tzji} \quad \forall i \in N_t, \forall z \in Z \forall t \in H \tag{4.26}$$

$$y_{t0jz} \geq t_{0j}x_{tz0j} \quad \forall j \in N_t \forall z \in Z \tag{4.27}$$

$$y_{tijz} \leq l_j \quad \forall i \in N_t, j \in N_t, z \in Z, t \in H \tag{4.28}$$

$$y_{tijz} \in [0, \infty[\tag{4.29}$$

Since maintenance decisions are not part of this model, m_{tz} and D_{tz} are not included and the fleet is always considered homogeneous. To choose maintenance opportunities, a simple strategy emulating preventive maintenance policies is applied. For each $v \in V$, components are replaced if a vehicle has travelled more than a predefined threshold distance $D_{benchmark}$. This threshold is defined in such a way that it mimics the order of magnitude of real preventive maintenance intervals.

Once routes and maintenance dates are established they are simulated. For each simulation, if, at any point W_z falls bellow w_{crit}, a failure is considered to happen. In the next working session degradation returns to an AGAN state, as a consequence of a corrective maintenance operation. The empirical simulation cost can be expressed as:

$$C_{simu} = \sum_{t\in H}\sum_{z\in Z}\sum_{j\in N_t}\sum_{i\in N_t} c_{km}x_{tzji}d_{tij} + c_{fail}n_{fail} + c_{maint}n_{maint} \tag{4.30}$$

where c_{fail} is a constant representing the monetary value of a failure, n_{fail} is the number of failures occurred and n_{maint} the number of maintenance operations performed. For all simulations, cost constants are as shown in Table 4.1. Maximum acceptable failure probabilities q_{max} :

c_{km}	c_{maint}	c_{fail}
0.4	100	2000

Table 4.1: Cost constants for numerical experiments

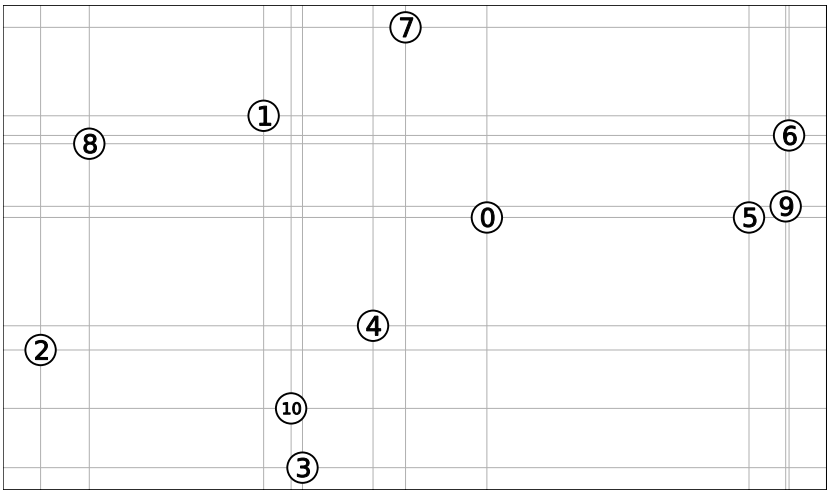

Figure 4.4: Example of random graph sampled from a 400x400 square used to define missions in a working session.

$$q_{max} = \frac{c_{maint}}{c_{fail}} = 5\% \tag{4.31}$$

as a thumb rule to achieve reasonable failure costs .

4.3.2.2 Numerical experiments for model comparison

Several experiments were designed to illustrate the differences between both models. In the first experiment, no maintenance opportunity is considered *i.e.* $V = \emptyset$ and H $= [0, 1, ..., 19]$. The fleet is composed of two vehicles whose parameters are shown in Table 4.2. Graphs G_t were obtained by randomly sampling 10 mission addresses from an uniform distribution on a 400x400 kilometer square and d_{tij} were computed as the Euclidian distance between each node in N_t. In each working session the headquarters (indicated by 0) position is the same, with coordinates [200,200], as seen in Figure 4.4. Deadlines were set guaranteeing that, at each working session, there was at least a feasible route.

Results are shown in Table 4.3. In this experiment, both models use exactly the same routes. This happens because in such a short horizon H, safety constraints could be easily respected and both models minimized the total traveled distance. As failure probabilities were neglectable, the empirical costs obtained were also the same. As expected, like the benchmark model, the PsM model minimizes fuel consumption costs when failure probabilities are not significant.

Vehicle	λ	σ_B	W_0	$E[D_{fail}]$	$D_{max}^{q=5\%}$
0	0.002	0.1	0	50000	33933.7
1	0.002	0.1	0	50000	33933.7

Table 4.2: Fleet parameters for experiment 1

	Consumption cost	$\bar{C}_{simu}$
PsM model	10583.5	10583.5
Benchmark model	10583.5	10583.5

Table 4.3: Simulation result of experiment 1

To address a case in which both models behave differently, a second experiment is performed with H = $[0, 1, ..., 35]$ and a fleet with parameters shown in Table 4.4. This fleet is heterogeneous since vehicle 1 has grater σ. This corresponds to greater degradation variance, leading to a lower $D_{max}^{q=5\%}$. With more restrictive safety constraints and a longer horizon, routing strategies were different in some working sessions. Figure 4.5 shows the routes used by both models in those cases.

The routes used by the PsM model are sub-optimal from the point of view of fuel consumption since they do not minimize the total travelled distance. However, those routes allow feasible solutions in terms of safety constraints making it possible for vehicle 1 to travel less than D_{max_1} and limiting failure probabilities under 5%. As a consequence, although the consumption cost of the solution found by the PsM is greater, the simulation cost is considerably lower since failures occurred more often with the benchmark model. The results are summarized in Table 4.5.

The two models also behave differently in terms of maintenance management. In the following numerical experiment, the fleet used is presented in Table 4.6. It has smaller λ values when compared to the previous fleets used. As a consequence, it allows for longer horizons in which decision on maintenance become relevant. To illustrate that, four instances of the problem with the same set G_t and a horizon $H = [0, 1...70]$ are solved. In the first instance, $V = \emptyset$ *i.e.* maintenance is not allowed. In the second, third and fourth instances, maintenance opportunities occur at $V = [20]$, $V = [50]$, $V = [68]$, respectively. Results are shown in Table 4.7.

The results in instance 1 show that there is a feasible solution in which respecting safety constraints is possible. As in previous examples, the PsM model is capable of limiting failure probabilities by using sub optimal routes, reducing failure costs. In instance 2, a maintenance opportunity is available at the beginning of the horizon. Since vehicles had not yet traveled more than $D_{benchmark}$, no maintenance is performed by the benchmark model, leading to significant failure costs. On the other hand, the PsM model performs a maintenance operation on vehicle 1, which allows it to take shorter routes when compared to instance 1, reducing consumption costs. In instance 3, the benchmark model chooses maintenance operations for

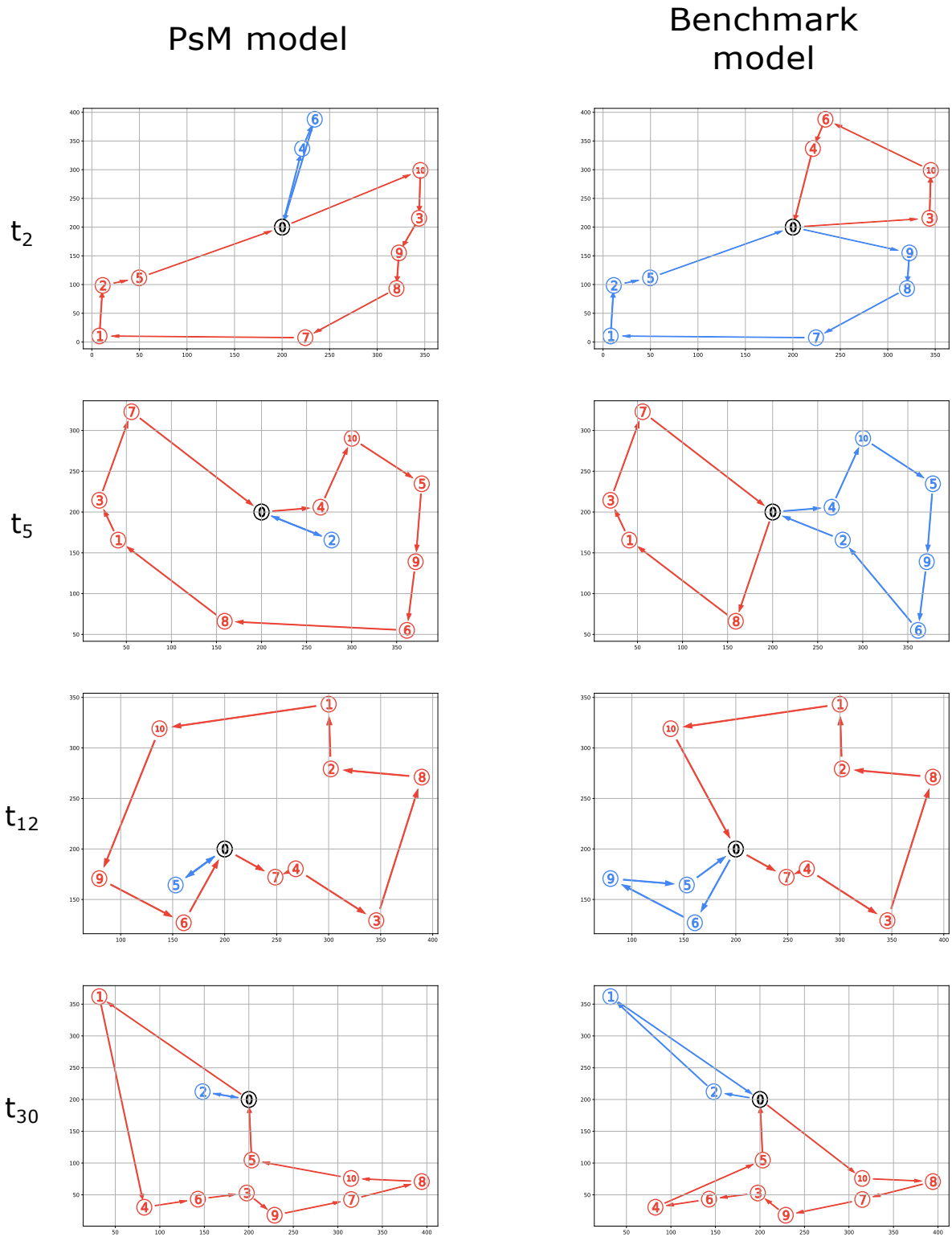

Figure 4.5: working sessions in which routes used by each model were different. Notice that the PsM model chooses routes that allow vehicle 1 (represented in blue) to travel shorter distances and respect its safety constraints.

Vehicle	λ	σ_B	W_0	$E[D_{fail}]$	$D_{max}^{q=5\%}$
0	0.002	0.1	0	50000	33933.7
1	0.002	0.5	0	50000	7805.4

Table 4.4: Fleet parameters for experiment 2. Those parameters were chosen in order to create an extremely heterogeneous fleet to give a clear example of problem instance in which both models behave differently.

	D_{total}^{vh0}	D_{total}^{vh1}	Consumption cost	$\bar{C}_{simu}$
PsM model	33619.5	7693.4	16525.4	16670.6
Benchmark model	22297.3	18980.4	16511.1	16788.7

Table 4.5: Simulation result of experiment 2. Columns D_{total}^{vh0} and D_{total}^{vh1} represent the total traveled distance for vehicle 1 and 0 respectively.

both vehicles, since it makes decisions purely based on traveled distance. The PsM model performs maintenance only for vehicle 1. As a maintenance opportunity was available in the middle of the horizon, it was possible to take only optimal routes on this instance and both models achieved the same consumption cost. Finally, in instance 4, maintenance opportunities were at the end of H. The benchmark model replaced both components, however, the PsM model did not perform a maintenance operation. Since the maintenance opportunity only happened at the end of H, fuel consumption savings due to the possibility of choosing better routes afterwards did not compensate the extra maintenance operation.

4.4 Heuristic pruning algorithms for faster computation

Although the proposed optimization model shows the importance of considering degradation in long-term routing, it is very demanding from a computational point of view. In practice, using common MILP solvers directly on the model presented in Section 4.3.1 can only solve problem instances with small fleets, few missions per working session and short horizons. To address this limitation, an algorithm for efficient solution space search is proposed. It is based on the fact that the optimization problem proposed can be seen through a different prism. As shown in Figure 4.7, solving the PsM problem is equivalent to, at each working session, choosing a valid route configuration (*i.e.* a combination of variables x_{tzij} that respects Constraints 4.5 - 4.13) and then assigning a specific route to a vehicle z, while satisfying safety constraints.

The concept of route configuration is illustrated more concretely in Figure 4.6. In terms of notation, S_t is the set of route configurations s_t, for a particular working session t. Each route configuration is a set of $|Z|$ routes r (one for each vehicle), with distances $r_i^{s_t}$. Those distances are sorted such that $r_i^{s_t} \leq r_{i+1}^{s_t}$. Additionally, the set S^* contains route configurations that:

Vehicle	λ	σ_B	W_0	$E[D_{fail}]$	$D_{max}^{q=5\%}$
0	0.0005	0.1	0	200000	90660.2
1	0.0005	0.5	0	200000	9586.5

Table 4.6: Fleet parameters for experiment 3

Instance	Psm model			Benchmark model		
	Consumption cost	**Maintenance cost**	**Failure cost**	**Consumption cost**	**Maintenance cost**	**Failure cost**
1	35884	0	191	35498.8	0	641
2	35679	100	207	35498.8	0	652
3	35498.8	100	217	35498.8	200	241
4	35884	0	211	35498.8	200	619

Table 4.7: Simulation result of experiment 3

$$S^* = \{s_t^* \quad \forall t \in H\} \tag{4.32}$$

in which s_t^* is the route configuration with the smallest total distance for working session t:

$$s_t^* = s_t \quad \sum_{i=1}^{|Z|} r_i^{s_t} \leq \sum_{i=1}^{|Z|} r_i^{s'_t} \quad \forall s'_t \in S_t \tag{4.33}$$

S^* can be obtained by solving a standard VRP for each graph G_t $t \in H$, separately.

The total traveled distance (and consumption cost, as a consequence) depends only on the choice of route configurations and not on which vehicle will perform each route. This fact is useful for pruning branches in the BB process. Once a feasible solution is found, any other solution that is built with the same route configurations can be pruned. Additionally, in instances with $V = \emptyset$, if there is a feasible solution made from S^*, it is optimal since it minimizes the total traveled distance. Furthermore, if for a given problem instance:

$$\sum_{t \in H} \sum_{i=1}^{|Z|} r_i^{s_t} \geq \sum_{z \in Z} D_{max_z} \quad s_t \in S^* \tag{4.34}$$

then, it has no solution, since considering other route configurations would increase the total traveled distance, disrespecting safety constraints even further.

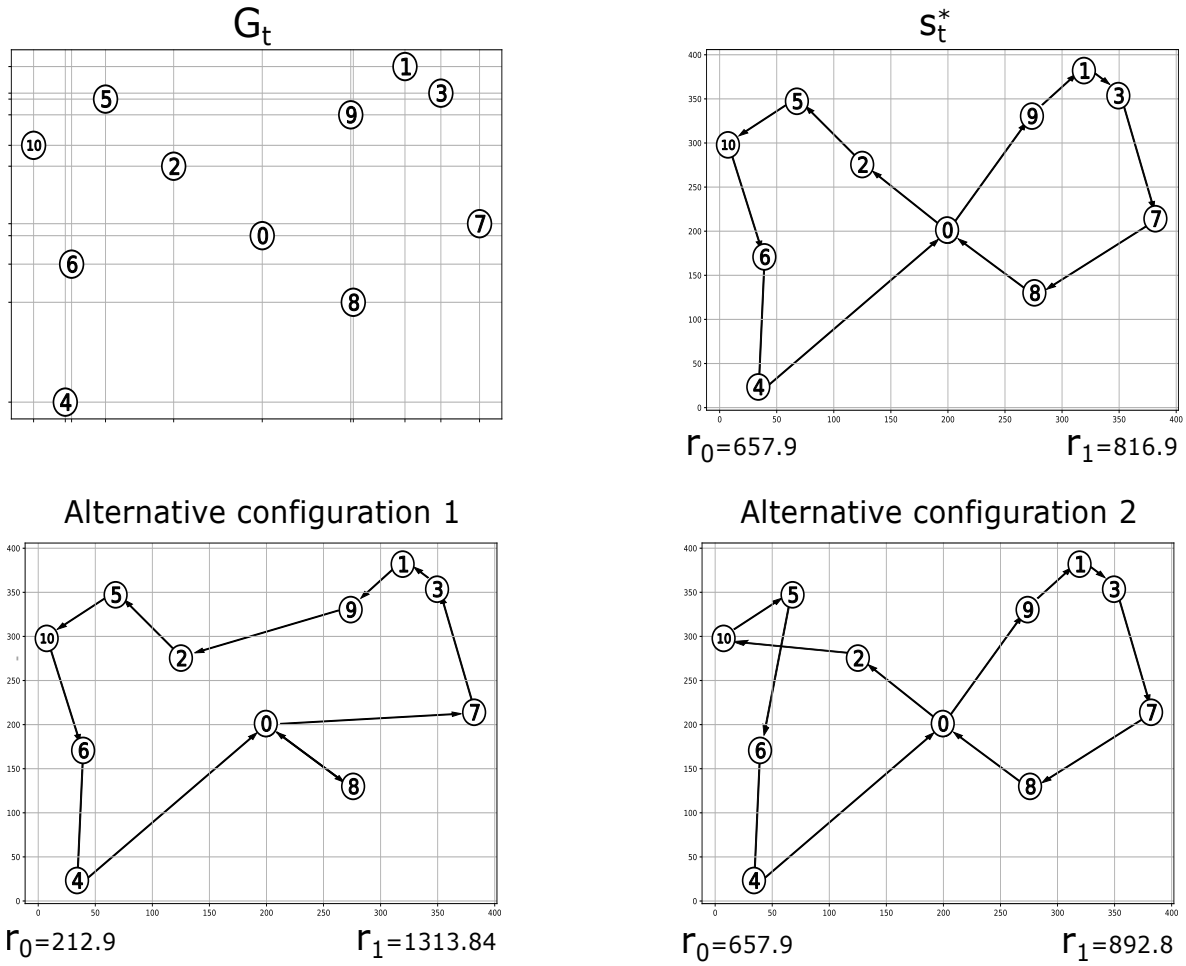

Figure 4.6: Route configuration concept illustration. G_t is the graph containing the points to be visited in working session t. s_t^* is the best route configuration from a fuel cost point of view, obtained through a classic VRP. Two alternative configurations are presented. For every configuration, r_0 and r_1 are the distance of the shortest and longest route, respectively.

If S^* does not lead to any feasible solution but condition 4.34 is not verified, other route configurations need to be considered. However, only a small subset of route configurations is worth exploring. Any configuration s_t in which:

$$r_i^{s_t} \geq r_i^{s_t^*} \quad i = 1, ...|Z| \tag{4.35}$$

is useless. Those configurations do not contribute to respecting safety constraints and increase consumption costs. Such an example can be seen in Figure 4.6, by analyzing s_t^*, it becomes clear that the alternative route configuration 2 cannot be part of the solution. It does not allow the most critical vehicle to travel shorter distances. On the other hand, route configuration 1 is a possible candidate since its shortest route has a length inferior to the routes in s_t^*.

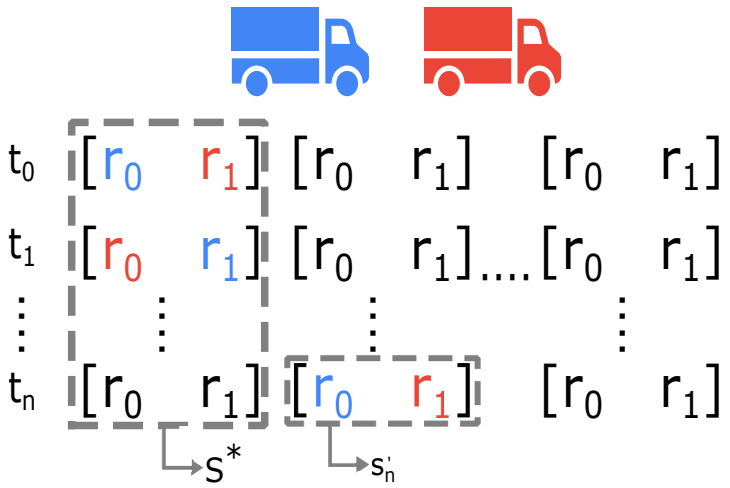

Figure 4.7: Illustration of the PsM optimization problem as successive choices of route configurations and vehicle assignment. In this particular example, the problem instance has n working sessions and two vehicles. Route configurations are represented by brackets. In the solution represented, routes from S^* were chosen for working sessions 1 and 2 while, in working session n, configuration $s_n^{'}$ was used.

Having all those concepts in mind, the PsM problem presented in Section 4.3.1 is equivalent to the following optimization model with decision variables[1]:

$$x_{zi}^{s_t} = \begin{cases} 1, & \text{if vehicle } z \text{ takes route } r_i^{s_t} \text{ from route configuration } s_t \\ 0 & \text{otherwise} \end{cases} \tag{4.36}$$

the PsM becomes:

$$\min \quad C_{psm} = \sum_{t \in H} \sum_{z \in Z} \sum_{s_t \in S_t} \sum_{i=1}^{|Z|} c_{km} x_{zi}^{s_t} r_i^{s_t} \tag{4.37}$$

Subjected to:

[1]Maintenance will be addressed in later sections, for now, the discussion revolves mainly around deciding routes in cases where $V = \emptyset$

$$\sum_{s_t \in S_t} \sum_{i=1}^{|Z|} x_{zi}^{s_t} = 1 \quad \forall t \in H, z \in Z \tag{4.38}$$

$$\sum_{z \in Z} x_{zi}^{s_t} \leq 1 \quad \forall t \in H, i \in [1, ..., |Z|] \tag{4.39}$$

$$\sum_{s_t \in S_t} \sum_{i=1}^{|Z|} x_{zi}^{s_t} - \sum_{s_t \in S_t} \sum_{i=1}^{|Z|} x_{z-1i}^{s_t} = 0 \quad \forall t \in H, z-1 \in Z \tag{4.40}$$

$$\sum_{t \in H} \sum_{s_t \in S_t} \sum_{i=1}^{|Z|} x_{zi}^{s_t} r_i^{s_t} \leq D_{max}^{z} \quad \forall z \in Z \tag{4.41}$$

$$x_{zi}^{s_t} \in \{0, 1\} \tag{4.42}$$

Constraint 4.38 ensures that, for each working session, vehicles are assigned exactly one route. Constraint 4.39 ensures that every route comes from the same route-configuration. Constraint prevents vehicles from taking the same route. Constraint 4.41 is the safety constraint and Constraint 4.42 establishes the appropriate support of each decision variable. With this equivalent formulation, this problem can be solved through Algorithm 3:

Algorithm 3 Faster algorithm for PsM solution based on the generic component

1: Obtain S^* by solving classical VRPs for each $G_t \quad t \in H$
2: **if** Feasible solution with S^* exists **then**
3: return feasible solution
4: **else if** Condition 4.34 == True **then**
5: return instance has no solution
6: **else**
7: Based on S^* create a set of useful route configurations
8: Set optimization model 4.37
9: Solve with BB
10: Prune branches of solutions built with the same route configurations of already evaluated branches.
11: **end if**

Step 4 restricts the search on the solution space even further by accounting only for the most promising route configurations. This step is discussed in depth in the following section.

4.4.1 Heuristics for finding useful route configurations

As discussed before, not all route configurations are useful. Excluding from evaluation configurations in which all s_t are greater than their counterparts in s_t^* drastically reduces the number of solution evaluations needed. It is possible to restrict the number of considered route configurations even further using a heuristic for promising route configurations genera-

tion. This heuristic procedure is now detailed for the particular case of two vehicle fleets but the ideas behind it can be extended to larger fleets.

If the instance was not deemed infeasible but no permutation of S^* led to a solution, there are two possible cases. One example of the first one is shown in Figure 4.8. It happens when assigning the shortest routes of each session for the vehicle with the lowest D_{max} is not enough to respect its safety constraints. In this case, a feasible solution can only be found by using route configurations s_t in which:

$$r_0^{s_t} < r_0^{s_t^*} \tag{4.43}$$

Those configurations can be obtained by successively adding, to the VRPs used to obtain S^*, constraints such as:

$$\sum_{j \in N_t} \sum_{i \in N_t} x_{tzji} d_{tij} < r_0^{s_t^*} \quad \forall z \in Z \tag{4.44}$$

The second possible case is illustrated in Figure 4.9. It arises when assigning the shortest routes to vehicle with the lowest critical distance satisfies its safety constraint but there is no permutation of routes in which safety constraint of the other vehicle is respected. In this case, it is necessary to consider route configurations in which the difference between routes lengths is smaller. That corresponds to configurations in which:

$$r_0^{s_t} > r_0^{s_t^*} \tag{4.45}$$

$$r_1^{s_t} < r_1^{s_t^*} \tag{4.46}$$

those configurations can be obtained by adding, to the VRPs used to obtain S^*, constraints such as:

$$r_0^{s_t^*} < \sum_{j \in N_t} \sum_{i \in N_t} x_{tzji} d_{tij} < r_1^{s_t^*} \quad \forall z \in Z \tag{4.47}$$

4.4.2 Including maintenance

So far, in this alternative formulation of the problem, maintenance was not discussed. To include maintenance, the problem is split on each session $v \in V$ and Algorithm 3 is used

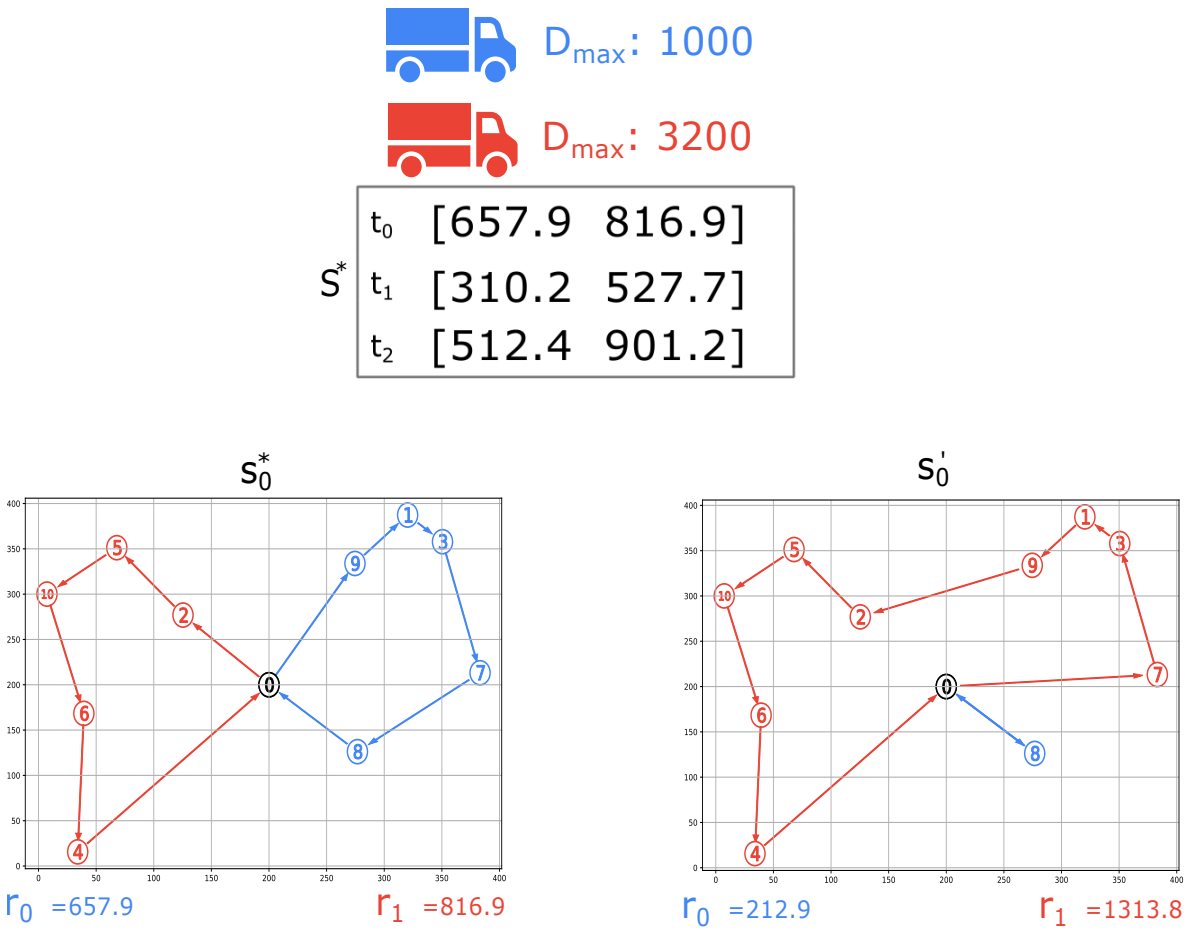

Figure 4.8: Illustration of promising route configuration search. In this instance, assigning the shortest routes for the red vehicle would violate its safety constraints, therefore, configurations such as $s^{'}$ must be considered.

to solve each arising sub problem as shown in Figure 4.10. It is important to highlight that once the first sub-problem is solved, the obtained route configurations can be used for each remaining problem, therefore, reducing the computations required. By analyzing the optimal cost function of each sub problem, it is possible to compare the gains of performing maintenance operations and making the decision that reduces the long-term cost.

4.4.3 Numerical experiments to quantify performance improvement

In order to quantify the performance of Algorithm 3 combined with the route configuration exploration heuristic, a series of numerical experiments were performed. In each one of those, the same instance of the problem was solved by Algorithm 3 and by a MILP solver[2] applied directly to the model proposed in Section 4.3.1. Results are shown in Table 4.8.

[2]SCIP was the chosen solver since it is one of the most competitive open-source options.

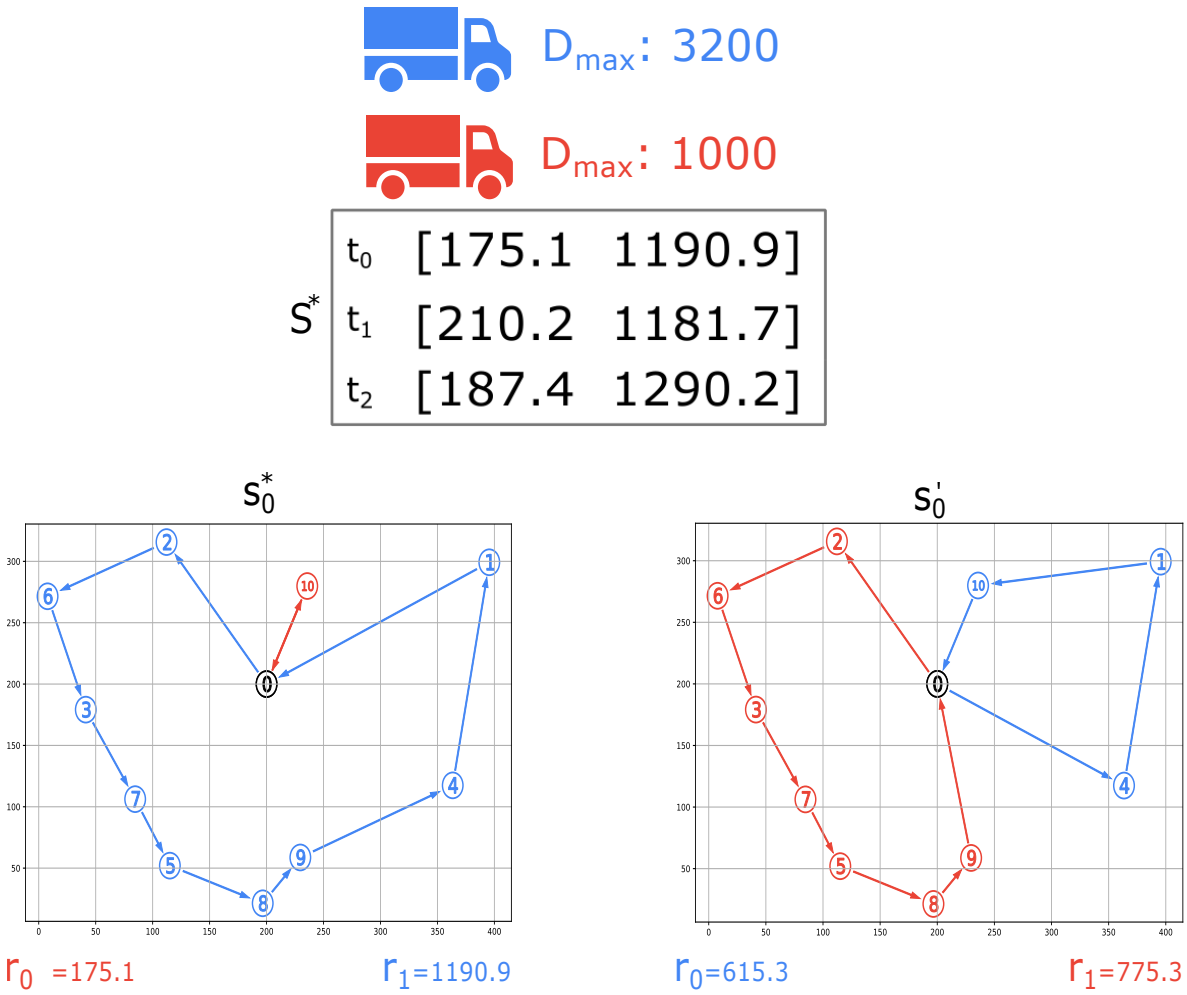

Figure 4.9: Illustration of promising route configuration search. In this instance, assigning the longest routes for the blue vehicle violates its safety constraints, therefore, configurations such as $s^{'}$ must be considered.

As can be seen, the proposed algorithm reduced the computation time drastically and led, in all cases, to the optimal solution, indicating that it is a viable tool for solving more complex instances.

4.5 Closing the loop

4.5.1 General approach

One of the defining features of PsM is the fact that the decision-making process must be done in closed-loop. So far, the optimization model was defined in a horizon H and decision variables were not updated. A natural way of closing the loop and adapt to the randomness of the degradation process is to use measures W_t, obtained through vehicle connectivity, to update

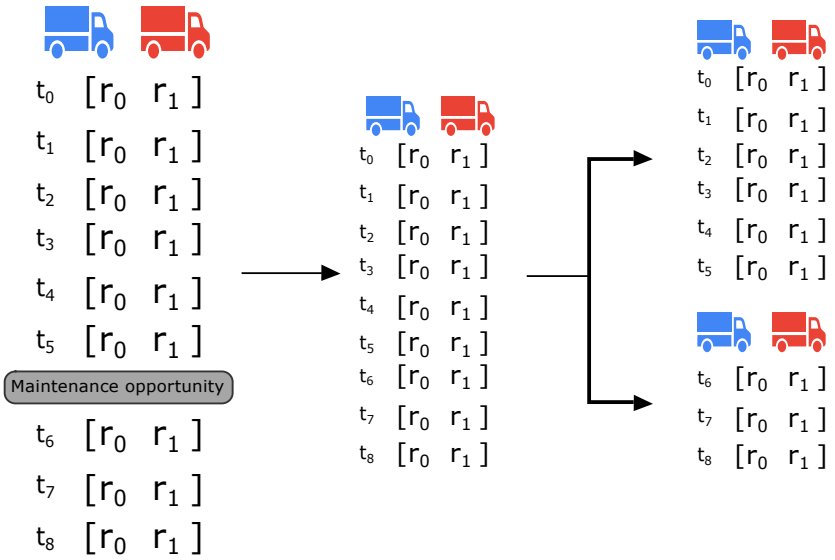

Figure 4.10: Solution strategy to address instances including maintenance

Instance				MILP Solver		Algorithm	
|Z|	|H|	|N_t|	V	Computation time (s)	Optimal cost	Computation time (s)	Optimal cost
2	5	8	∅	2	2119	4	2119
2	10	10	∅	27	5596	12	5596
2	10	10	[5]	31	5561	18	5561
2	35	10	∅	7217	17561	50	17561
2	35	10	[10,20]	6813	16573	67	16573
2	80	10	∅	30127	36118	230	36118
2	80	10	[10,20]	29314	35880	284	35880

Table 4.8: Algorithms performance comparison

safety constraints. Therefore, after a working session t, the updated distribution becomes:

$$f^t_{D_{fail}}(d) = \frac{w_{crit} - W(t)}{\sqrt{2\pi d^3 \sigma_B^2}} \exp \frac{-(w_{crit} - W(t) - \lambda d)^2}{2\sigma_B^2 d} \tag{4.48}$$

As such, D^q_{max} is updated after every measure and routes can be then adapted if necessary. Algorithm 3 is then applied once again, taking advantage of the fact that routes configurations were previously computed improving routes and maintenance decisions and minimizing the long-term exploitation cost.

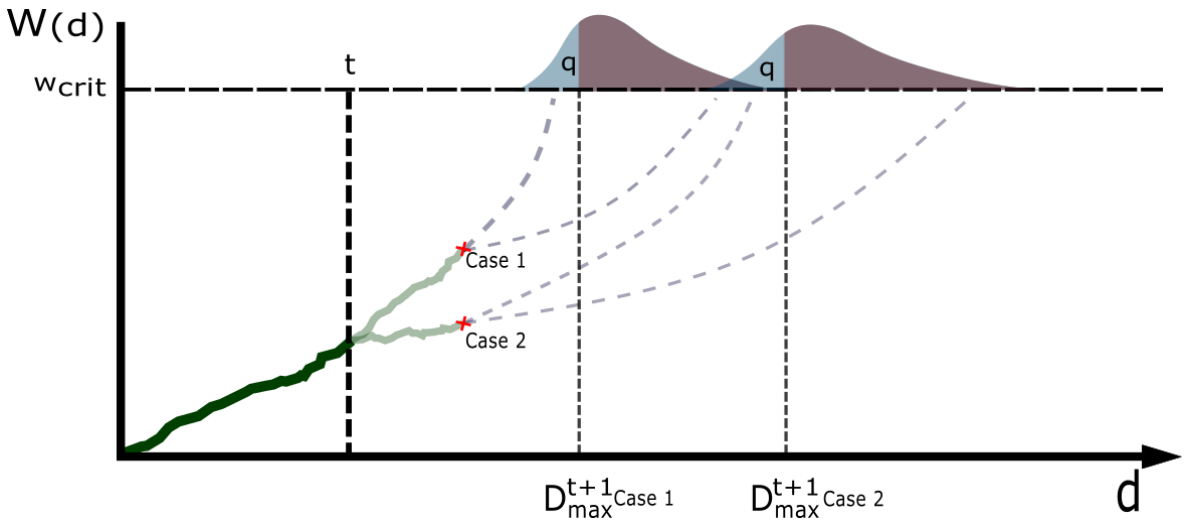

Figure 4.11: Illustration of the closed-loop approach for failure distance distribution updates.

4.5.2 Numerical experiments comparing open and closed-loop approaches

In this final numerical experiment, different instances of the problem are solved and simulated. Through the simulations, the closed-loop approach is tested and the empirical costs are compared in Table 4.9.

Notice that in both instances, failure costs were significantly lower in closed-loop. This is a reflex of the fact that routes can be adapted whenever degradation evolves faster than expected. Likewise, maintenance costs were also lower since in few simulations, it was not necessary to do it in order to respect safety constraints. Consumption costs were slightly higher in the second instance in which the open-loop solution minimized the total distance. This happened because in some instances, to minimize failure probabilities, it was necessary to use sub-optimal routes.

4.6 Conclusion

In this chapter, a first PsM application was developed. It was based on vehicle reliability defined as a FHT degradation model designed to be as generic as possible and, therefore, useful for representing different vehicle components. The trade-off for this flexibility is that this model is not capable of representing complex nuances of the degradation process of real components. As such, the scope of PsM actions was restricted to classical maintenance actions and routing.

Despite its limited scope, this application led to a new optimization model capable of addressing the intricate relationship between vehicle usage and degradation. Although its cost function is rather simple, this model routes achieved significant lower empirical costs when compared to a benchmark model designed to mimic a typical fleet manager. The proposed

Instance				Closed-loop approach			Open-loop approach		
|Z|	**|H|**	**|N_t|**	**V**	**Consumption cost**	**Maintenance cost**	**Failure cost**	**Consumption cost**	**Maintenance cost**	**Failure cost**
2	**70**	**10**	$\emptyset$	**35782**	**0**	**31**	**35884**	**0**	**207**
2	**70**	**10**	**[50]**	**35581**	**87**	**32**	**35498**	**100**	**221**

Table 4.9: Closed and open loop comparisons

MILP takes the whole long-term context into account, determining routes that always limiting failure probabilities and reducing downtime.

This new optimization model is computationally challenging and for instances with several clients or long horizons, dedicated algorithms are needed. In this chapter, a simple algorithm is proposed, exploiting specific properties of the problem to search the solution space more effectively, drastically decreasing computation time and still finding the optimal solutions.

There are several promising future research ideas worth exploring. For example, even if vehicle failure probabilities are constraint, as fleets grow the overall risk of downtime can become non-neglectable and ideally, maximum failure probabilities should be determined systematically taking into account failure costs.

Furthermore, the hypotheses that, in a horizon H, all missions are known beforehand is only realistic in very specific vehicle applications and should be relaxed. In future works, for example, it would be interesting to consider a case in which decision-making is done sequentially without fixed horizon assumption and with mission addresses that are only known at the beginning of a working session.

Chapter 5

Prescriptive maintenance for electric vehicles: degradation model for the energy storage systems

Contents

5.1 Introduction

Throughout the first part of this manuscript, the importance of considering the particularities of EVs when proposing modern services for heavy vehicles was highlighted. In the two remaining chapters of this document, EVs become the focus of a PsM application that is designed around the Energy Storage System (ESS). Due to the complexity of this component, this chapter is dedicated exclusively to introducing a suitable PsM degradation model for it.

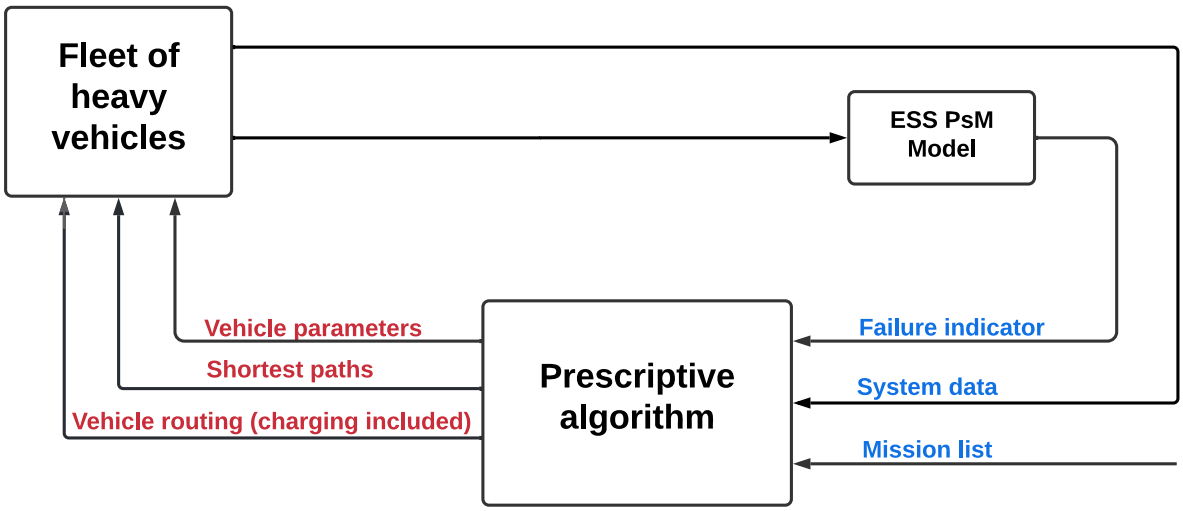

Figure 5.1: ESS PsM solution loop.

The optimization problems that arise when accounting for ESS degradation will be detailed in Chapter 6 and Figure 5.1 shows the structure of this ESS PsM solution.

In contrast to the generic component used in Chapter 4, the ESS has a longer useful life and, ideally, it is not replaced. As a matter of fact, it often defines the life of the vehicle, since replacing it is most times not economically viable and in general, it is more beneficial to buy a new vehicle. Therefore, classical maintenance decisions are no longer included. ESS RUL will be optimized in the context of mission performance, ensuring minimal exploitation cost. On the other hand, as the ESS is a very complex component with several degradation mechanisms, its health can be affected by different action. Therefore, the scope of the optimization problem addressed in Chapter 6 involves:

- Vehicle Parameters (VPs) optimization: Limiting speeds and accelerations when possible to reduce ESS degradation and energy consumption while ensuring that missions are still performed without penalties.
- Shortest Paths: Finding the best path to reach any point in space in terms of degradation and energy consumption. As will be further detailed, it is interesting to notice that paths with similar energy consumption can have different impact in terms of ESS State of Health (SoH).
- Vehicle Routing: Optimizing a mission plan, considering logistical constraints, charging stations and battery degradation. Not only the order of missions is important as it can reduce vehicle usage and therefore, ESS SoH.

To connect those different decisions to degradation, an original degradation model is required. This chapter gives the reader a clear picture of how the ESS works and what are its main stress factors. It also introduces a realistic model that, in Chapter 6, is included

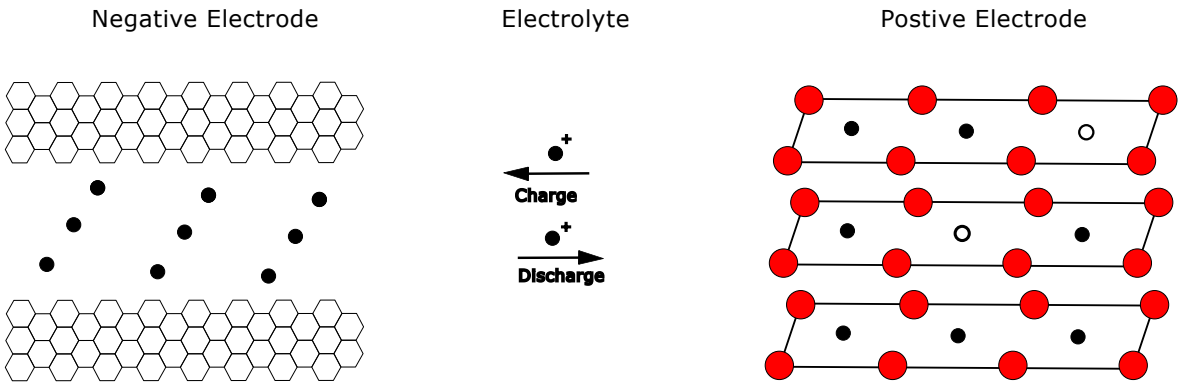

Figure 5.2: Illustration of a Lithium-ion battery cell.

in optimization problems related to the actions listed in Figure 5.1. The different actions considered are justified and this model is compared with similar ones used in EVRPs, showing the importance of realistically considering battery dynamics for routing and SPPs, specially when considering degradation.

5.2 Principles of battery usage and degradation

The ESS is responsible for providing electrical energy to EVs and can be seen as its power source. It is composed of different sub systems, dedicated to manage charges, control temperature and ensure safety. However, the most important sub component of the ESS is the battery pack which is in turn composed of battery cells. Cells are the basic structure of any battery and their function is to transform chemical energy into electrical energy. In most EVs, they are arranged in series, forming the aforementioned pack. Packs can have up to 180 cells, in order to provide the required current and voltage, which, depending on the application can reach more than 720 V and 70 A respectively.

Cells are composed of three parts, the positive electrode which acts like a cathode in discharge, the negative electrode which acts as an anode in discharge and the electrolyte that allows ions exchange between both electrodes as shown in Figure 5.2. Most EVs have lithium metal oxides positive electrodes. While recharging, chemical reactions happen in the positive electrode, liberating positive ions that will flow through the electrolyte and will be "absorbed" into the negative electrode by means of another chemical reaction. During discharge, lithium ions flow from the negative electrode to the positive electrode. Figure 5.2 illustrates this process. Those reactions are presented below for the case of a cell made of $LiCoO_2$:

Positive electrode reaction:

$$\mathrm{LiCoO_2} \longrightarrow \mathrm{Li_{1-x}CoO_2} + \mathrm{xLi^+} + \mathrm{xe^-}$$

Negative electrode reaction:

$$6C + xLi^{+} + xe^{-} \longrightarrow Li_xC_6$$

Total reaction:

$$6C + LiCoO_2 \longrightarrow Li_xC_6 + Li_{1-x}CoO_2$$

Lithium-ion have become popular because they present advantages with respect to other materials. The most important ones are:

- High energy density: Lithium presents a small atomic number and big electrical potential which leads to high energy densities (around 260 kWh/kg) [Wu15].
- High output voltage: Cells can provide up to 4V which is three times higher than Ni-Cd batteries, for example [Wu15].
- Low self discharge: Less than 3% per month [Wu15].
- No memory effect : Partial discharges have no influence on subsequent discharging cycles, which is not the case for Ni-Cd and Ni-MH batteries, for example [Wu15].

When it comes down to materials for the negative electrode, the most popular options are variations of carbon materials such as graphite. They are often used because of their resistance, inertness, conductivity and cost. Although the vast majority of positive electrodes is made from lithium ions and negative electrodes from carbon, there are several different economically viable alternatives for electrolytes, such as liquid electrolytes, all-solid electrolytes and gel polymer electrolytes. High ionic conductivity is the most important feature among all electrolyte types.

Throughout the useful life of a cell, the amount of lithium ions that are able to go from electrode to electrode declines due to different physical processes. This means that the total electricity the battery can provide in a complete discharge decreases. This phenomenon is called *capacity fade* and this term is often used in the literature as a synonym of battery degradation. For authors that treat capacity fade as battery degradation, SoH is often defined in terms of the amount of electricity that can still be delivered in a full discharge:

$$SoH(t) = \frac{Q(t)}{Q_0} \tag{5.1}$$

where $Q(t)$ is the battery capacity at instant t and Q_0 is its initial capacity. It is important to acknowledge that, some authors define battery SoH only in terms of impedance growth while others consider SoH to be a combination of both impedance growth and capacity. In this work, SoH will be defined as in Equation 5.1, accounting only for capacity fade, since it is the most common approach in the literature. Furthermore, as capacity fade and impedance growth

stress factors overlap, usage optimization directed at minimizing one can also be beneficial for the other. To further justify that choice, some of those stress factors are now discussed in detail.

5.2.1 Battery degradation mechanisms

Battery degradation is a complex combination of different phenomena and is still a very prominent research topic. In this section, the main physical mechanisms responsible for battery degradation are presented. As time goes by, batteries loose their ability to provide electricity. Although this list is not complete and a deep discussion around the physical laws behind them is outside the scope of this chapter, it allows the reader to get a feeling of what are the concrete changes on batteries throughout their lives.

As mentioned before, capacity is a measure of the electricity a battery can provide in discharge and is usually expressed in Ampere hours (Ah). As capacity fades through the degradation processes cited, the SoH decreases until reaching a critical threshold after which the battery must be replaced. This threshold varies from application to application but for vehicles, it is usually in the range of 75% to 80%.

Several phenomena are responsible for battery degradation. The main ones take place on the positive and negative electrode [Bar+13b]. On the negative electrode, the most important degradation mechanism is the expansion of the Solid Electrolyte Interphase (SEI). The SEI is a solid layer that forms between the negative electrode and the electrolyte during the first charges of the battery [Bar+13b]. It plays an important protective role for the battery, reducing corrosion on the negative electrode and ensuring safety through the separation of electrode and electrolyte. However, the SEI expands throughout time, inducing loss of lithium ions, electrolyte decomposition and loss of active surface. Other degradation mechanisms on the negative electrode are related to interactions between the electrolyte and graphite. Even with the SEI, those interactions can lead to graphite exfoliation and the liberation of gasses that promote impedance growth and loss of capacity. Additionally, irreversible side reactions happen in the negative electrode compromising the availability of lithium-ions.

Degradation phenomena also happen on the positive electrode. For example, electrode cracks, wear of active lithium material, material dissolution on the electrolyte and oxidation have been seen and studied by researchers [Bar+13b]. However, the positive electrode does not show relevant morphological changes throughout its life. This indicates that the negative electrode is more important degradation wise [Bar+13b]. All the aforementioned degradation mechanisms lead to capacity fade and impedance growth and the most important as schematically represented in Figure 5.3.

PsM is concerned with usage optimization in a broad sense, and explicitly modeling those phenomena to describe degradation is impractical since connecting them to logistical decisions, maintenance or parameter reconfiguration would be impossible. A much more useful approach in this context is to correlate them to battery usage metrics that can be included in an optimization set-up. In the next section, those usage metrics are presented.

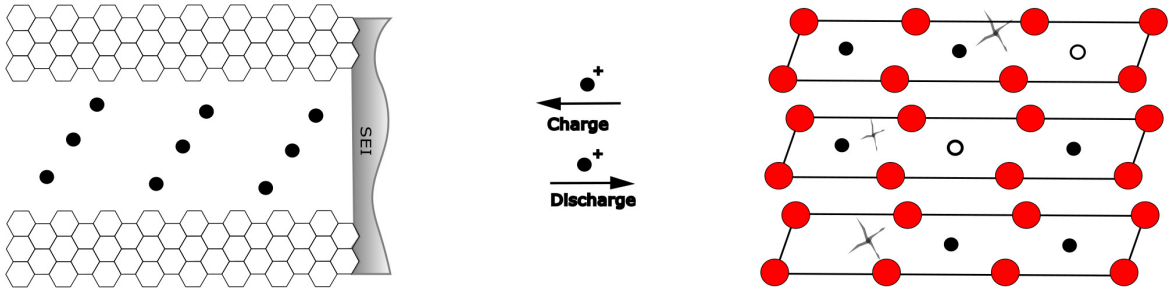

Figure 5.3: Illustration of degradation mechanisms in a Lithium-ion battery cell.

5.2.2 Battery usage metrics

Battery usage impacts battery health in several ways. For example, under high temperatures the SEI can dissolve into less permeable materials that will increase the internal impedance of the cell. However, under very low temperatures, SEI's ability to diffuse ions is reduced, not only increasing impedance but also causing lithium platting which is responsible for capacity fade [Bar+13b]. Besides temperature, another important quantity to characterize battery usage in a quantitative way is the State of Charge (SoC). It represents the amount of electricity remaining in the battery during a cycle of charge or discharge. It is expressed as:

$$SoC(t) = \frac{Q_{remaining}(t)}{Q} \tag{5.2}$$

where $Q_{remaining}(t)$ represents the amount of electricity remaining in the battery at instant t. Despite the similarities in the definitions, while SoH relates to the amount of electricity that *can be* stored, SoC relates to the amount of electricity stored at a given point in time. This is represented in Figure 5.4.

Both SoC and SoH are crucial for batteries usage and health monitoring. Those quantities can not be measured directly through sensors and therefore, several methods for estimating them [LTW15]; [Zho+21] have been developed. To understand future modeling assumptions, it is useful to discuss some SoC estimation methods. The most famous one is based on the concept of Coulomb counting which relies on the following relationship:

$$SoC(t) = SoC(t_0) + \int_{t_0}^{t} \frac{I(t)}{Q} \tag{5.3}$$

where $I(t)$ is the electrical current flowing through the battery, considered negative in discharges. Coulomb counting consists, therefore, in monitoring $I(t)$ through sensors, numerically approximate its integral with respect to time, normalize it and subtract it from the last estimate of $SoC(t)$. This method has two significant problems. The first one is that due to its recursive nature, this algorithm will accumulate measurement errors, leading to an estimation with increasing variance. The second problem is the fact that it is necessary to know the initial value of $SoC(t)$ in order to apply this method. To address those issues it is possible to exploit

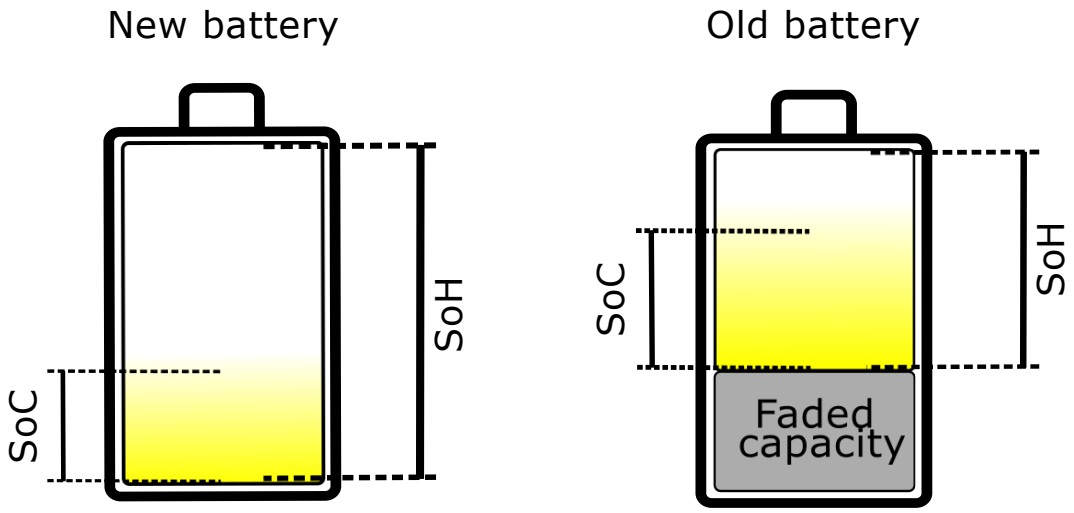

Figure 5.4: Illustration of the differences between SoC and SoH. While the first is related to the instantaneous electricity stored in the battery, the former is a measure of the maximum amount of electricity.

the relationship between SoC and the Open Circuit Voltage (OCV) which is the voltage in the cell terminal when there is no load connected to it. There is a direct relationship between SoC and OCV which can be obtained empirically and depends on the cell chemistry. Figure 5.5 shows this relationship for a lithium-ion cell.

Although OCV gives a reliable SoC estimation directly, it can not be measured during battery operation. The battery needs to be disconnected for sufficient time to stabilize its terminal voltage so that OCV can be measured. Therefore, this method is only used to estimate the initial SoC value and to calibrate its estimation when the battery is disconnected.

SoC trajectory, $SoC(t)$, not only contains most of the information of battery usage but it is also related to the most important stress factors (all but temperature) that accelerate capacity fade. Those stress factors are:

- **Mean SoC (mSoC):** defined as the average value of $SoC(t)$. Operating in high mSoc values accelerates degradation mechanisms in the negative electrode [Bar+13b].
- **Depth of Discharge (DoD):** defined as the amplitude of SoC variation in a discharge cycle. Higher DoD often lead to accelerated capacity fade [Bar+13b].
- **C-rate:** defined as the rate in which the battery is discharged or charged. It can be estimated through the SoC variation rate. Operating on specific values of C-rate is known to accelerate degradation.

Figure 5.6 illustrates the impact of those factors. Two cells are charged and discharged repeatedly at the same temperature. One is discharged from 80% to 30% while the other is discharged from 98% to 30%. As can be seen, even if both cells have provided the same energy

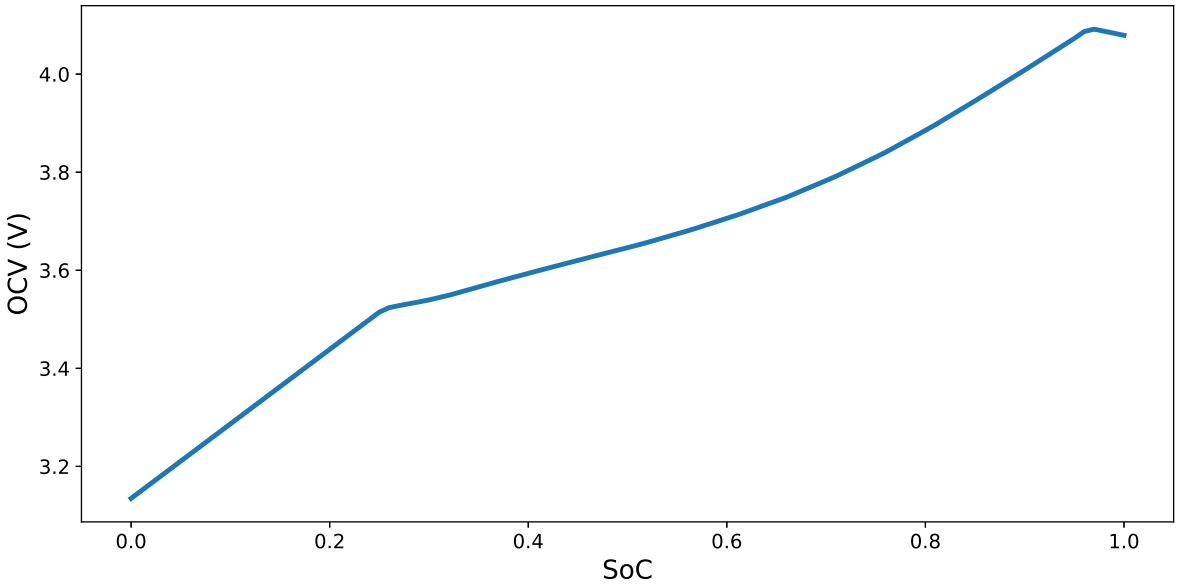

Figure 5.5: OCV SoC curve for a lithium-ion cell.

throughput, there is significant difference in terms of SoH. This is due to the fact that bigger DoDs and high values of mSoC tend to accelerate degradation.

5.3 Models for degradation and SoC

A ESS PsM degradation model must capture vehicle usage impact on battery degradation. In this section, a review on SoH models is made in order to understand the state-of-the art and choose a modeling approach suitable for PsM. Furthermore, since SoC is a direct reflex of usage and contains information on stress factors, SoC models used in the decision-making literature related to transportation science are also reviewed.

5.3.1 Battery degradation models

As detailed in Section 5.2.1, battery degradation is caused by a complex combination of phenomena that take place on a microscopic level. Some degradation models are directly based on those phenomena and are usually referred to as physical-based models. However, for most vehicle decision-making problems, they cannot be directly applied due to their complexity. Furthermore, it is difficult to correlate those chemical reactions with vehicle usage to degradation with them [Pel+17]. Therefore, for PsM application, other alternatives mt be considered.

Black-box models (or data-driven) [Wan+21]; [Ard+20]; [Wan+23]; [Zha+23]; [JMZ13]; [Joh+20] use battery SoH (or capacity) data to train regression algorithms that predict capacity evolution or failure time. The main drawback of this approach is the fact that it relies

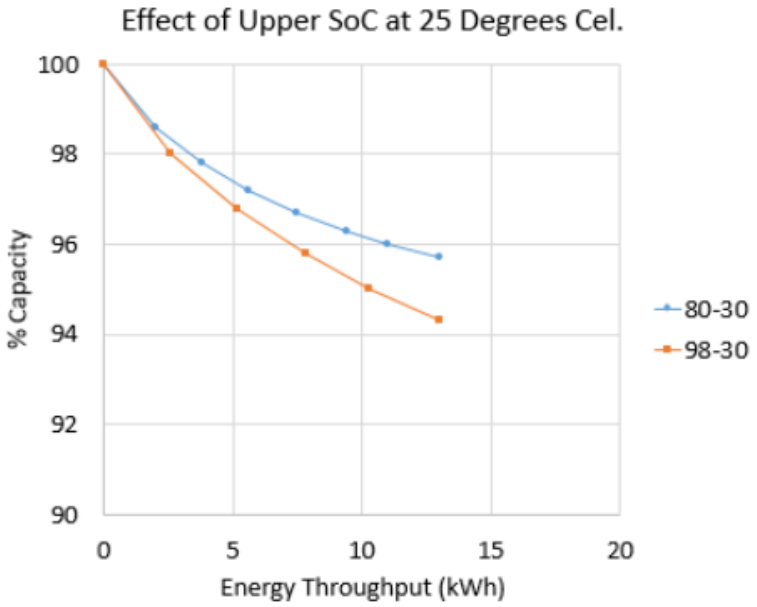

Figure 5.6: Effect of battery usage on capacity fade.

on large amounts of data, which is rarely available for real vehicle applications where usage conditions can widely vary.

The most suitable models for vehicle decision-making problems are the semi-empirical models because they combine data and theoretical principles. They are easier to include in EVRPs than physical-models since they do not model the chemical reactions responsible for degradation but account for stress factors such as DoD, mSoC, C-rate and others, which can be connected to vehicle usage [Pel+17]. Furthermore, they require less data than a pure black-box approach. For those reasons, they have been employed in degradation-aware decision-making problems [XWT21]; [GRD22]; [PA20]; [ZMO22]; [PJL18]. However, most of the used degradation models present limitations. They are often too simplistic or are not able to account for degradation caused by driving cycles (*i.e.* capturing the effect of accelerations or current fluctuations caused by different traffic conditions). They are also incapable of considering the effects of opportunistic charges (*i.e.* SoC that is recuperated when braking or driving downhill) and neglect some important stress factors.

Among the semi-empirical models, one promising alternative is to use models based on SoC cycle decomposition [Pel+17], such as [Xu+16]. They consider $SoC(t)$ as a combination of simpler parts, referred to as SoC cycles, obtained, for example, through the Rainflow-Counting algorithm [DS82]. Stress factors for each cycle are computed and the total capacity fade estimated accordingly. The main advantage of cycle decomposition models is that usage conditions are not assumed to be static and they can be employed for charge and discharge cycles. Even for battery types that are more sensible to degradation while charging, the cycle decomposition is still useful because it accounts for opportunistic charging. To fully exploit the potential of such models, however, it is necessary to realistically model SoC, as such, the

most common approaches for SoC modeling are examined in Section 5.3.2 .

5.3.2 SoC models for driving cycles

In this section, several SoC modeling approaches used in transportation decision-making problems are reviewed. A special emphasis is put on EVRPs, however, the goal of this section is not to extensively review the literature of EVRPs but to analyze recent contributions in terms of models used to define vehicle range and SoC, discussing their hypothesis and possible limitations.

SoC is not only useful for estimating degradation, but also to define vehicle range. However, most authors define their range constraints in terms of energy consumption [Pel+17]. This approach is less robust than using SoC, potentially leading to unfeasible routes. The main problem comes from the fact that, power output comes from the product of battery voltage and current. Since battery voltage depends on SoC, even for a constant required power, SoC variation will not be constant. As a consequence, the same net energy consumption can produce different current profiles and discharge batteries differently. This is not considered when defining range in terms of energy.

Some authors refer to their range constraints as SoC, but treat SoC and energy variation as synonyms [Bar+13a]; [İÇ22]. The implicit assumption is that the terminal battery voltage is constant, neglecting the internal dynamics of the battery and considering its behaviour to be static. This can lead to significant estimation errors even in simple cases as will be seen in Section 5.5. Another practical limitation of this approach comes from the fact that EVs range is also limited by battery terminal voltage. In order to avoid certain degradation mechanisms, batteries are disconnected upon reaching a specific cut-off voltage value. Ignoring SoC dynamics prevents researchers to add those constraints since cut-off voltage can be reached in different SoC levels depending on current profile. This can also lead to unfeasible routes as demonstrated by [Pel+17].

Besides this common misconception that SoC variation is equivalent to energy consumption, most of the energy models used in EVRPs are oversimplified. Several authors do not discuss how to estimate either energy or SoC variation [Kar21]; [Mon+17]; [Goe19]; [Fro+19]. In other cases [İÇ22]; [SSG14]; [Zuo+19]; [RW16]; [Ces+21], energy consumption is considered to be directly proportional to the traveled distance. This leads to significant errors in urban networks as seen in [Bas+19]. Another popular approach is to estimate energy assuming that vehicles move with constant speed. Power-train efficiency is often considered constant and acceleration effects are neglected [MCD22]; [AA20]; [Afr+14]; [FPR18]; [Ma+21].

A more realistic energy estimation model is used in [Bar+13a]. They rely on vehicle dynamics equations combined with prior speed profiles obtained from historical data to compute energy consumption. This approach can lead to realistic estimates but knowledge on speed profiles can be restrictive in most scenarios due to the lack of data. A simpler approach can be found in [Bas+19]. A two-step EVRP is solved, in which the energy model is based on road topography, making assumptions on driving cycles and accounting for power-train efficiency.

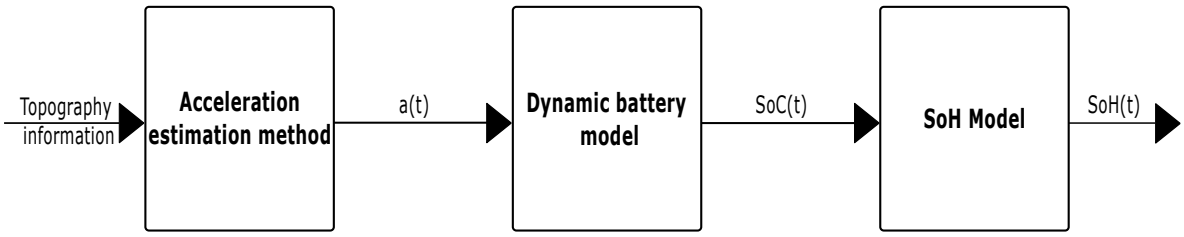

Figure 5.7: Sub-parts of the ESS PsM degradation model

This model is compared with real vehicle data and presents a mean square error close to 12%. In the associated optimization model, constraints related to vehicle range are defined in terms of energy.

Even if good alternatives for realistic energy consumption exist, no realistic SoC model has been included in decision-making problems related to EV exploitation. This is not only important for describing range constraints but also for battery SoH optimization [Pel+17]. In the next sections, a ESS PsM degradation model is proposed in order to fill some of those scientific gaps. It is composed of a SoC model inspired by the same principles applied in [Bas+19] and can be included in different realistic optimization set-ups as will be seen in Chapter 6.

5.4 Prescriptive degradation model for the energy storage system

To be included in a PsM solution, a degradation model must connect degradation to usage. For the ESS, it means connecting battery SoH to vehicle displacements, fleet routing and VPs such as maximum speed and maximum acceleration. Figure 5.7 illustrations how this model works.

The model is composed of three sub-parts. The first one consists of estimating, based on road topography information that can be easily obtained through free APIs, an acceleration function $a(t)$. This function is used in a dynamic battery model to obtain an estimation for $SoC(t)$. Finally, $SoC(t)$ is used to feed a SoH model that estimates the degradation caused by this particular displacement. Each sub-part is now further detailed.

5.4.1 Acceleration estimation in realistic use cases

Some of the literature on decision-making problems related to transportation applications relies on very strong assumptions on vehicle speeds, as could be seen in Section 5.3.2. One of the best approaches [Bar+13a] used a data set of real vehicle speed measures in order

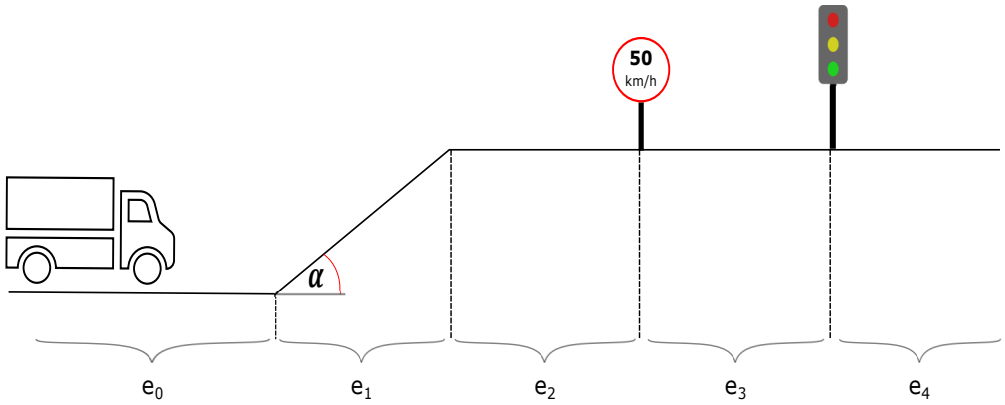

Figure 5.8: Example of how road links are defined. In this example, four links are shown. Links are created to represent differences on the parameters relevant to acceleration or power estimation. In this example, e_1 and e_2 are created due to a inclination differene with respect to the previous link. e_3 is defined due to a speed change and e_4 is due to the presence of a traffic light.

to estimate $a(t)$, however, in most cases such data sets are not available. A more suitable option is to use a method similar to the one presented in [Bas+19] in the context of energy estimation. This method is based on road information such as maximum allowed speed, traffic lights location, crossroads locations, inclination and road segment lengths, which are promptly available through several APIs for several cities in the world.

The first step of this method is to use all this aforementioned road information to build a road graph $G_r = (N_r, E_r)$. The nodes N_r are either road intersections or changes on the parameters necessary for mechanical power estimation (see Section 5.4.2). For example, changes in maximum allowed speed,road inclination, the presence of crossroads, traffic lights or very steep curves (which are expected to make vehicles brake) define the nodes in N_r. The edges E_r represent directed road segments referred to as *road links*. A road link e_r:

$$e_r = \begin{bmatrix} l \\ v_{road}^{max} \\ \alpha \\ Stop \\ \mathrm{r} \end{bmatrix} \tag{5.4}$$

is defined by a length l, an inclination α, a maximum allowed speed v_{road}^{max}, a binary variable *Stop* that is equal 1 if there is a possible stop at the end of the link (crossroad and traffic lights, for examples) and 0 otherwise. Variable r is the radius of the curve at the end of the link. If $r = 0$ it indicates that there is no curve at the end of e_r. Figure 5.8 shows an example of how links are defined based on road information.

The acceleration estimation method consists in making assumptions over driver behaviour

based on e_r. It considers that a vehicle will accelerate constantly, with maximum vehicle acceleration, until reaching a target speed v_{tgt} as shown in Figure 5.9. Originally in [Bas+19] the target speed was always v_{max}^{road}. Considering eventual limitation caused by VPs, v_{tgt} becomes:

$$v_{tgt} = \min[v_{max}^{road}, v_{max}^{vh}] \tag{5.5}$$

where v_{max}^{vh} is the maximum vehicle speed, which can be optimized and will be included the optimization models presented in Chapter 6.

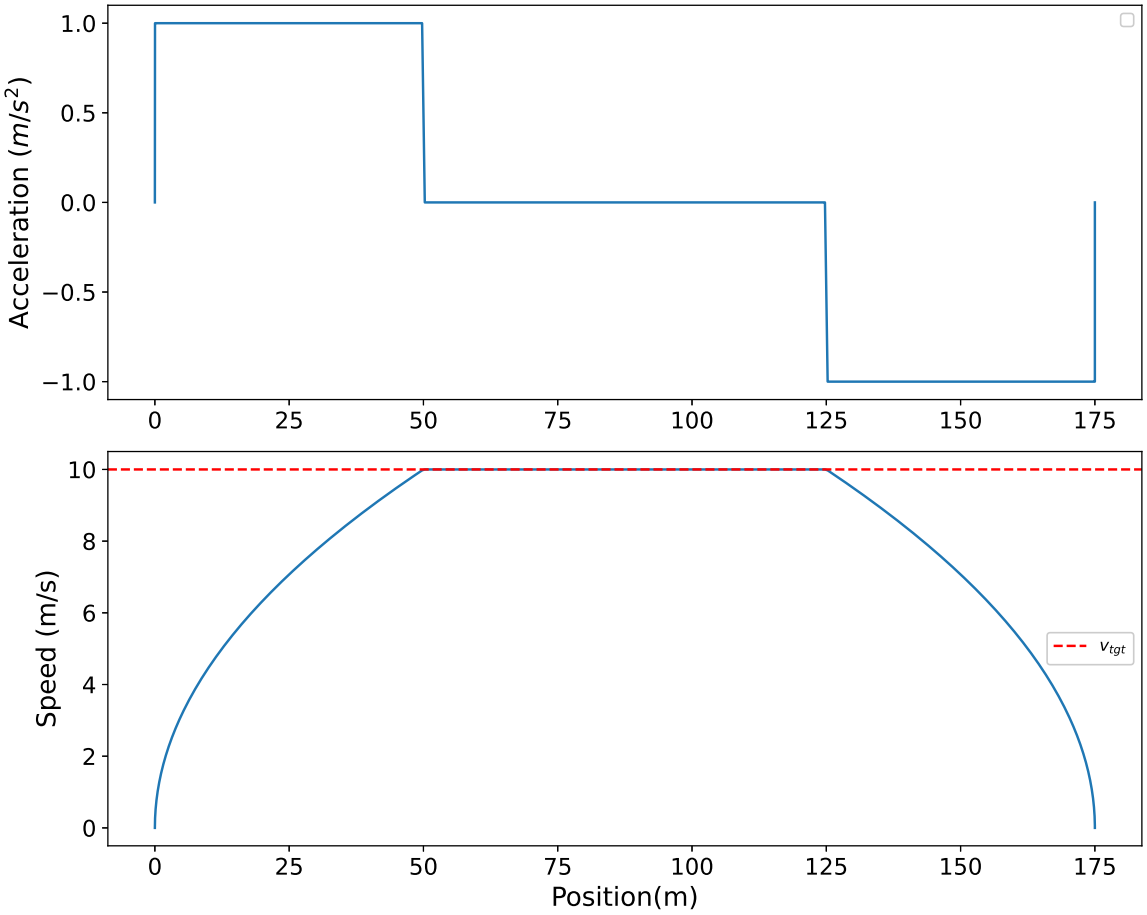

Figure 5.9: Vehicle speed starting at idle and going through a road link with a stop at the end.

To obtain acceptable results in real world applications, it is necessary to consider corner cases. Two such cases were considered by [Bas+19]. Figure 5.10 illustrates the first one. It happens when the target speed of two consecutive road links is different. If the target speed in the first one is higher, the vehicle needs to brake before entering the next link. The second case happens when a road link is too short and v_{target} can not be reached. Figure 5.11 illustrates it. It shows the speed of a vehicle in a road link between two stopping points. The vehicle has not enough space to reach v_{target}.

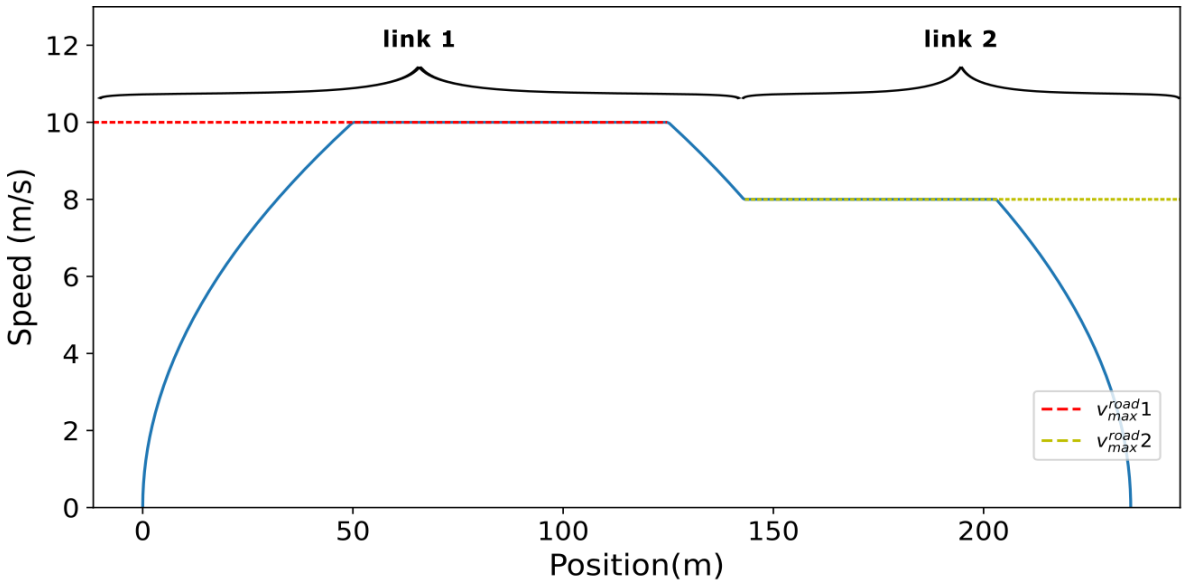

Figure 5.10: Speed with vehicle travelling through two consecutive road links.

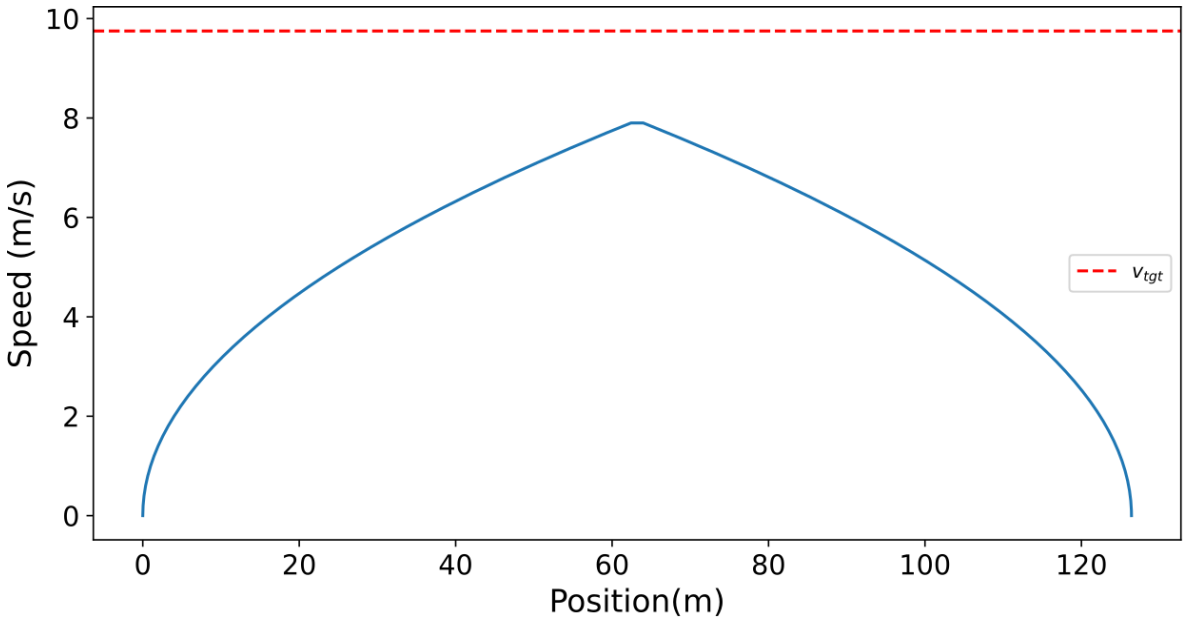

Figure 5.11: Speed in a short link with stop point at beginning and end. The vehicle cannot reach target speed.

In addition to those two cases, originally addressed by [Bas+19], the effect of curves is also considered. In [Bas+19], authors dealt with curves by considering very steep curves as stopping points. In order to be less conservative but also consider the effect of less steep curves on the speed, in this work, vehicles are assumed to make turns with constant centripetal acceleration. Therefore, their speeds before the curve should be, at most:

$$v_{curve} = \sqrt{r \quad a_{centripetal}} \tag{5.6}$$

with $a_{centripetal}$ being vehicle maximum centripetal acceleration. Considering all those particular cases leads to a method capable of estimating $a(t)$ for a particular displacement. Once this function is known, it is possible to, considering vehicle and battery dynamics, estimate $SoC(t)$ by solving a system of differential equations, presented in the next section.

5.4.2 SoC estimation method for driving cycles

All realistic energy estimation methods rely on considering the usual forces applied in a vehicle, represented in Figure 5.12, to compute the required mechanical power. To compute $SoC(t)$ it is also necessary to explicitly account for battery dynamics. A second-order Equivalent Circuit Model (ECM), shown in Figure 5.13 is chosen since it is widely used in the literature [Xia+17] and can capture opportunistic charges. Combining battery and vehicle dynamics, the following system of algebraic and differential equations is obtained:

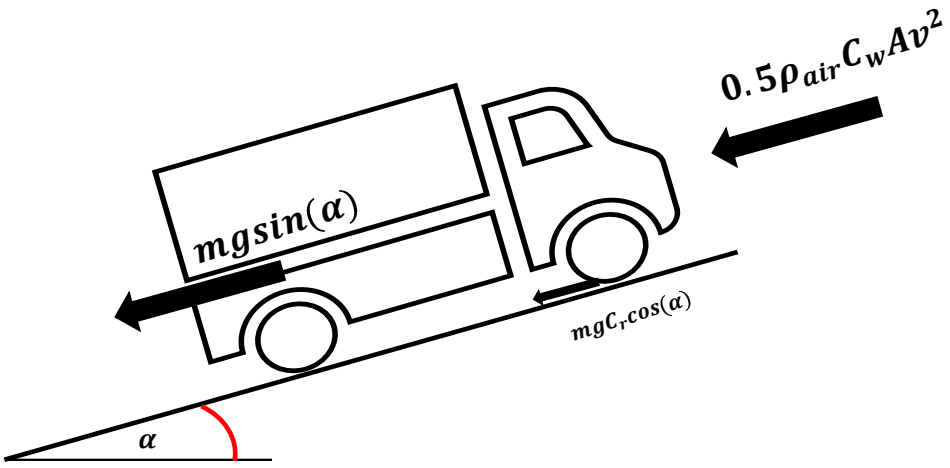

Figure 5.12: Vehicle longitudinal dynamics.

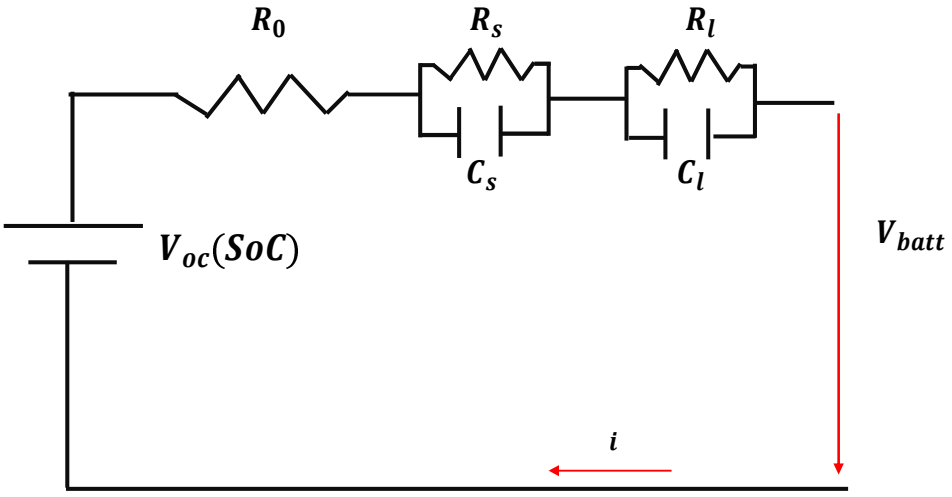

Figure 5.13: Second-order ECM for a battery.

$$\dot{v} = a(t) \tag{5.7}$$

$$P_{mec}(t) = \frac{\rho_{air} C_w A v(t)^3}{2} + mgv(t)\sin\alpha + mgC_r v(t)\cos\alpha + ma(t)v(t) \tag{5.8}$$

$$P_{elec}(t) = \frac{P_{mec}(t)}{\eta(v(t), a(t))} \tag{5.9}$$

$$I(t) = \frac{1}{2R_o}(V_{OC}(SoC(t)) - V_l(t) - V_s(t) - \sqrt{(V_{OC}(SoC(t)) - V_l(t) - V_s(t))^2 - 4R_o P_{elec}(t)}) \tag{5.10}$$

$$\dot{V}_s = -\frac{V_s}{R_s C_s} + \frac{I(t)}{C_s} \tag{5.11}$$

$$\dot{V}_l = -\frac{V_l}{R_l C_l} + \frac{I(t)}{C_l} \tag{5.12}$$

$$\dot{SoC} = -\frac{I(t)}{Q_0} \tag{5.13}$$

Equation (5.7) relates the speed $v(t)$ and the acceleration $a(t)$. Equation (5.8) describes the mechanical power based on the longitudinal dynamics of a vehicle, m is the total mass of the vehicle, g is the gravity acceleration, α is the instantaneous road inclination, C_r is the rolling resistance coefficient, C_w is the drag coefficient, A is the frontal area of the vehicle and ρ_{air} is the air density. Equation 5.9 connects mechanical and electrical power through the power-train efficiency function $\eta(v(t), a(t))$.

Equations (5.10-5.13) are derived from the second-order ECM. $V_{batt}(t)$ is the battery voltage, $I(t)$ is the instantaneous current, $V_s(t)$ and $V_l(t)$ are electric potential differences in each sub circuit, with R_0, R_s, R_l being resistances, C_l and C_s capacitors and $V_{OC}(SoC(t))$ representing the open circuit voltage which depends on SoC.

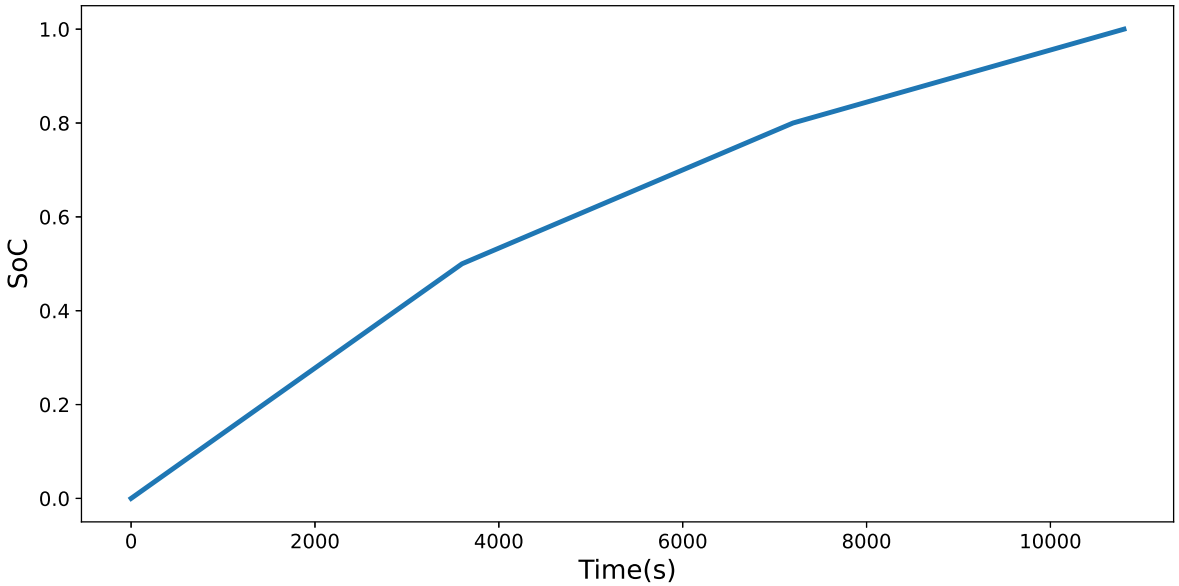

Figure 5.14: Non-linear charging process approximated by a piece-wise linear function.

This system can be solved knowing the initial values of v, V_s, V_l, $SoC(t)$ and $a(t)$ that is estimated as described in the previous section. $V_{OC}(SoC)$ is known for several different cell types. It can also be determined by look-up tables usually provided by battery suppliers or described by functions whose coefficients are fitted to data points as done in [Pel+17].

5.4.2.1 SoC estimation method for charging

The methodology described so far for estimating $SoC(t)$ is only valid for driving. As charging plays a very important role both in terms of degradation and logistics alike, it is necessary to describe $SoC(t)$ realistically at those moments. Modeling the dynamics of charges can be achieve by solving another system of differential equations [Pel+17]. However, since charging is subjected to less exogenous disturbances, simplified models can yield to satisfying results. To model SoC while charging the same approach as the one used in [Mon+17] is applied. SoC is considered to evolve according to a piece-wise linear function as shown in Figure 5.14.

With this model, $SoC(t)$ is fully determined by the SoC level with which the vehicle has arrived at a recharge station and the time spent charging. As discussed before, $SoC(t)$ contains information on different stress factors. It can therefore, be used to estimate degradation. A SoH model is therefore necessary to quantify capacity fade caused by a particular displacement. In the next section, the SoH model used through this work is presented.

5.4.3 SoH model

The SoH model used is proposed in [Xu+16]. It was chosen because of its flexibility which comes from the fact that it is based on cycle decomposition. This model is built upon the fact that SoC contains information on several relevant stress factors. It decomposes $SoC(t)$ into smaller stress cycles. The amplitude (DoD, denoted by σ) and mean (mSoC, denoted by δ) contribute for the degradation of the battery.

The cycle decomposition is done through the Rainflow-Counting algorithm. This algorithm does not have a closed mathematical form. It is also recursive, making it hard to include in decision-making problems. A more profound analyses of this algorithm and its consequences to optimization problem is given in Chapter 6. This model expresses SoH as:

$$SoH(t) = e^{-f_d(t)} \tag{5.14}$$

with a damage function f_d defined as:

$$f_d(SoC(t)) = \sum_{i=1}^{n(SoC(t)))} w_i \; S_{\delta_i} \; S_{\sigma_i} \; S_{T_i} \tag{5.15}$$

where $n(SoC(t))$ is the number of SoC cycles up to time t, w_i is 1 for a full cycle or 0.5 for a partial cycle, S_{δ_i}, S_{σ_i} and S_{T_i} are stress coefficients related respectively to DoD, mSoC and temperature. Those stress coefficients are determined empirically. The chosen functions, adapted from [Xu+16], are described by:

$$\begin{aligned} S_{\sigma_i} &= e^{k_\sigma(\sigma_i - \sigma_{ref})} \\ S_{T_i} &= e^{k_T(T_i - Tref)\frac{T_{ref}}{T}} \\ S_{\delta_i} &= (k_{\delta_1}\delta_i^{k_{\delta_2}} + k_{\delta_3})^{-1} \end{aligned} \tag{5.16}$$

The terms k_σ, k_T, k_{δ_1}, k_{δ_2} and k_{δ_3} are constants determined empirically by experiments, while σ_{ref} and T_{ref} are experimental reference values for mSoC and temperature, respectively. T_i is taken as the average temperature of cycle i, which, in this work, is assumed to be normally distributed around the temperature that should be guaranteed by the battery management system. Notice that C-rate is not explicitly accounted for in this model. This could be done by introducing new terms into the model.

5.5 Experimental results

Throughout most of this chapter, the proposed ESS PsM degradation model was presented. It is more complex than most models used in transport science literature and, as a result, including it in optimization models leads to significantly computational difficulties. This

Quantity	MSE	Final error
Current (A)	0.08	.21
Terminal Voltage (V)	0.29	-0.7
SoC	0.014	-
Depletion time (h)	-	1.8

Table 5.1: Summary of numerical experiment dedicated to compare the performance of the proposed model with classical literature approaches. Mean Squared Error (MSE) was computed in the horizon in which both batteries haven't reached full depletion. Final error represents the difference between each PsM model and the benchmark when depletion is reached. As can be seen, the benchmark model tends to be more optimistic and fails to capture changes on battery operation.

choice is justified by the theoretical reasons discussed in this chapter, however, in this section, numerical experiments are performed to quantify the performance of the ESS PsM degradation model when compared to classical options used in most EVRPs.

5.5.1 Battery dynamics effect

The first main difference between the proposed ESS PsM degradation model and most used ones is that battery dynamics are accounted for. To quantify the consequences of such consideration, PsM SoC model is compared to a SoC model based on the constant battery voltage assumption which is a very common one in the literature. The details of this benchmark SoC model can be found in Appendix A.1.

Figure 5.15 shows the comparison of the two models. It illustrates three relevant electrical quantities, current, battery terminal voltage and SoC. In this experiment, a constant electrical power is assumed. This setup represents an idealized case in which a vehicle constantly drives with a low steady speed. The power value was chosen to represent a heavy vehicle in low speed (approximately 10 km/h) and for both models, batteries were considered to have a 41 Ah capacity, started with full SoC and were discharged until full depletion.

The benchmark model relies on the assumption that battery voltage remains constant around its nominal value. As a consequence, current also remains constant for a given required power which leads to a completely linear $SoC(t)$. The ESS PsM model, in contrast, considers battery dynamics, as such, even with a constant power, both battery terminal voltage and current change through time which also affects SoC trajectory. As a consequence, battery depletion is considered to be reached approximately 1.8 hours later than in reality by the benchmark model. This difference is already relevant in long-haul applications and can be even more relevant for different power inputs. Furthermore, as previously discussed, the benchmark approach is incapable of incorporating range constraints related to reaching cut-off voltage. The summary of the experiment can be found in Table 5.1.

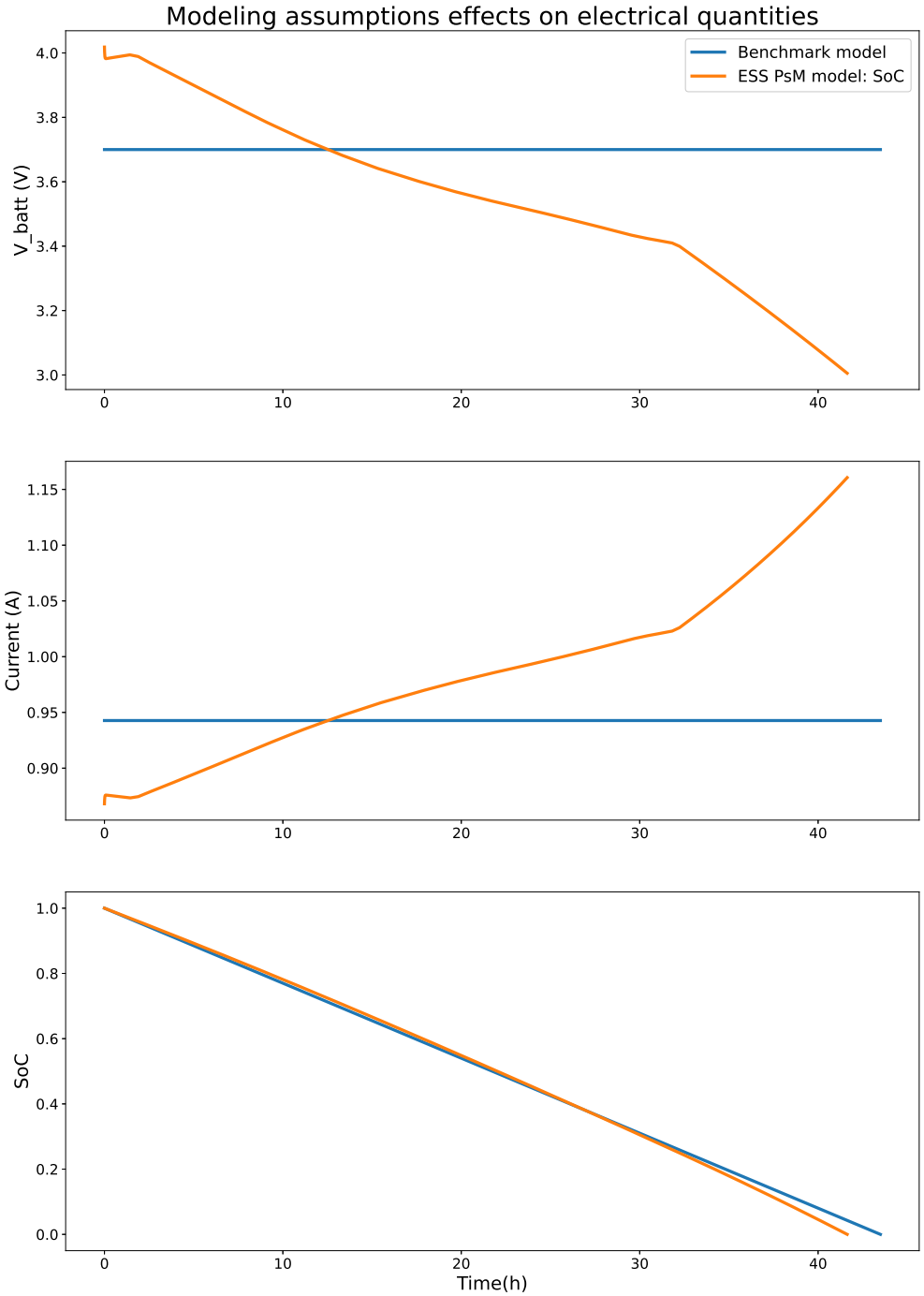

Figure 5.15: Modeling assumption effects on electrical quantities.

5.5.2 Acceleration model effect

As seen in the previous section, by simply considering battery dynamics, a relevant difference is already visible. However, in the previous experiment, both models were discharged with the same constant electrical power. In practice, power is not constant. It is in fact estimated as part of the ESS PsM model. This aspect of the model is compared to another benchmark model, detailed in Appendix A.2, that works based on constant speed assumption, as commonly done in the literature.

Numerical experiments were made emulating realistic displacements in urban areas. Vehicles perform the same displacement, passing through different road links, that contain different speeds, lengths, etc. The differences between the proposed approach and the benchmark one are illustrated in Figure 5.16. As can be seen, speeds are significantly different for both models. In some cases, links are not long enough to reach target speed and acceleration and brakes have non neglectable effects on speed. As a consequence, the duration of the displacement $t_{displacement}$ is different according to both models. This can have serious consequences when dealing with optimization models whose constraints are based on mission deadlines.

Furthermore, the benchmark model not only considers different speeds but also does not accounts for acceleration when estimating power. This causes SoC estimations to be sensibly different. Even for a relatively small displacement of 25 km, the difference in SoC is already 2%. Once again, for longer displacements, this can lead to optimization solutions which are not feasible, since the benchmark model tends to be more optimistic.

5.5.3 Overall impact on degradation estimation

By comparing the proposed approach with benchmarks, it is possible to see significant improvements in terms of SoC estimation, which translates to avoiding unfeasible routes. However, PsM is also concerned with degradation prediction. In this section, the same SoH model presented in Section 5.4.3 is used to estimate battery end of life. In the first cases, it will be used with SoC profiles obtained through the PsM model and in the second case, with the benchmark approaches previously described. $SoC(t)$ will be obtained, in both cases for the displacement shown in Figure 5.16. Figure 5.17 shows the resulting SoH comparison.

The error introduced by SoC estimation gives a significant SoH difference in the long-term. If each cycle is equivalent to a working-session, the estimation difference is approximately six months. That difference can be even bigger if vehicles perform longer displacements per session.

5.5.4 Traffic conditions impact on degradation estimation

In the previous experiments, vehicles were always alone, performing displacements in free-flow. To estimate the robustness of the proposed model in terms of traffic conditions, SUMO

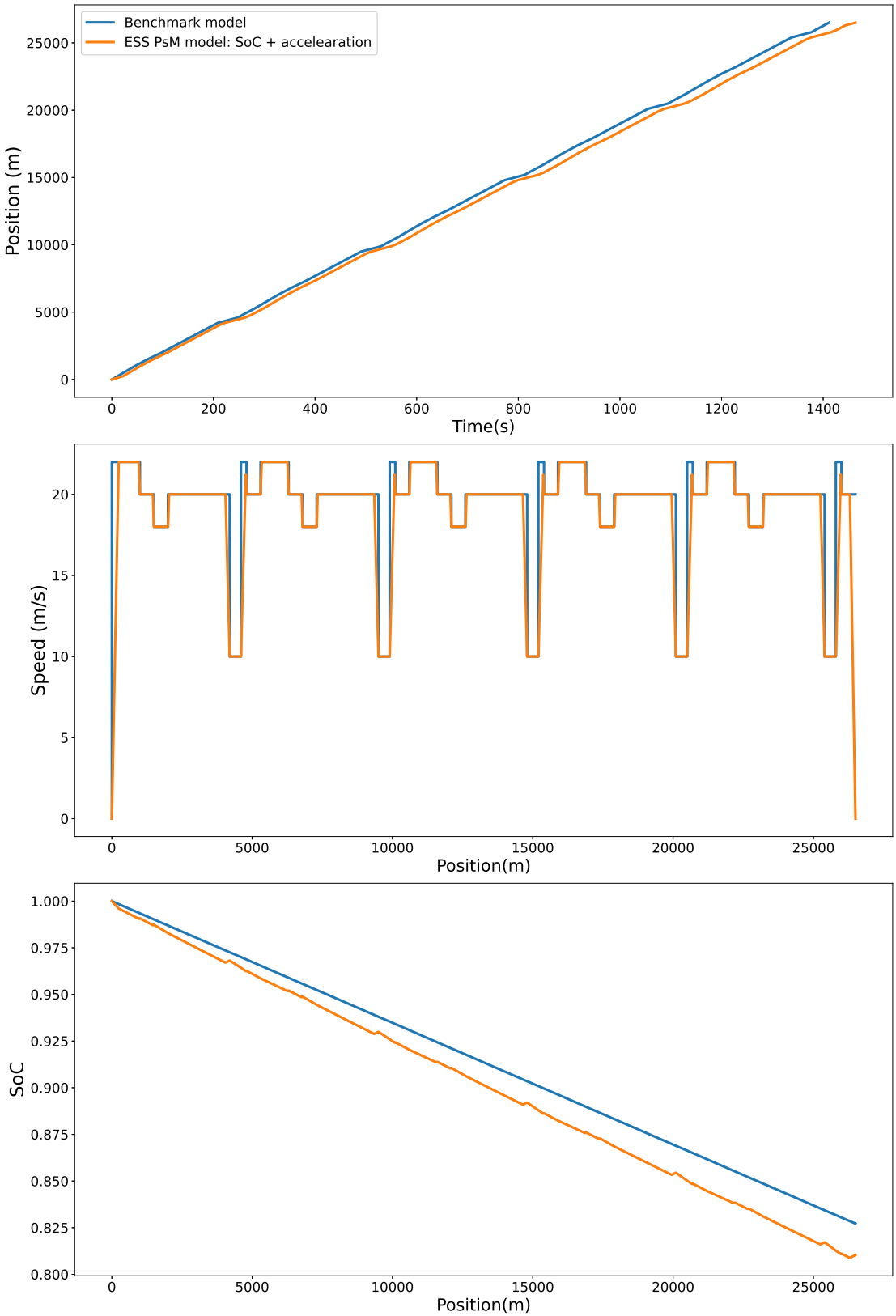

Figure 5.16: Comparison between position, speed and SoC as estimated by the two different models

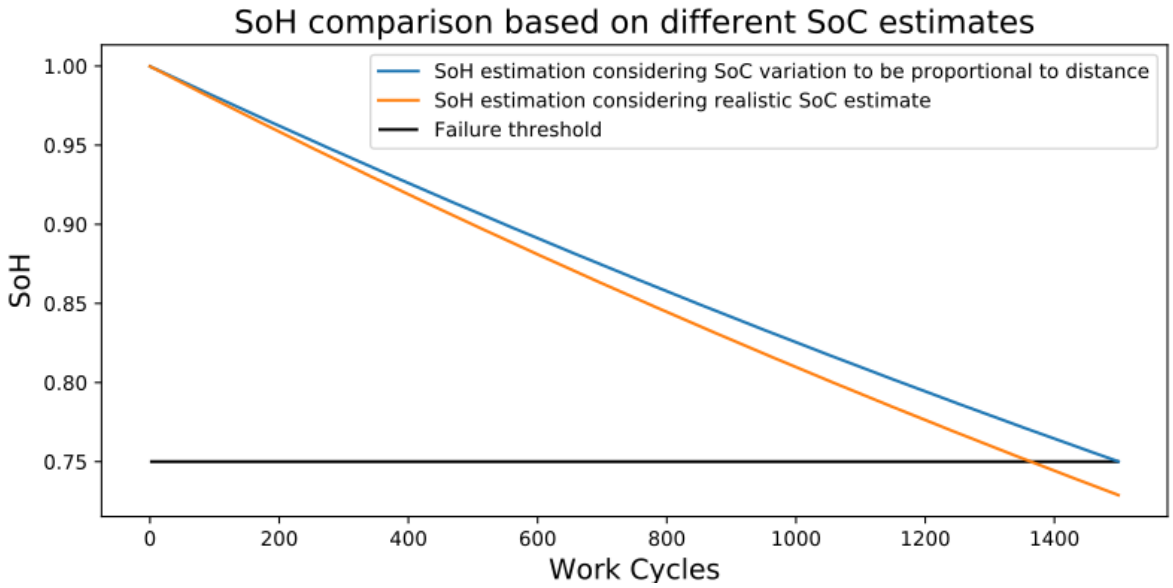

Figure 5.17: Comparison of end of life estimation: PsM SoC model vs benchmark model.

[Lop+18] was used. SUMO is an open source, microscopic, multi-modal traffic simulator, with which it is possible to quantify how the randomness of a more realistic environment can affect degradation estimation based on routes. In SUMO, different vehicles interact with each other, which causes unpredictable stops and deceleration, impacting the quality of the SoC profile estimation. Figure 5.18 shows the comparison between speed and SoC profile, both in a simulation in free flow and in a simulation with other vehicles, randomly moving through space.

In the free flow simulation, the vehicle can freely accelerate until reaching road nominal speed, at which it remains having to break only once due to a curve. The simulation with more vehicles starts similarly but while in road nominal speed, the vehicle reaches a point of the route where it interacts with other vehicles, having to brake and keeping a speed inferior to the nominal one, until being able to accelerate once again. It can also be seen that the presence of other vehicles affected SoC. In free flow, due to the bigger average speed, charge was consumed faster in steady speed. Because charge is intensively consumed while accelerating the total SoC variation was similar in both cases, however, as seen in Figure 6.2, in some cases that does not corresponds to similar degradation.

To quantify how traffic randomness affects cycle degradation estimation, Monte Carlo simulations were carried out. In all simulations a random number of vehicles make random displacements. A chosen vehicle makes the same displacement in every simulation. The PsM ESS model is applied to this displacement, estimating SoH variation. This estimation is compared to the real variation obtained. The results can be seen in Table 5.2 in terms of the damage function f_d.

As can be seen, the error for free flow scenarios is around 6%, which reflects the difference between speed and acceleration profiles predicted through Figure 5.18 and the ones obtained

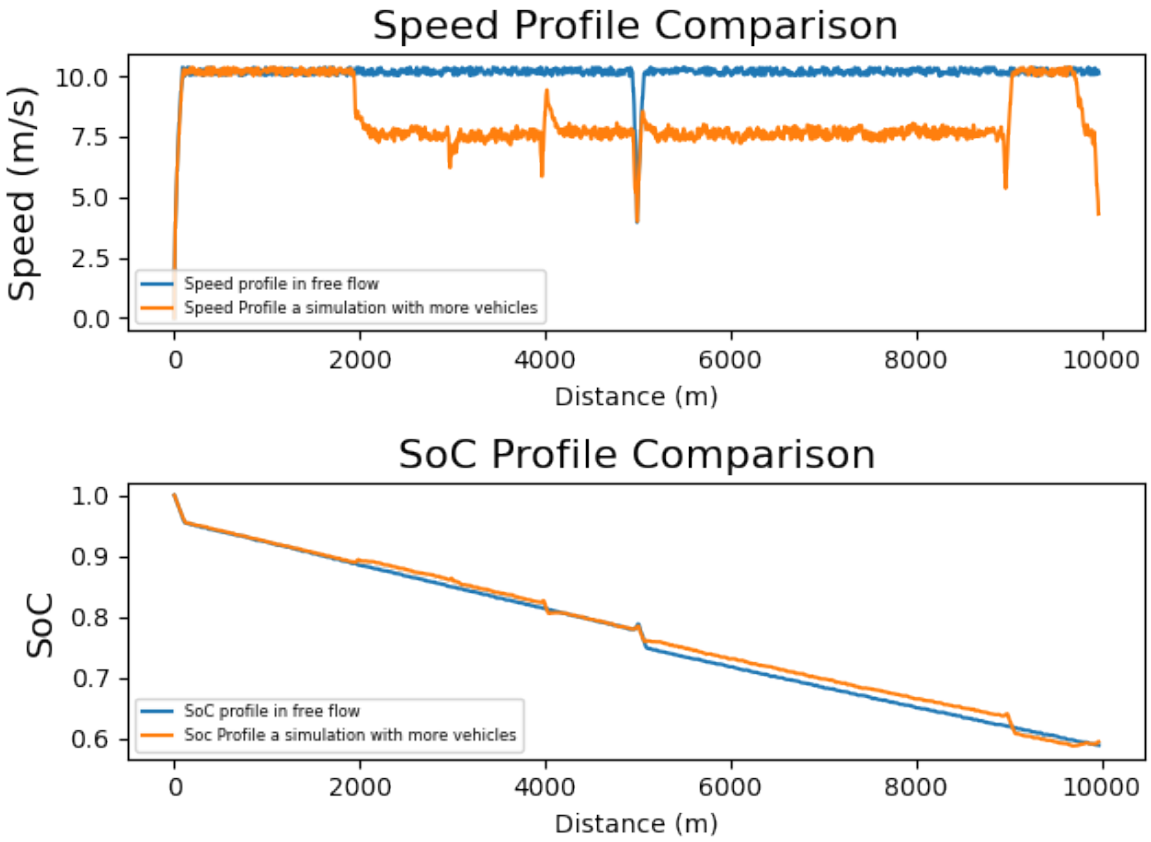

Figure 5.18: Comparison between simulations in free flow and with other vehicles

with SUMO simulations. Error value remains constant for scenarios with few vehicles. With more than 100 random vehicles, their interactions start reducing the accuracy of the f_d estimation.

5.6 Conclusions

In this chapter, a PsM degradation model that can be used to define EV reliability in terms of ESS SoH was presented. To connect degradation to different usage conditions and PsM actions, this model relies on SoC decomposition, which requires accounting battery dynamics and road topology, in order to obtain realistic SoH estimations. Although this PsM model is more complex than common alternatives used in transportation science, its advantages were shown through a set of numerical experiments that illustrate the fact simpler models tend to be more optimistic and can lead to unfeasible optimization solution in reality.

In the next chapter, this model is included in several different PsM optimization problems in order to consolidate the solution presented in Figure 5.1. The computational difficulties introduced by it will be discussed and addressed in details. Numerical experiments are then

Number of vehicles	Normalized f_d error
0	.062
10	.062
50	.064
100	.087
200	.093
400	.128

Table 5.2: Effect of random traffic on the f_d estimation. The f_d function is directly responsible for SoH computation as seen in equation 5.14

performed to validate our optimization model proposes.

Chapter 6

Prescriptive maintenance for electric vehicles: optimization models and implementation

Contents

6.1 Introduction

With the PsM degradation model for the ESS presented in Chapter 5, it is possible to define PsM optimization models to prescribe actions that minimize the overall exploitation cost and optimize vehicle usage in terms of logistics and VPs, as shown in Figure 5.1. In this chapter, different optimization models are presented, corresponding to the different outputs of the PsM ESS application. As such, those optimization models correspond to:

- An original SPP formulation that can account for battery degradation as well as for energy consumption, presented originally in [Lon+22].

- An original EVRP capable that considers energy consumption, time windows and realistic charging profiles, described in [LBE23].
- An extension of this original EVRP in which VPs are also included as decision variables.

Since those original optimization models are based on the ESS degradation model presented in Chapter 5, they become computationally demanding. The exact causes of this computational complexity are discussed in detail in Section 6.2, in order to justify the choices of algorithms and some of the modeling assumptions made.

It is also important to notice that, in the proposed approach, SPPs and EVRPs are solved separately. However, they are connected as the first is used to define paths between missions addresses that become the edges on the graph of the second. Furthermore, since in this original SPP, the cost function depends on the initial SoC and mass of a vehicle, as will be seen in Section 6.3, a series of numerical experiments are necessary to justify solving them independently. Those experiments are presented in Section 6.3.3.2.

6.2 Practical challenges for ESS degradation inclusion on optimization problems

Including the PsM ESS degradation model (Section 6.4) in any optimization problem is non-trivial. The first obvious difficulty arises from the non-linearity of its SoH part. However, two other sources of difficulty deserve special attention. The first one is related to the fact that the SoH model used (Section 5.4.3) relies on SoC cycle decomposition. The second one comes from the fact that the SoC model 5.4.2 used relies on differential equations.

6.2.1 Cycle decomposition and Rainflow counting

SoH estimation depends on breaking SoC in simpler parts refereed to as cycles, as seen in Section 5.4.3. Each cycle contributes to degradation based on its amplitude (DoD), mean value (mSoC) and average temperature. This approach for SoH estimation is useful due to its flexibility and its ability to account for opportunistic recharge. However, cycle decomposition is a non-trivial task. The most used method for that is the Rainflow Counting algorithm. Proposed in 1968 [ME68], in the context of fatigue analyses, it has been used for different application domains [CLS22]; [Mar+16]. Figure 6.1, provides a concrete example of Rainflow decomposition and this algorithm can be informally described as done is [LT12] by:

- Rotate the loading history 90° such that the time axis is vertically downward and the load time history resembles a pagoda roof.
- Imagine a flow of rain starting at each successive extremum point.

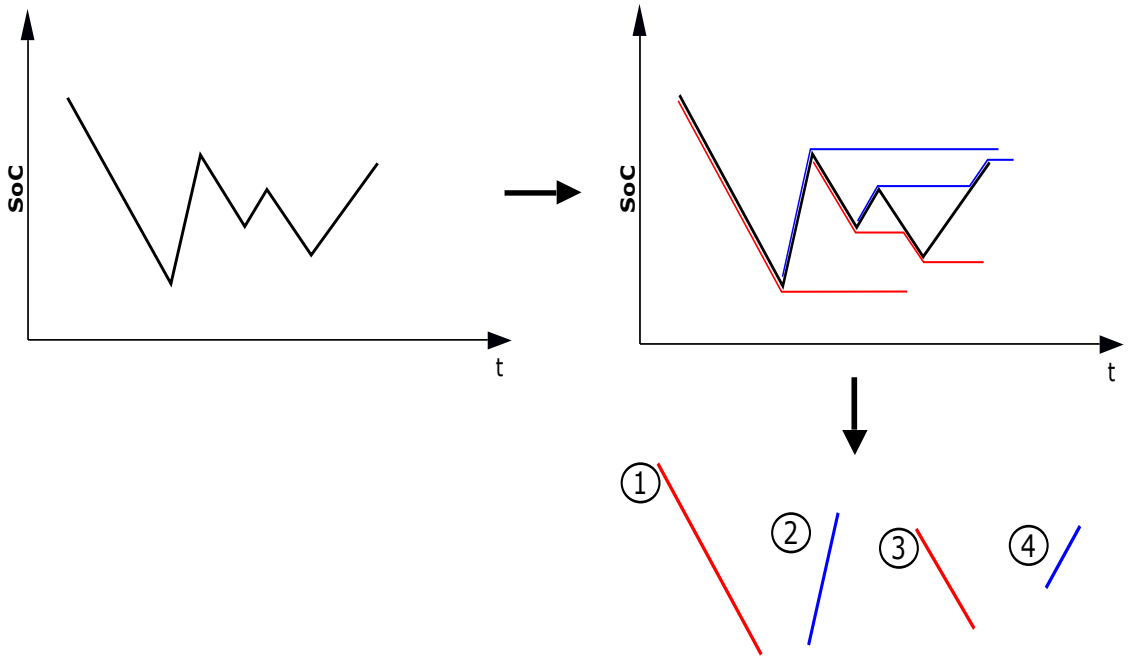

Figure 6.1: Rainflow-Counting applied to a simple $SoC(t)$.

- Define a loading reversal (half-cycle) by allowing each rainflow to continue to drip down these roofs until either:
  - it falls opposite a larger maximum (or smaller minimum) point.
  - it meets a previous flow falling from above.
  - it falls below the roof.
- Identify each hysteresis loop (cycle) by pairing up the same counted reversals.

Its most popular computational implementation is shown in Algorithm 4 [DS82]:

Incorporating this algorithm in a PsM optimization model to characterize degradation is a challenge. The main complication comes from its recursive nature, *i.e.* cycles can only be completely determined by analyzing $SoC(t)$ from beginning to end. For example, if in Figure 6.1 the SoC shown continues to go up, eventually cycle 2 and 4 would be combined, leading to a completely different decomposition. This has significant consequences in terms of optimization models. For instance, as seen in Chapter 3, Dijkstra's algorithm relies on the fact that each edge cost c_{ij} is constant and independent of each other. Using Rainflow Counting to define degradation costs breaks this assumption and paths must be evaluated on their entirety.

Furthermore, this cycle decomposition method is non-linear [Shi+18]. However, there have been optimization applications considering Rainflow Counting that circumvented this problem by exploiting the fact using cycle parameters (such as amplitude and average) as inputs for convex functions, does not affect their convexity, as proven by [Shi+18]. Therefore, including

Algorithm 4 One Pass Rainflow Algorithm [DS82]

Step 1: Read the next peak or valley (if out of data, go to Step 6)
Step 2: Form ranges X and Y (if the vector contains less than 2 points past the starting point, go to Step I)
Step 3: Compare ranges X and Y
if X<Y **then**
go to step 1
end if
if X = Y and Y contains S **then**
go to Step 1
end if
if X> Y and Y contains S **then**
go to Step 4
end if
if X $\geq$ Y and Y does not contain S **then**
go to Step 5
end if
Step 4: Move S to the next point in the vector Go to Step 1
Step 5: Count range Y Discard the peak and valley of Y Go to Step 2
Step 6: Read the next peak or valley from the beginning of the vector E(n) (if the starting point, S, has already been reread, STOP)
Step 7: - Form ranges X and Y (if the vector contains less than 2 points past the starting point, go to Step 6)
Step 8: Compare ranges X and Y
if X<Y **then**
go to Step 6
end if
if X$\geq$Y **then**
go to Step 9
end if
Count range Y Discard the peak and valley of Y
Go to Step 7

Rainflow Counting leads to non-linear optimization models that are at least convex, and, as such, more manageable from a computational point of view.

6.2.2 Battery dynamics as differential equations

As seen in Section 5.5, considering battery dynamics is useful for having better estimates of $SoC(t)$, which leads to more realistic evaluations of vehicle maximum range and battery degradation. However, as seen previously, this requires solving a system of differential equations. Albeit the existence of several efficient numerical integration methods, exact VRP optimization requires evaluating a large number of possible candidates, which in practice can be limiting.

Furthermore, since SoC evolution in each road link depends on the values of the dynamic variables presented in Section 5.4.2, SoC variation will depend on previously visited edges of the graph. This makes classical formulations of constraint SPPs and EVRPs, hard to mimic, since resource consumption cannot be seen as constant and independent of previous displacements.

Possible approaches for circumventing the use of differential equations are discussed in [Pel+17]. They propose either simplifying battery dynamics by considering constant OCV and discretizing the differential equations describing SoC. However, it is possible to find an optimal path or route that would be unfeasible in reality, since battery dynamics could be over simplified. To avoid this issue, in this work, candidate solutions of the optimization problems will always be evaluated by considering battery dynamics as described in Section 5.4.2. In future works, though, the simplifications proposed by [Pel+17] could be used for deriving surrogate models and reduce computation time.

6.3 Shortest paths problem accounting for battery degradation

6.3.1 Motivation and problem formulation

In most SPPs for EVs, cost functions are defined in terms of energy consumption and travel time [Bau+20]; [Tu+20]; [Sto12]. However, when analyzing the SoH model presented in Section 5.3.1, it is possible to see how including degradation may affect a SPP. For example, Figure 6.2 shows an example of two $SoC(t)$ obtained with paths P^1_{st} and P^2_{st}. As can be seen, net SoC variation is the same, which means that energy consumption is also probably similar, however, $SoC_1(t)$ present more opportunistic recharges, which create small SoC cycles and cause more degradation. In classical SPPs, both paths would be considered equivalent, justifying the inclusion of battery degradation in addition to energy consumption in a SPP, in order to achieve RUL extension in realistic scenarios. A discussion on the impact of degradation on path selection can also be found in [PA20], even though authors have employed over simplified degradation models.

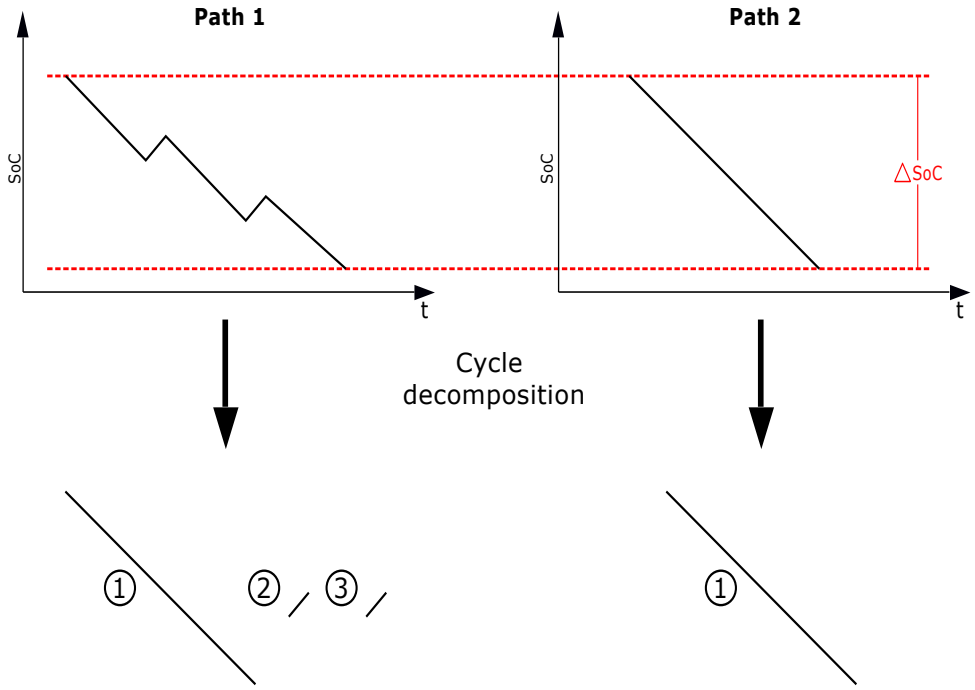

Figure 6.2: $SoC(t)$ for paths considered equivalent in classical SPPs

To define a SPP optimization model capable of including degradation, it is necessary to define a graph $G_r = (N_r, E_r)$ that represents the real road network with E_r being road links, defined in Section 5.4.1, and N_r representing road links intersections. Then, by defining P_{st} as a path connecting source and target nodes s and $t \in N_r$ and the following decision variables x_{ij}:

$$x_{ij} = \begin{cases} 1, & \text{if the road link between i and j is part of} P_{st} \\ 0, & \text{otherwise} \end{cases} \tag{6.1}$$

two costs can be considered. The first one represents energy consumption costs. It is commonly included in SPP problems for EVs and can be expressed as:

$$c^{sp}_{energy} = c_e \sum_{i \in N_r} \sum_{j \in N_r} e_{ij} x_{ij} \tag{6.2}$$

where c_e is a constant that describes the energy price and e_{ij} is the total energy consumed while going from node i to node j, calculated by integrating the electrical power (Equation 5.9). The second one represents degradation and is designed specially for PsM applications. It can be expressed as:

$$c^{sp}_{deg} = c_{bat}(SoH(X) - SoH_0) \tag{6.3}$$

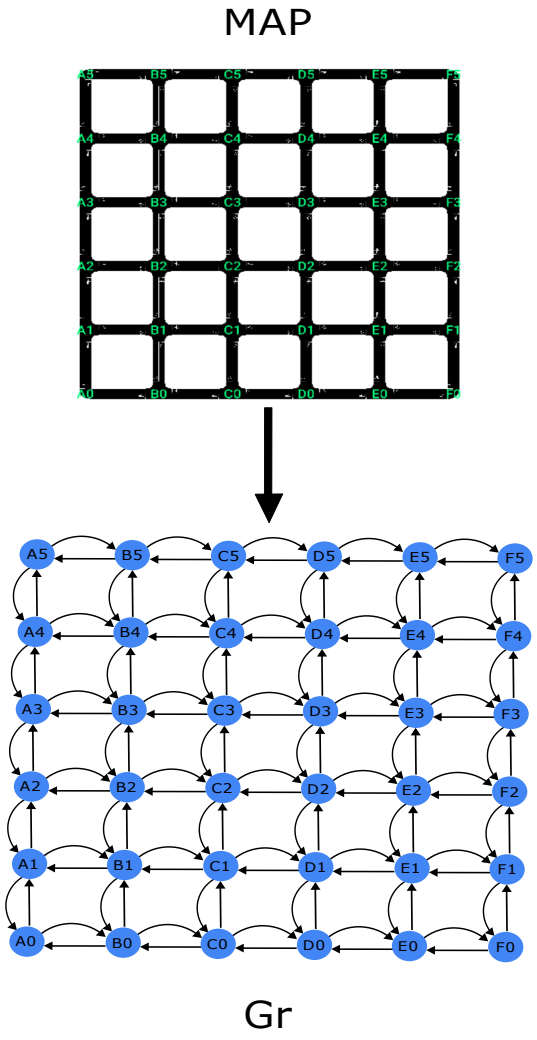

Figure 6.3: G_r construction. This graph is generated based on the concept of road link, discussed in Section 5.4.1. In this example, G_r is built upon a very simple Manhattan and therefore. Links are only defined by crossroads and steep curves, therefore, N_r corresponds to the intersections of the grid, as can be seen.

where $X = \{x_{ij} : x_{ij} = 1\}$. Constant c_{bat} is proportional to a new battery cost. SoH_0 is the initial SoH at source node s. $SoH(X)$ is the SoH after traveling through the path, estimated with the PsM model presented in Section 5.4. It requires using X and the corresponding visited edges E_r to estimate $a(t)$ on the path, solving the differential equations that define $SoC(t)$ and applying the cycle decomposition SoH model. The complete SPP-PsM model can then be expressed as:

$$\min \quad c^{sp}_{energy} + c^{sp}_{deg} \tag{6.4}$$

Subjected to:

$$\sum_{i \in N_r} x_{ij} - \sum_{j \in N_r} x_{ji} = \begin{cases} 1, & \text{if } j = t \\ -1, & \text{if } i = s \\ 0 & \text{otherwise} \end{cases} \quad \forall i, j \in N_r \tag{6.5}$$

$$SoC(t, X) \geq SoC_{crit} \quad \forall z \in Z, \forall t \tag{6.6}$$

$$x_{ij} \in \{0, 1\} \forall i, j \in N_r \tag{6.7}$$

where $SoC(t, X)$ is the $SoC(t)$ obtained through numerical integration as discussed in Section 5.4.2. Constraint 6.5 ensures that the solutions correspond to path starting at s and ending in t with all nodes in between connected. Constraint 6.6 guarantees feasible paths in terms of vehicle range. Constraint 6.7 defines the appropriate range of decision variables. Additionally, the following hypothesis are made:

- All information necessary to characterize each road link in E_r is known in advance, which includes maximal allowed speed, road inclination, presence of crossroads, traffic lights, etc.
- All relevant variables to solve the dynamic system defining SoC are known, such as resistances and capacitors values, initial SoC, etc.

6.3.2 Optimization algorithm

As previously discussed, since the cost function depends on the ESS PsM model, using classical optimization algorithms is unpractical due to the presence of differential equations and the recursiveness of cycle decomposition. Therefore, meta-heuristic techniques called Genetic Algorithm (GA) [KCK21] were used. GA is a technique for solution space search that is based on evolution theory. This technique revolves around creating an initial set of solution candidates (chromosomes), evaluating each of them, and combining the best ones (crossover), obtaining a new set of solution candidates. This process is repeated until a stopping condition

Algorithm 5 Classical GA structure [KCK21]

```
Generate an initial population of candidate solutions
Set Stop = False
while Stop == False do
    Compute the fitness of each chromosome
    Select pairs of chromosomes based on fitness
    Apply crossover operations on selected pairs to obtain a new population
    Apply mutation operators on the new population
    Evaluate stop condition
end while
Return best chromosome found
```

is triggered and the best chromosome found is used and an approximation of the optimal solution [KCK21]. In its classical formulation, it can be described by Algorithm 5.

There are several ways of generating the initial population. The most common approach is to initialize it at random. At each step of the process, the population fitness (usually the inverse of the cost function) is computed and chromosomes are selected to go through crossover which is the process of mixing chromosomes to efficiently search the solution space. Finally, the population of new candidate solutions goes through mutation, which is an operation that introduces random changes on chromosomes in order to avoid local minima. This process is repeated until a stop condition is met. In most cases, this condition relates to maximum number of iterations. For this SPP variation, the chromosome representation, crossover mechanism and mutations were the same as proposed in [GCW97]. To account for the SoC Constraint 6.6, the chosen approach is to penalize infeasible solutions through their fitness metric, which, for this algorithm, is:

$$fit = \frac{e^{-\zeta}}{c^{sp}_{energy} + c^{sp}_{deg}} \tag{6.8}$$

with

$$\zeta = \alpha \; max[SoC_{limit} - SoC_{min}(r, v_{max}, a_{max}), 0] \tag{6.9}$$

where α is a positive constant. This approach penalizes solutions that do not respect the constraint over SoC, making them unlikely to be selected as optimal, but also allows the algorithm to explore those solutions through generations, potentially avoiding local minima. The selection of parents for crossover is done by tournament selection, *i.e.* pairs of possible chromosomes are randomly selected and their fitness function is compared. The one with the higher fit is selected to go through crossover.

6.3.3 Numerical experiments

6.3.3.1 Benefits of considering degradation on path selection

To asses the benefits of the proposed approach when compared to classical SPPs, a first set of simulations was performed. They were based in the Manhattan-like grid map shown in Figure 6.3, in which nominal speeds were different for each segment. As a benchmark solution, a typical SPP, based on travel time minimization, was used. The cost constants used were $c_{bat} = 5000$ and $c_e = 0.1(\$/kWh)$. To asses long-term impacts of the PsM SPP, the routes found by each model, to go from $A_0 \rightarrow F_5$, were repeated several times in order to estimate the effects on SoH as seen in Figure 6.4. In this example, linearly extrapolating SoH in both cases, for an end of life threshold of 75%, a vehicle repeating the PsM SPP would be able to perform this displacement approximately 7.2% more times than in the benchmark path.

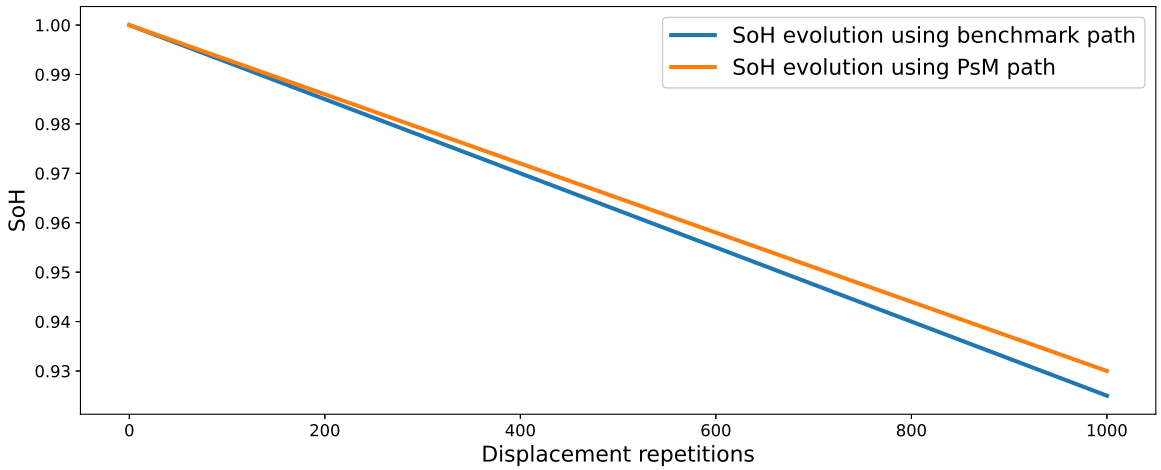

Figure 6.4: Long term comparison between the two vehicles, following the different paths found, in terms of SoH

It is also important to highlight that this experiment was conducted in an extremely simple map in which there were not several different path possibilities to go from source to target. In more complex maps, it is safe to suppose that the effects could be even more significant.

6.3.3.2 Paths and routing independency

SPPs are important to VRPs, since they are used to build the edges on the VRP graph. In most cases, SPPs can be solved separately to VRPs, since the length of the path does not depend on the order missions are performed. However, as discussed before, this is not the case when considering the PsM degradation model. To justify solving EVRPs and SPPs independently, it is necessary to study the impact that variables such as SoC and vehicle mass, that change during vehicle displacements, have on the paths found. A second set of numerical experiments was performed with that purpose and the results are shown in Table 6.1.

Origin–Destination	Initial Conditions	Route	Cost
$A_0 \to F_5$	M = 10700, $SoC_0 = 100$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	4.48
$A_0 \to F_5$	M = 11700, $SoC_0 = 100$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	4.91
$A_0 \to F_5$	M = 12700, $SoC_0 = 100$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	5.33
$A_0 \to F_5$	M = 10700, $SoC_0 = 80$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	4.49
$A_0 \to F_5$	M = 11700, $SoC_0 = 80$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	4.91
$A_0 \to F_5$	M = 12700, $SoC_0 = 80$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	5.35
$A_0 \to F_5$	M = 10700, $SoC_0 = 60$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	4.49
$A_0 \to F_5$	M = 11700, $SoC_0 = 60$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	4.92
$A_0 \to F_5$	M = 12700, $SoC_0 = 60$	A0, A1, A2, A3, A4, A5, B5, C5, D5, E5, F5	5.32
$A_0 \to D_4$	M = 10700, $SoC_0 = 100$	A0, A1, A2, A3, A4, B4, C4, D4	3.22
$A_0 \to D_4$	M = 11700, $SoC_0 = 100$	A0, A1, A2, A3, A4, B4, C4, D4	3.51
$A_0 \to D_4$	M = 12700, $SoC_0 = 100$	A0, A1, A2, A3, A4, B4, C4, D4	3.81
$A_0 \to D_4$	M = 10700, $SoC_0 = 80$	A0, A1, A2, A3, A4, B4, C4, D4	3.22
$A_0 \to D_4$	M = 11700, $SoC_0 = 80$	A0, A1, A2, A3, A4, B4, C4, D4	3.52
$A_0 \to D_4$	M = 12700, $SoC_0 = 80$	A0, A1, A2, A3, A4, B4, C4, D4	3.81
$A_0 \to D_4$	M = 10700, $SoC_0 = 60$	A0, A1, A2, A3, A4, B4, C4, D4	3.21
$A_0 \to D_4$	M = 11700, $SoC_0 = 60$	A0, A1, A2, A3, A4, B4, C4, D4	3.51
$A_0 \to D_4$	M = 12700, $SoC_0 = 60$	A0, A1, A2, A3, A4, B4, C4, D4	3.81

Table 6.1: Influence of initial conditions on the optimal path

As expected, the costs of each path are affected by the initial conditions. Heavier masses require more energy, which is expected to generate SoC cycles with larger amplitude, causing more degradation. Those differences, however, were not extremely significant, and, as can be seen, the shortest path never changed for different initial conditions. This indicates that addressing SPPs and EVRPs independently is reasonable in this PsM application. Similar conclusions were found in [Bas+19], for more complex maps in the context of energy estimation. Knowing the path selection is robust to initial conditions, this SPP can be used to set-up an EVRP that accounts for battery degradation. This original EVRP formulation is presented in the following section.

6.4 Vehicle routing accounting for battery degradation

6.4.1 Problem formulation

A second optimization model is proposed to address routing. It considers a new graph $G_{evrp} = (N_{evrp}, E_{evrp})$. With $N_{evrp} = C \cup S \cup 0$ where C is the set of nodes representing mission addresses, S is the set of charging stations and 0 represents the headquarters, where vehicles start and to where they must come back at the end of their missions. The set E_{evrp} represents the paths connecting those each node. Therefore, the graph G_{evrp} can be built from G_r by solving the PsM SPP for each node pair in N_{evrp} as discussed and illustrated by Figure 6.5. Additionally, a set Z representing the fleet of vehicles is considered together with the following decision variables:

$$x_{ijz} = \begin{cases} 1, & \text{if vehicle } z \text{ drives from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases} \tag{6.10}$$

and

- p_{ijz}, the payload of vehicle z while going from i to j
- y_{ijz}, the arrival time of vehicle z at node j from node i
- f_{jz}, the time spent by vehicle z on recharge station i

Notice that, in contrast to the PsM routing model presented in Chapter 4, p_{ijz} is also considered since vehicle mass impacts power and, as a consequence, SoC. Therefore, those decision variables define all relevant aspects of a route, both in terms of logistics and degradation. Analogously to the SPP presented in Section 6.3, a set X_z is considered:

$$X_z = \{x_{ijz} = 1 \forall i, j \in N_{evrp}, z \in Z\} \tag{6.11}$$

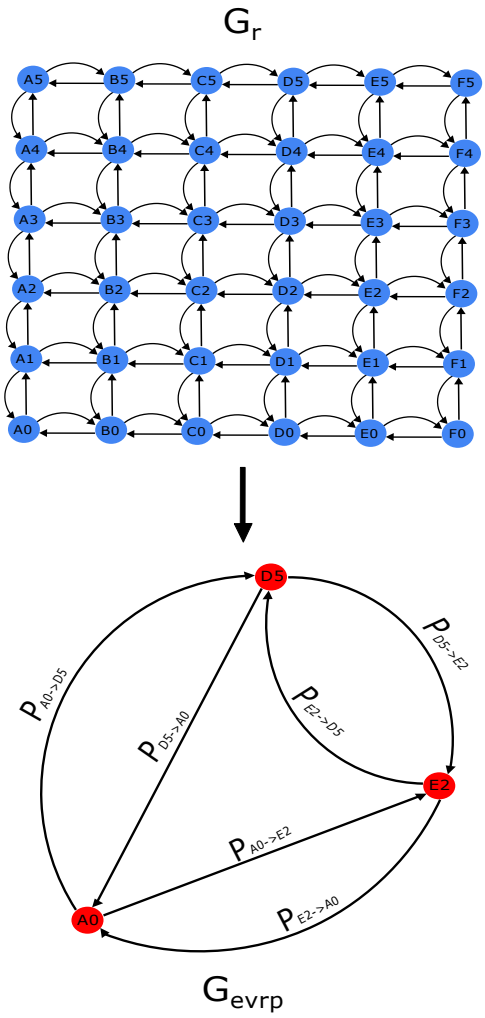

Figure 6.5: G_{evrp} construction. It is build from G_r, considering only the headquarter and nodes where deliveries and charges can occur. The nodes of G_{evrp} correspond to the shortest paths between its nodes.

defining the routes of vehicle z. In order to establish all constraints of this EVRP, it is useful to define the following variables:

- P, the maximum vehicle payload.
- t_{ij}, the time necessary to go from i to j
- $SoC(t, X_z)$ which indicates SoC at instant t for a vehicle following a mission plan X_z
- e_{ijz} which is the energy consumed by vehicle z to go from node i to node j.
- l_j which is the deadline of point j.
- p_i which is the total mass variation of a vehicle after performing a delivery in node i.

The cost function used for describing this EVRP is composed of three terms:

$$C^{evrp} = c^{evrp}_{deg} + c^{evrp}_{energy} + c^{evrp}_{delay} \tag{6.12}$$

- The degradation cost c^{evrp}_{deg} is proportional to the amount of SoH lost in a particular mission plan and can be expressed as:

$$c^{evrp}_{deg} = c_{batt} \sum_{z \in Z} (SoH_{0z} - SoH(X_z)) \tag{6.13}$$

  where SoH_{0z} is the initial SoH of vehicle z and $SoH(X_z)$ is the expected SoH after following a mission plan z.

- The energy cost c^{evrp}_{energy} is directly proportional to the consumed energy and is described by:

$$c^{evrp}_{energy} = c_e \sum_{z \in Z} \sum_{i \in N_{evrp}} \sum_{j \in N_{evrp}} e_{ijz} x_{ijz} \tag{6.14}$$

- The delay cost c^{evrp}_{delay} is considered to be proportional to delays and can be expressed as:

$$c^{evrp}_{delay} = c_d \sum_{z \in Z} \sum_{i \in N_{evrp}} \sum_{j \in C} x_{ijz} \max[y_{ijz} - l_j, 0] \tag{6.15}$$

The final optimization problem can then be described as:

$$\min \quad C^{evrp} \tag{6.16}$$

Subjected to:

$$\sum_{z\in Z}\sum_{j\in C} x_{ijz} = 1 \quad \forall i \in N_{evrp} \tag{6.17}$$

$$\sum_{j\in N_{evrp}} x_{0jz} = 1 \quad \forall z \in Z \tag{6.18}$$

$$\sum_{j\in S} x_{ijz} \leq 1 \quad \forall i \in N_{evrp}, \forall z \in Z \tag{6.19}$$

$$\sum_{j\in N_{evrp}} x_{ijz} - \sum_{j\in N_{evrp}} x_{jiz} = 0 \quad \forall i \in N_{evrp}, \forall z \in Z \tag{6.20}$$

$$\sum_{z\in Z}\sum_{j\in N_{evrp}} p_{ijz} - \sum_{z\in Z}\sum_{j\in N_{evrp}} p_{jiz} = p_i \quad \forall i \in N_{evrp} \tag{6.21}$$

$$p_j x_{ijz} \leq p_{ijz} \leq (P - p_i)x_{ijz} \quad \forall i \in N_{evrp}, \forall z \in Z \tag{6.22}$$

$$y_{0jz} \geq t_{0j} x_{0jz} \quad \forall j \in C \cup S, \forall z \in Z \tag{6.23}$$

$$\sum_{z\in Z}\sum_{j\in N_{evrp}} y_{ijz} - \sum_{z\in Z}\sum_{j\in N_{evrp}} y_{jiz} \geq t_{ij} x_{ijz} \quad \forall i \in C \tag{6.24}$$

$$\sum_{z\in Z}\sum_{j\in N_{evrp}} y_{ijz} - \sum_{z\in Z}\sum_{j\in N_{evrp}} y_{jiz} \geq t_{ij} x_{ij} + f_{iz} \quad \forall i \in S \tag{6.25}$$

$$SoC(t, X_z) \geq SoC_{crit} \quad \forall z \in Z, \forall t \tag{6.26}$$

$$x_{ijz} \in \{0, 1\} \tag{6.27}$$

$$x_{ijz} \in \{0, 1\} \tag{6.28}$$

$$p_{ijz} \geq 0 \tag{6.29}$$

$$y_{ijz} \geq 0 \tag{6.30}$$

Inequality (6.17) ensures that every client is visited once. Constraint (6.18) guarantees that the number of vehicles used does not exceed the fleet size $|Z|$. Constraint (6.19) limits the number of visits to recharge stations. To allow multiple visits to the same station, copies of that station must be added to the set S. Constraint (6.20) ensures that there is one outgoing arc to each incoming arc. Constraint (6.21) guarantees that, at each delivery, the payload is reduced accordingly since $p_i = 0 \quad \forall i \in S \cup 0$, while (6.22) ensures that the maximum payload P is respected. It also forces $p_{ijz} = 0$ when $x_{ijz} = 0$. Constraints (6.23) through (6.25) describe arrival time evolution, ensuring that the displacements and charging duration are respected. Constraint (6.26) imposes range limitations through SoC, which model is obtained through the PsM degradation model. Finally, Constraints (6.27) through (6.30) define the acceptable range of each decision variable.

Notice that, in contrast to the VRP proposed in Chapter 4, there are no constraints related to arrival times. This choice is made since GAs are used for this PsM application. From the point of view of a GA, adding constraints and penalizing solutions through cost increase is equivalent. By explicitly introducing c^{evrp}_{delay} instead of a constraint, this penalization can be

done in a less aggressive way. This is useful to ensure chromosome variability through the generations, specially when considering VP optimization, that, as will be seen, has a direct impact on arrival times.

6.4.2 Including parameter reconfiguration into routing

As discussed in Chapter 3, due to the nature of heavy vehicle applications, it is necessary to consider parameter reconfiguration within the context of logistics. This is specially true for the ESS, since the Vehicle Parameters (VPs) considered, are related to speed and acceleration limitations and will impact deadlines. To add this PsM action in the routing process, besides the decision variables listed in Section 6.4 the following are also included:

- $a^{vh}_{max_z}$ which is the maximum acceleration of vehicle z.
- $v^{vh}_{max_z}$ which is the maximum speed of vehicle z.

Furthermore, since several variables are affected by $a^{vh}_{max_z}$ and $v^{vh}_{max_z}$, notation must change, which leads to the following terms:

- $t_{ij}(v^{vh}_{max_z}, a^{vh}_{max_z})$, the time necessary to go from i to j for a vehicle with maximum acceleration $a^{vh}_{max_z}$ and maximum speed $v^{vh}_{max_z}$.
- $SoC(t, X_z, v^{vh}_{max_z}, a^{vh}_{max_z})$ which indicates SoC at instant t for a vehicle with maximum acceleration $a^{vh}_{max_z}$ and maximum speed $v^{vh}_{max_z}$ following a mission plan defined by X_z.
- $e_{ijz}(v^{vh}_{max_z}, a^{vh}_{max_z})$ which is the energy consumed by vehicle z to go from node i to node j for a vehicle with maximum acceleration $a^{vh}_{max_z}$ and maximum speed $v^{vh}_{max_z}$.

The cost function considering VPs is then:

$$C^{evrp-vp} = c^{evrp-vp}_{deg} + c^{evrp-vp}_{energy} + c^{evrp-vp}_{delay} \tag{6.31}$$

where degradation cost $c^{evrp-vp}_{deg}$ is:

$$c^{evrp-vp}_{deg} = c_{batt} \sum_{z \in Z} (SoH_0 - SoH(X_z, v^{vh}_{max_z}, a^{vh}_{max_z})) \tag{6.32}$$

with $SoH(X_z, v^{vh}_{max_z}, a^{vh}_{max_z})$ depending on $v^{vh}_{max_z}$ and $a^{vh}_{max_z}$. The energy cost $c^{evrp-vp}_{energy}$ becomes:

$$c^{evrp-vp}_{energy} = c_e \sum_{z \in Z} \sum_{i \in N_{evrp}} \sum_{j \in N_{evrp}} e_{ijz}(v_{max_z}, a_{max_z}) x_{ijz} \tag{6.33}$$

where now, the consumed energy $e_{ijz}(v_{max_z}, a_{max_z})x_{ijz}$ depends on v_{max_z} and a_{max_z}. The delay cost $c_{delay}^{evrp-vp}$ remains the same as the one in Section 6.4, since the effect of VPs on y_{zij} is captured by $t_{ij}(v_{max_z}^{vh}, a_{max_z}^{vh})$. The final optimization problem is then:

$$\min \quad C^{evrp-vp} \tag{6.34}$$

Subjected to:

$$\sum_{z\in Z}\sum_{j\in C} x_{ijz} = 1 \quad \forall i \in N_{evrp} \tag{6.35}$$

$$\sum_{j\in N_{evrp}} x_{0jz} = 1 \quad \forall z \in Z \tag{6.36}$$

$$\sum_{j\in S} x_{ijz} \leq 1 \quad \forall i \in N_{evrp}, \forall z \in Z \tag{6.37}$$

$$\sum_{j\in N_{evrp}} x_{ijz} - \sum_{j\in N_{evrp}} x_{jiz} = 0 \quad \forall i \in N_{evrp}, \forall z \in Z \tag{6.38}$$

$$\sum_{z\in Z}\sum_{j\in N_{evrp}} p_{ijz} - \sum_{z\in Z}\sum_{j\in N_{evrp}} p_{jiz} = h_i \quad \forall i \in N_{evrp} \tag{6.39}$$

$$p_j x_{ijz} \leq p_{ijz} \leq (P - p_i)x_{ijz} \quad \forall i \in N_{evrp}, \forall z \in Z \tag{6.40}$$

$$y_{0jz} \geq t_{0j}(v_{max_z}, a_{max_z})x_{0jz} \quad \forall j \in C \cup S, \forall z \in Z \tag{6.41}$$

$$\sum_{z\in Z}\sum_{j\in N_{evrp}} y_{ijz} - \sum_{z\in Z}\sum_{j\in N_{evrp}} y_{jiz} \geq t_{ij}(v_{max_z}^{vh}, a_{max_z}^{vh})x_{ijz} \quad \forall i \in C \tag{6.42}$$

$$\sum_{z\in Z}\sum_{j\in N_{evrp}} y_{ijz} - \sum_{z\in Z}\sum_{j\in N_{evrp}} y_{jiz} \geq t_{ij}(v_{max_z}^{vh}, a_{max_z}^{vh})x_{ij} + f_{iz} \quad \forall i \in S \tag{6.43}$$

$$min \quad SoC(t, X_z, v_{max_z}, a_{max_z}) \geq SoC_{crit} \quad \forall z \in Z, \forall t \tag{6.44}$$

$$x_{ijz} \in \{0, 1\} \tag{6.45}$$

$$p_{ijz} \geq 0 \tag{6.46}$$

$$y_{ijz} \geq 0 \tag{6.47}$$

$$v_{max_z} \in [v_{max}^-, v_{max}^+] \tag{6.48}$$

$$a_{max_z} \in [a_{max}^-, a_{max}^+] \tag{6.49}$$

Constraints 6.35 to 6.47 are equivalent to the ones presented in Section 6.4 while 6.48 and 6.49 determine the range of v_{max_z} and a_{max_z} respectively.

6.4.3 Optimization algorithm

As with the SPP, this optimization problem is solved with GAs. Since the representation of chromosomes in this case is original, it will be detailed in this section. In this EVRP,

chromosomes consist of four parts: a mission plan π, a set of maximum speeds v_{max_z}, a set of maximum accelerations a_{max_z} and a set of recharge times f_{iz}. Figure 6.6 shows an example of a chromosome. It encodes a solution for a two vehicle fleet. Vehicle 1 goes from node A0 to B3, then to E4 and so on. Its speed is limited to 60 km/h and its acceleration to 1 m/s^2. Similarly, Vehicle 2 goes from A0 to C5 and so on, with a speed limited to 80 km/h and a maximum acceleration of 0.5 m/s^2. Both of them will recharge their batteries for 1800 seconds in recharge station $E4$.

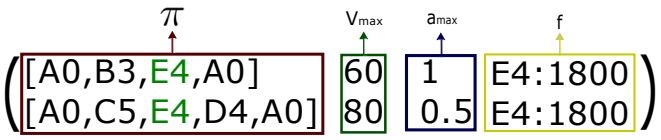

Figure 6.6: Solution representation.

To initiate the algorithm, random solutions are created. The mission plan is created by first choosing a permutation of the client nodes C. Recharge stations are randomly chosen from nodes S and can be placed between each mission with probability 0.5 and finally, the headquarters is assigned at the beginning and end of the mission plan. This ensures that no client is visited more than once, and that all vehicles return to the headquarters. To generate the VPs, v_{max_z} and a_{max_z} are sampled from a uniform distribution on the respective ranges of those variables.

Chromosome fitness is computed analogously to the SPP case. The best solution candidate go through crossover. The first step of the crossover operation is illustrated in Figure 6.7. It starts by splitting a candidate solution into two different parts, the first of which contains the set of missions, in the order they were assigned to each vehicle. The second one contains VPs and recharge times. The set of missions is then split once again into a part containing missions and the other, recharge points alongside with zeros. Notice that, in this process, the headquarters is ignored. The mission part will undergo order cross over, while the recharge parts undergo a one-point crossover, with the constraint that off-springs must contain the same number of zeros (representing the clients) as the parents. Finally, the remaining crossover mechanism for the scalar part (VPs and recharging times) is simply the average of speeds and acceleration of each vehicle and recharging time in case both candidate solutions share the same recharging station. After this process, the clients and recharge parts are recombined and split into the fleet. This split process is performed keeping the number of missions per truck as close as possible to that of the parents. An additional correction is made to ensure that no consecutive points in the solution form 6.6 are the same.

The proposed mutation operator splits the candidate solutions in missions, VPs and recharge times once again. In the mission part, random swaps can happen as shown in Figure 6.8. The scalar quantities of the solution are perturbed by random noise.

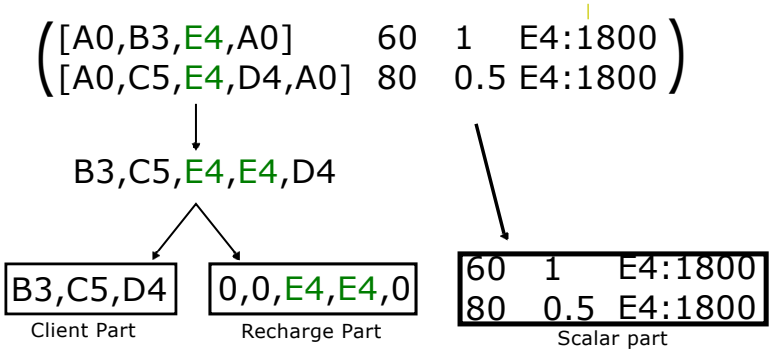

Figure 6.7: First step on the crossover operation.

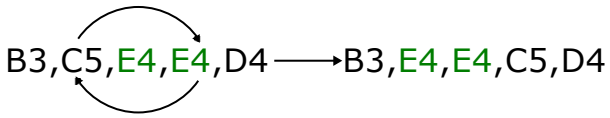

Figure 6.8: Mutation operation for the mission part

6.4.4 Numerical experiments

6.4.4.1 Results on a synthetic network

This first set of experiments was conducted in the same Manhattan-like map used for the SPPs. Different instances of the problem were created by randomly selecting the nodes to define G_{evrp}. They were solved with different cost parameters to investigate how taking degradation into account impacts routes. Solving an instance considering $c_{batt} = 0$ is equivalent to a classic EVRP. When $c_e = 0$ routes minimize only degradation, ignoring energy consumption. Finally having $c_{batt} \neq 0$ and $c_e \neq 0$ the problem becomes the discussed PsM version of the EVRP. The vehicle and battery parameters used are shown in Table 6.2.

The results are reported in Table 6.3. It is possible to see that accounting for degradation ($c_{batt} \neq 0$) impacts the mission plan. Plans that account for degradation either have

Parameter	Value
m	10700 (kg)
SoC_0	1
C_s	1498.26 (F)
R_s	0.01902(Ω)
C_l	120 (F)
R_l	0.02221 (Ω)
R_0	0.03417(Ω)
C_0	65453.28 (F)

Table 6.2: Simulation parameters

Instance	c_{batt}	c_d	c_e	Mission plan	$C^{evrp-vp}$
1	10000	1	0.18	A0, E0, $E1^*$, E3, D5, A4, A2, A0	8.60
1	0	1	0.18	A0, E0, E3, D5, A4, A2, A0	8.63
1	10000	1	0	A0, E0, $E1^*$, E3, $D4^*$, D5,A4, A2, A0	8.62
2	10000	1	0.18	A0, E0, $E1^*$, E3, E5, A4, A2, A0	9.55
2	0	1	0.18	A0, E0, E3, E5, A4, A2, A0	9.60
2	10000	1	0	A0, E0, $E1^*$, E3, E5, $D4^*$, A4, A2, A0	9.57
3	10000	1	0.18	A0, B1, C5, F5, F2, $D2^*$, A2, A0	9.56
3	0	1	0.18	A0, B1, C5, F5, F2, A2, A0	10.52
3	10000	1	0	A0, B1, C5, F5, F2, $D2^*$, A2, $A1^*$, A0	9.58
4	10000	1	0.18	A0, B1, B3, $D3^*$, F3, C0, A0	7.65
4	0	1	0.18	A0, B1, B3, F3, C0, A0	7.73
4	10000	1	0	A0, B1, B3, $D3^*$, F3, $C1^*$, C0, A0	7.68

Table 6.3: EVRP result when considering different costs for 4 instances. Recharge stations are indicated with a $*$ and $A0$ is the headquarters in all instances. Each instance is solved three times with different c_{batt}, c_e. These solutions are then evaluated with $c_{batt} = 10000$, $c_d = 1$ and $c_e = 0.18$ to compare the advantages of considering degradation in EVRPs

extra recharges or make charges at different moments. Most of these charges are not strictly necessary from the point of view of respecting SoC constraints. They are included to reduce degradation by introducing less damaging cycles, with a lower DoD. This is seen in Figure 6.9, which shows SoC for the different routes obtained in the same instance, accounting for both degradation and energy ($c_{batt} \neq 0$ and $c_e \neq 0$), only for energy ($c_{batt} = 0$) and only for degradation ($c_e = 0$). Figure 6.10 shows the routes obtained in each case for instance 1.

Notice that, when only energy is considered, no charge is planned. This solution reduces the energy cost by minimizing displacements and stops. However, it generates cycles that are more damaging. When only degradation is considered, two charges take place, inducing smaller cycles and causing less degradation. Since vehicles need to stop at charging stations to recharge, extra charging sessions result in higher energy consumption, making this solution sub-optimal from the energy point of view when compared to the case $c_e \neq 0$. Finally, by jointly taking into account costs of degradation and energy (*i.e.* $c_{batt} \neq 0$ and $c_e \neq 0$), a third solution is obtained. Only one charge is planned, finding a balance between extra energy consumption and degradation reduction. Figure 6.10 shows these three different solutions on the map. In instance 3, considering degradation led to a 10% improvement in costs when comparing with the solution that accounted only for energy consumption. Even for instances where the improvement was more modest, because SoH evolves slowly through time, a small degradation reduction can lead to significant battery life duration increase.

Therefore, considering degradation can impact routing and improve the performance of the fleet in the long run, but some considerations must be made. Adding extra charges to reduce degradation is only beneficial when the energy consumed due to this extra stop is not significant when compared to the degradation cost. Therefore, charging station availability plays an

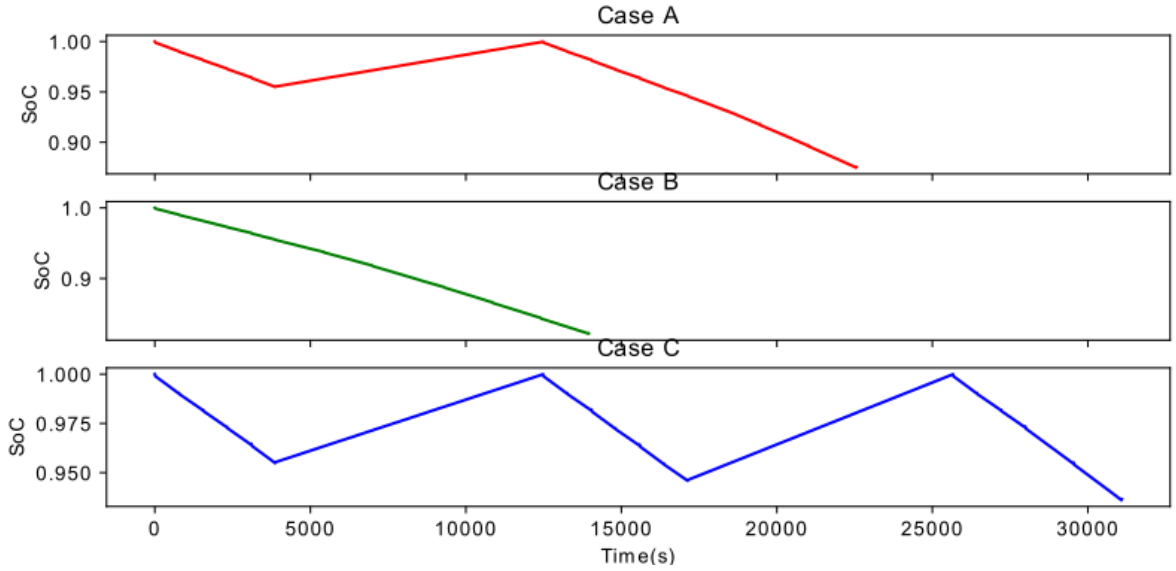

Figure 6.9: Comparison of SoC for optimal mission plan for different optimization cases: Case A accounts for both degradation and energy ($c_{batt} \neq 0$ and $c_e \neq 0$), case B only for energy ($c_{batt} = 0$) and case C only for degradation ($c_e = 0$).

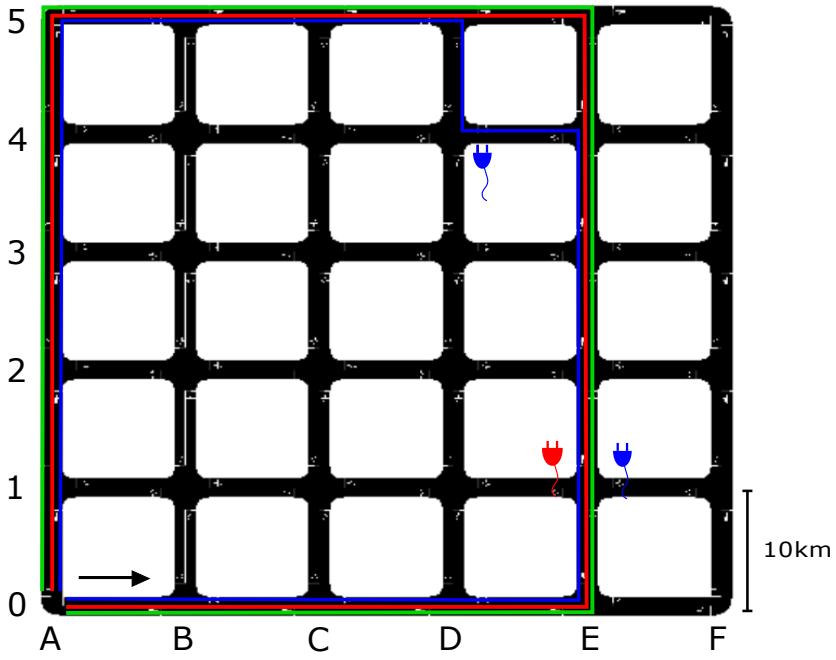

Figure 6.10: Different routes for instance 1. Power plugs represent charges. The solutions for the case where only degradation is considered is represented in blue, in green the solution accounting only for energy consumption and in red the complete solution. The arrow indicates the sense the vehicles travelled.

Clients #	**Charging stations** #	**Improvement ratio**
5	1	0.05
5	10	0.8
5	20	1
10	1	0.1
10	10	0.85
10	20	1

Table 6.4: Proportion of instances in which accounting for degradation yielded a better solution than only considering energy for different numbers of clients and charging stations.

Clients #	**Charging stations** #	$C^{evrp-vp}$ (**not** acting on VPs)	$C^{evrp-vp}$ (acting on VPs)
5	7	6.90	6.39
5	8	7.20	6.74
10	10	11.3	10.6
5	10	6.83	6.27
3	7	4.83	4.36

Table 6.5: Comparison of the impact of including Vehicle Parameters (VPs) on the average cost $C^{evrp-vp}$

important role on degradation minimization. To quantify this phenomenon, random instances of the problem were once again generated. Each instance is solved twice, once considering only energy ($c_{deg} = 0$) and a second time considering both degradation and energy. The proportion of instances in which considering degradation improved the solution is registered in Table 6.4. The column *Improvement ratio* indicates the ratio between instances in which considering degradation yielded to a better solution and those for which minimizing energy and degradation was equivalent.

As expected, the availability of charging stations plays an important role in degradation minimization. Another important consideration is that the optimal plan also depends on the battery dynamics and the parameters of the degradation model. Therefore, different types of batteries can result in different mission plans that will be more or less impacted by degradation.

A second set of experiments is performed to determine the importance of limiting speeds and accelerations. In these experiments, different instances are randomly generated and solved with the optimization model including VPs and the version without them. The cost parameters are once again $c_d = 1$, $c_e = 0.18$, $c_{batt} = 10000$.

As it can be seen in Table 6.5, limiting speeds and accelerations reduces the total cost of a mission plan. The decrease comes mainly from the energy cost, which is a direct consequence of equation (5.9), but also from the degradation cost, since stress cycles presented a smaller DoD (which can be seen in Figure 6.11).

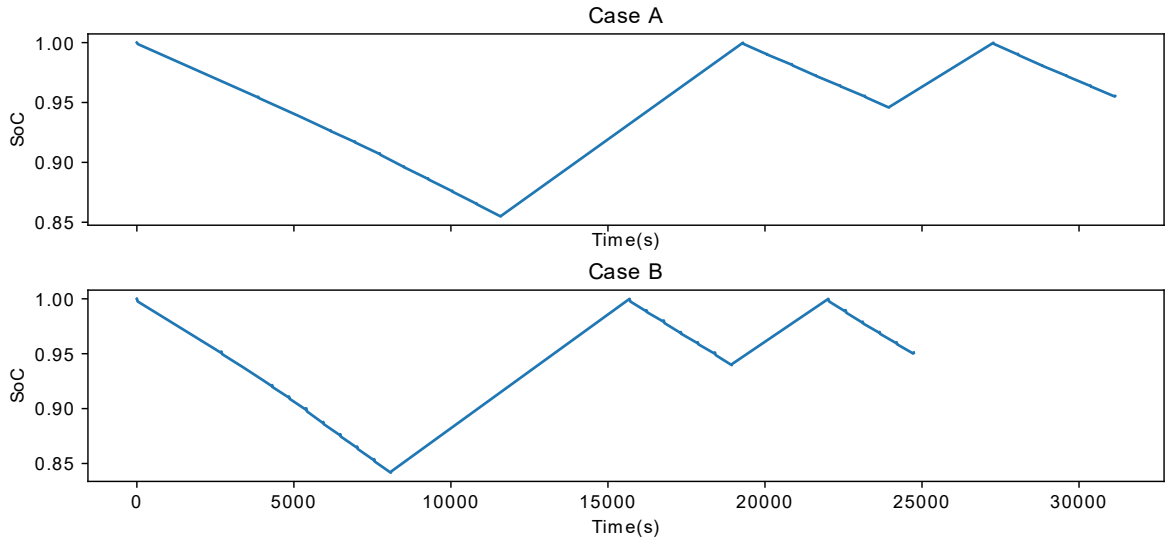

Figure 6.11: Comparison of SoC for optimal mission plan. Case A: acting on driving parameters, Case B: not acting on driving parameters. Notice that in Case B, the mission plan ends earlier because of different driving parameters (higher speed and acceleration)

In the case where speeds and accelerations are limited (Case A in Figure 6.11), the SoC decrease more slowly as a reflex of smaller energy consumption. Charges happened with SoC at 86% and 94% . In case Case B, where VPs are not affected, charges happened at 82% and 93%, leading to more damaging cycles. Affecting VPs can thus improve the overall efficiency of a vehicle, reducing both degradation and energy costs.

6.4.4.2 Results on a realistic map

To assess the impact of incorporating degradation in more realistic scenarios, different instances of the routing problem were generated in the map of Luxembourg, shown in Figure 6.12. Instances were created choosing a specific number of random points in the map that are either charging stations or clients. As before, they are solved once considering c_{bat} to be zero and once with $c_{bat} \neq 0$. Table 6.6 shows the comparison between the results obtained with or without accounting for battery degradation. Like in the previous map, accounting for degradation led to better solutions. This is related to the fact that charges are planned optimally, leading to stress cycles that are less damaging. As it can be seen, the benefits are related to the number of charging stations, since charging to reduce degradation may lead to bigger energy consumption and will only occur if displacements to arrive at charging stations are relatively small.

To assess the impact of maximum speed and acceleration in realistic cases, another set of experiments is made. Instances are generated and solved with and without maximum speed and accelerations as decision variables. The results are shown in Table 6.7. As it can be seen, limiting speed and acceleration is beneficial in terms of cost. This is related to the fact that it

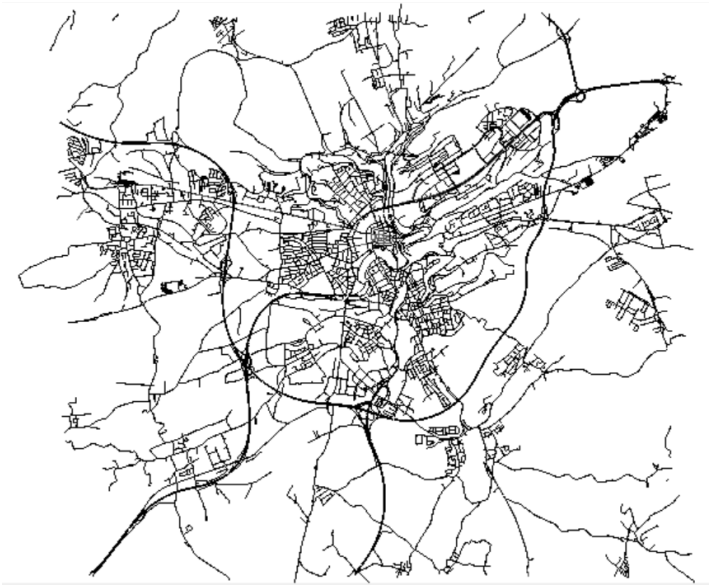

Figure 6.12: Luxembourg map used for the realistic use-case.

Clients #	**Charging stations** #	C_{ess} of solutions obtained through **classic EVRPs**	C_{ess} of solutions obtained **with PsM**
10	2	2.25	2.20
10	5	2.16	2.08
20	5	3.73	3.67
20	10	3.82	3.64
30	10	5.01	4.73
30	15	4.95	4.67

Table 6.6: Comparison between average cost of solutions found considering degradation and solutions without accounting for degradation.

reduces energy consumption which in turn is also beneficial from a degradation point of view.

6.5 Conclusion

In this chapter, the different optimization models of the ESS PsM solution were explored. The SPPs and EVRPs were described as original optimization problems that extended their classical formulations. They were built upon the PsM ESS degradation model, which makes them non-linear. Furthermore, all cost functions rely on solving a system of differential equations and cycle decomposition. Those two facts combined made the optimization computationally challenging. Since classical optimization methods will not be practically useful to solve those original optimization problems, GAs were used.

Clients #	**Charging stations** #	**Average cost not** affecting vehicle parameters	**Average cost** affecting vehicle parameters
10	2	2.32	2.16
10	5	2.26	2.12
20	5	3.68	3.47
20	10	3.64	3.42
30	10	4.97	4.81
30	15	4.92	4.79

Table 6.7: Comparison between average cost of solutions found affecting driving parameters and solutions without affecting driving parameters

Through a series of numerical experiments, the advantages of formulating those optimization problems to account for degradation were shown. Battery useful life was extended both by path optimization and routing. There are, however, several possible improvements to be done in future research. For example, GAs could be improved through solving surrogate optimization models for creating the initial population. It would also be interesting to perform sensitivity analyses in order to see what are the impacts of battery and vehicle parameters on the solutions found. Finally, addressing the randomness related to traffic conditions and other external factors could be valuable.

Chapter 7

Conclusions

Contents

7.1 Thesis overview

This document sums up the works of a three year research project dedicated to investigate the connections between heavy vehicle maintenance and usage in order to create insights that could be used as basis for future services. Exploiting the fact that contemporary technologies, such as vehicle connectivity, data collection, and vehicle electrification, allows for an expanded view of maintenance actions that encompass software parameters changes, logistical optimization and so on. This approach to maintenance is often referred to as PsM. Since this term is vaguely defined from a scientific point of view, several pages of this manuscript were dedicated to a deep inquiry on the definition of different maintenance policies, in order to define PsM in a robust and distinct way.

Based on this definition, a development framework for PsM solutions was proposed. It was then applied to heavy vehicle fleets, delimiting the scope of the concrete scientific problems addressed through part two. The general form of the PsM application for heavy vehicles is seen in Figure 7.1. Solving a PsM problem in this context corresponds therefore to optimize logistical decisions such as path selection, routing and charging, changing software parameters when necessary and determining the best maintenance opportunities to make replacements.

To formalize an optimization model capable of representing such problem, some considerations must be made. The main one is that, the choice of how to define vehicle reliability is crucial to establish the scope of the actions considered. To illustrate that, two concrete applications are developed. In the first one, presented in Chapter 4, a simple and generic stochastic degradation model was used to define reliability. As a consequence, optimization included only maintenance and routing. The optimization model was formalized as a MILP and could be seen as a long-term VRP variation constraining failure probabilities. Several

simulations were carried out to assess the benefits of PsM when compared to traditional approaches for routing and maintenance decision-making. Although this optimization model reduces exploitation costs, it is computationally demanding, therefore dedicated algorithms were developed in order to make this PsM application practical.

In Chapters 5 and 6, another way of defining vehicle reliability was explored. Instead of choosing a generic degradation model, a critical EV component, the ESS, is considered. Chapter 5 presents basic concepts of batteries, and battery degradation. It also provides a brief review of degradation and usage models commonly used on transportation applications. A PsM degradation model is then introduced to address the main short comes of those aforementioned models. Despite its complexity, through a series of numerical experiments, the benefits and constraints with simpler models commonly used in the literature are shown.

Finally, in Chapter 6, this model is included in different optimization problems. Cost functions evaluation require solving differential equations and applying a non-linear cycle decomposition algorithm. Therefore, traditional optimization methods cannot be applied and a meta-heuristic genetic algorithm is used to solve all of them. Several different instances of those problems are solved and compared to more traditional versions of EVRPs and SPPs, showing the benefits of considering battery degradation when exploiting fleets of EVs.

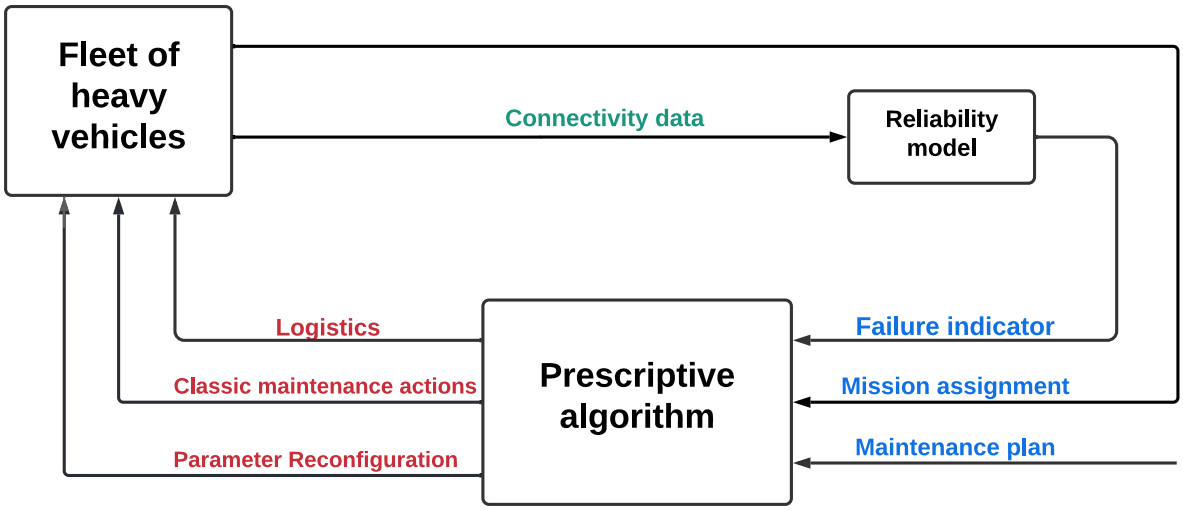

Figure 7.1: General PsM loop for heavy vehicles

7.2 Short-term perspectives

This work addressed some aspects of PsM for heavy vehicle applications. There are, however, several interesting possibilities for extending this research and improving the solutions proposed. For example, in the contribution made in Chapter 4, related to long-term routing and maintenance, maximum allowed failure probabilities were computed in an over simplified manner, considering only the ratio of failure and preventive maintenance costs.

In large fleets, the overall risk of downtime can become non-neglectable even if failure probabilities are limited on a vehicle level. Ideally, maximum failure probabilities must be determined systematically on a fleet level. Furthermore, since fleets are heterogeneous, each vehicle can have different maximum failure probabilities, depending on their degradation parameters.

Additionally, considering all missions over the horizon H to be known beforehand is a strong hypothesis that should be relaxed. In future works, for example, it would be interesting to consider a case in which decision-making is done sequentially without fixed horizon assumption and with mission addresses that are only known at the beginning of a working session.

The ESS application, presented in Chapters 5 and 6, could also be improved. In terms of solution methods, GAs could be made more efficient by initiating chromosome population based on surrogate optimization models solution. It would also be interesting to perform sensitivity analyses in order to see what are the impacts of battery and vehicle parameters on the routes and paths.

It would also be interesting to model additional pertinent decisions related to using fast or normal charging, for example, considering more complex logistical contexts with multiple depots or battery swapping, for example. Finally, addressing the randomness related to traffic conditions and other external factors could be valuable.

7.3 Long-term perspectives

This thesis was born with the intent of enabling future service development for exploitation cost reduction. Although important steps were taken in this direction, several challenging implementation difficulties must be overcome to create such services.

For example, in future research projects, it would be important to extend the concepts developed in this work to a multi-component set-up. As heavy vehicle have several subsystems, it is important to address their intricate and complex relationships.

Another important milestone on implementing PsM solutions in real life would be to validate the proposed optimization models with real fleet managers. With a pilot project in collaboration with Volvo's clients, it would be possible to validate some of the assumptions made, identify and correct weaknesses and quantify the gains of the proposed methods.

Finally, another important trend that was oversight in this work is circularity. More and more components are reused, either by other vehicles or in completely different applications. Decision-making must account for that and consider the impacts on both the first and second life of components.

Appendix A

Benchmark Models

A.1 Benchmark SoC model

The benchmark model used in Section 5.5.1 is based on the very common assumption, in EV decision-making problems, that battery terminal voltage remains constant and equals to its nominal value. As a consequence, the equations that define SoC are:

$$I(t) = \frac{P_{elec}(t)}{V_{batt}^{nominal}} \tag{A.1}$$

$$\dot{SoC} = -\frac{I(t)}{Q_0} \tag{A.2}$$

where $V_{batt}^{nominal}$ is the battery nominal value. As can be seen, when comparing this model to the one presented in Section 5.4.2, the dynamics of the battery are immediately disregarded once battery voltage is assumed to be constant.

A.2 Benchmark acceleration model

The benchmark model used in Section 5.5.2 is based on a traditional assumption that vehicles assume road nominal speed instantaneously, neglecting acceleration effects. This approach can be found in [GS15]. The resulting equations describing vehicle dynamics are:

$$v(t) = v_{nominal} \tag{A.3}$$

$$P_{mec}(t) = \frac{\rho_{air} C_w A v(t)^3}{2} + mgv(t)\sin\alpha + mgC_r v(t)\cos\alpha \tag{A.4}$$

$$P_{elec}(t) = \frac{P_{mec}(t)}{\eta} \tag{A.5}$$

where $v_{nominal}$ is the nominal speed on the edge the vehicle is currently at.

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Résumé — Avec la numérisation, l'internet des objets et la popularisation des services centrés sur les données, différents secteurs économiques ont connu des changements importants dans leur modèle d'entreprise. Pour le secteur automobile en particulier, ces changements concernent l'évolution vers des offres davantage axées sur les services. La vente d'un véhicule n'est plus le dernier contact avec le client, car les services après-vente représentent une part importante du chiffre d'affaires des constructeurs automobiles. Dans cette optique, le principal objectif de ce projet de recherche est de jeter les bases des futurs services pour les véhicules lourds.

Ce travail souligne l'importance de l'optimisation de la maintenance ainsi que sa relation avec l'utilisation du véhicule. Dans le passé, la maintenance se limitait à des remplacements correctifs de pièces défectueuses, ce qui entraînait de longues périodes d'inactivité. Cela avait un impact sur l'activité du transporteur, ainsi que sur ses coûts de réparation. L'introduction de systèmes de surveillance et les techniques de communication actuelles permettent de développer de nouvelles méthodes d'optimisation dans lesquelles, non seulement les dates de remplacement sont déterminées de manière optimale, mais aussi l'utilisation du véhicule est modifiée en conséquence, ce qui permet d'optimiser les coûts et d'allonger continuellement la durée de vie utile des camions. Grâce à la technologie actuelle, ces méthodes d'optimisation pourraient être transformées en services qui aident les clients à définir les dates de remplacement, à gérer la logistique pour minimiser les niveaux de dégradation de la flotte, ou même à modifier les paramètres du logiciel du véhicule pour minimiser les coûts à long terme.

Cette approche pour la maintenance, dans laquelle la durée de vie est prolongée par une myriade d'actions différentes englobant plusieurs aspects de l'utilisation du véhicule, est souvent appelée maintenance prescriptive. Bien que la maintenance prescriptive ait été dès le départ un élément important de ce travail, sa définition est assez controversée dans la littérature. Par conséquent, un effort conceptuel est fait dans ce document afin de clarifier la portée de ce type de paradigme de maintenance. Avec des définitions plus précises et un champ d'application clair, la maintenance prescriptive est appliquée dans le contexte des véhicules lourds.

Les applications de maintenance prescriptive pour les véhicules lourds peuvent être considérées comme des problèmes d'optimisation originaux dans le domaine de la science des transports. Tout au long de l'étude de ces méthodes, des contributions scientifiques significatives ont été apportées. Tout d'abord, la maintenance prescriptive nécessite des modèles qui peuvent relier de manière réaliste la dégradation et l'utilisation du véhicule. De tels modèles sont difficilement adaptés aux problèmes de prise de décision et nécessitent une adaptation. Dans ce document, ces modèles sont étudiés en détail. Par exemple, au chapitre 5, un nouveau modèle d'état de charge/état de santé est proposé pour quantifier l'impact de certaines stratégies de routage sur la durée de vie utile des camions électriques.

En outre, ces modèles de dégradation permettent de mettre en place des configurations d'optimisation dans lesquelles différentes actions qui sont rarement envisagées dans le domaine des transports sont prises en compte. Par exemple, au chapitre 6, l'itinéraire classique d'un véhicule électrique est étendu afin de prendre en compte la dégradation. En outre, l'application de limitations aux vitesses et aux accélérations des véhicules est incluse dans le champ d'optimisation. Par conséquent, grâce à des expériences numériques, il a été possible de quantifier les impacts d'une telle restriction non seulement en termes de consommation d'énergie, mais aussi en termes de prolongation de la durée de vie utile. Même les actions qui ont des effets sur des échelles de temps très différentes sont prises en compte. Au chapitre 4, la maintenance et le routage sont combinés, et leur effet conjoint a pu être observé à long terme. L'optimisation de la logistique en tenant compte des calendriers de maintenance et de la dégradation a conduit à une réduction significative des coûts par rapport aux stratégies d'optimisation classiques.

La résolution des problèmes d'optimisation susmentionnés est une tâche non triviale. Toutes les formulations susmentionnées nécessitent un effort de calcul important pour être résolues avec exactitude. Ainsi, une autre dimension de la contribution de ce travail est le développement d'algorithmes adaptés à la résolution de ces problèmes. Les méthodes classiques sont adaptées en tirant parti des propriétés particulières des modèles utilisés et des heuristiques capables de combler l'écart d'optimisation en un temps raisonnable sont développées.

Grâce aux outils capables de trouver des solutions à ces problèmes de prise de décision en matière de maintenance normative, on obtient des informations sur l'exploitation des véhicules. Des mesures quantitatives peuvent enfin être calculées, ce qui permet de comparer systématiquement la qualité de la gestion logistique et de l'utilisation en général. Cela peut servir de base à de nouveaux services après-vente dans lesquels les clients auront accès à un ensemble de recommandations différentes (maintenance, mais aussi modes d'utilisation et d'exploitation) pour maintenir la flotte opérationnelle au maximum tout en minimisant tous les coûts pertinents.

Mots clés: Maintenance prescriptive, modélisation de la degradation, prise de decision, optimisation, vehicules électriques.

Abstract — With digitalization, the internet of things and the popularization of data-centric services, different economy sectors have gone through significant changes in their business model. For the automotive sector in particular, those changes relate to moving towards more service-oriented offers. Selling a vehicle is no longer the last contact with the client, as aftermarket services are responsible for a significant part of vehicle manufacturer's revenue. With that in mind, the main concern of this research project is to lay down the foundations for enabling future services for heavy vehicles.

This work stresses the importance of maintenance optimization as well as its relationship with vehicle usage. In the past, maintenance was limited to corrective replacements of faulty parts resulting in long idle periods. This impacted the activity of the transporter, as well as its repair costs. The introduction of monitoring systems along with the current communication techniques allow the development of new optimization methods in which, not only replacement dates are determined optimally but also, vehicle usage is changed accordingly, ensuring cost optimization, and continuously extending trucks remaining useful life. With today's technology, those optimization methods could be turned into services that help clients defining replacement dates, manage logistics to minimize degradation levels of the fleet, or even change vehicle software parameters to minimize the long-term costs.

This approach to maintenance, in which life is extend through a myriad of different actions encompassing several aspects of vehicle usage, is often referred to as prescriptive maintenance. Although prescriptive maintenance was from the beginning an important element of this work, its definition is rather controversial in the literature. As a consequence, a conceptual effort is done in this document in order to clarify the scope of this kind of maintenance paradigm. With more precise definitions and a clear scope, prescriptive maintenance is applied in the context of heavy vehicles.

Prescriptive maintenance applications for heavy vehicles can be seen as original optimization problems in the realm of transportation science. Throughout the investigation of such methods, significant scientific contributions were made. First and foremost, prescriptive maintenance requires models that can realistically connect degradation and vehicle usage. Such models are hardly adapted for decision-making problems and require adaptation. In this document, such models are studied in detail. For example, in Chapter 5 a new State of Charge/State of Health model is proposed to quantify the impact of certain routing strategies on the useful life of electric trucks.

Additionally, these degradation models enable optimization set-ups in which different actions that are hardly thought of in transportation are considered. For example, in Chapter 6 the classical electrical vehicle routing is extended in order to consider degradation. Furthermore, applying limitations to vehicle speeds and accelerations is included in the optimization scope. As a result, through numerical experiments, it was possible to quantify the impacts of such restriction not only in terms of energy consumption but in terms of useful life extension as well. Even actions which have effects in very different time scales are considered. In Chapter 4, maintenance and routing are combined, and their joint effect could be seen in the long-term. Optimizing logistics considering maintenance schedules and degradation led to significant cost reduction when compared to classical optimization strategies.

Solving those aforementioned optimization problems is a non-trivial task. All of the aforementioned formulations required significant computational effort to be solved exactly. As such, another dimension of this work contribution is the development of algorithms suitable for solving them. Classical methods are adapted taking advantage of particular properties of the models used and heuristics capable of closing the optimization gap in a reasonable time are developed.

With the tools capable of finding the solutions for those prescriptive maintenance decision-making problems, insights on vehicle exploitation are obtained. Quantitative metrics can finally be computed, leading to a systematic way of comparing the quality of logistics management and usage in general. This can be used as the basis for new aftermarket services in which clients will have access to a set of different recommendations (maintenance, but also usage and operating modes) to keep the fleet operational to the maximum while minimizing all relevant costs.

Keywords: Prescriptive maintenance, degradation modeling, heavy vehicles, decision-making, optimization, electric vehicles.

Laboratoire de Grenoble-Images, Parole, Signal et Automatique (GIPSA-lab), 11 rue des mathematiques
Saint-Martin-d'Hères