Control strategy and predictive methods for performance and component lifetime enhancement in vehicle powertrain

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Ph.D. Thesis

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Quisiera dedicar esta tesis a mi toda familia. Vosotros me habéis mantenido con energía
y me habéis animado a conseguir mis metas en las condiciones más adversas.
Quiero dar las gracias a mis compañeros de Volkswagen por esta experiencia tan
enriquecedora para mí y, por último aunque no menos importante,
gracias a mi familia de Wolfsburg. Os echaré mucho de menos.

Álvaro

Abstract

In the past years, battery electric vehicles have been gaining market share. These vehicles are progressively seen as a viable option by customers of all kind. However, although manufacturers and research institutions are putting their effort on improving the capacity of the battery, the reduced kilometric range of the vehicle is the main drawback and what maintains nowadays customers hesitant. To solve this issue, research is trying to innovate on materials to be used on batteries and components, as well as trying to reduce the weight of the vehicle to increase the range. Another way of improving the performance of these vehicles is via software optimization. By having a software operation strategy, the vehicle can improve its performance without any change of hardware, which is a great benefit for both the manufacturer and the customer. This thesis addresses the topic of software operation strategy which, with the hardware already available in a vehicle, has the ability of optimizing several parameters, such as cooling power. Previous research has shown that Dynamic Programming provides an optimal solution but requires high computational performance and is not real-time feasible. In this thesis, the availability of a power boost function will be discussed and enhanced with a software operation strategy. This function allows the vehicle to deliver a temporary power boost when required. The main issue with this function and the reason why it cannot be delivered at all times is the temperature control. Temperature greatly affects the behavior of the components, reduces their lifetime and must be monitored. To deal with this issue, this thesis proposes prediction of the velocity of the driving cycle using Artificial Neural Networks (ANNs). The main idea is to predict the complete driving cycle in order to have a previous knowledge of all the parameters before driving. As a result of this approach, the vehicle is able to condition the system to deliver the power boost at the precise moment that it will be required, since complete knowledge of the trip environment is known. This optimizes the energy consumption of the cooling system and the availability of the *Power Boost* function is enhanced. To ensure correct working of the function, the machine learning algorithm that predicts the driving velocity is combined with an online algorithm. The online algorithm will work real-time on the vehicle and is in charge of acquiring data from the individual driver to perform a so-called fine tuning of the ML model. Because of individualization, the speed forecasting will not be generic, but tuned to each driver or vehicle, depending if the vehicle counts with driver recognition or not.

Parallel to the predictor, an optimizer uses the information of the predicted speed and the slope of the driving cycle to maintain the battery and the EM always below the derating temperature. If the temperature of a component is lower than its derating temperature, maximum power delivery and safe operation can be ensured, thus delivering the so-called *Power Boost* function. Moreover, the optimizer ensures that the minimum cooling level is selected in order to bring an efficiency benefit simultaneously. The methods have been tested on a the cooling system of the electric motor, by operating the coolant pump, as well as on the tempering system of the battery, by actuating both the chiller and the PTC heater. The results of the optimization performed have shown a reduced cooling/heating energy and, consequently, an increased kilometric range. An additional benefit of the optimized software operation strategy, along with a temporary power boost and more efficient tempering system, is a best tracking of the components lifetime. This allows to track individually the degrading rate of the components, as well as to increase the value of the vehicle by knowing its current state. Compared to the current function developed, prediction also allows minimizing the aging of the vehicle's components. The proposals planned in this thesis aim to improve the performance of electric vehicles by taking advantage of the connectivity in the vehicles to optimize a large number of parameters.

Resumen

En los últimos años, los vehículos eléctricos han ido incrementando su cuota de mercado. Estos vehículos son vistos progresivamente como una opción viable por clientes de todo tipo. Sin embargo, aunque los fabricantes e instituciones de investigación se esfuerzan por mejorar la capacidad de la batería, la reducida autonomía kilométrica del vehículo es el principal inconveniente y lo que preocupa a los clientes en la actualidad. Para resolver este problema, la investigación está tratando de innovar en los materiales que se utilizarán en las baterías y los componentes, así como tratando de reducir el peso del vehículo para aumentar la autonomía. Otra forma de mejorar el rendimiento de estos vehículos es mediante la optimización del software. Al tener una estrategia de operación de software, el vehículo puede mejorar su desempeño sin ningún cambio de hardware, lo cual es un gran beneficio tanto para el fabricante como para el cliente. Esta tesis trata el tema de la estrategia de operación del software que, con el hardware ya disponible en un vehículo, tiene la capacidad de optimizar varios parámetros como la potencia de refrigeración. Investigaciones anteriores han demostrado que la Programación Dinámica proporciona una solución óptima pero requiere un alto rendimiento computacional y no es factible en tiempo real. En este proyecto, se proporcionará una función de aumento de potencia (*Power Boost*). Esta función permite que el vehículo entregue un aumento de potencia temporal cuando sea requerida. El principal problema con esta función y la razón por la que no se puede entregar en todo momento es el control de temperatura. La temperatura afecta en gran medida al comportamiento de los componentes, reduce su vida útil y debe controlarse. Para hacer frente a este problema, esta tesis propone la predicción de la velocidad del ciclo de conducción utilizando redes neuronales artificiales (ANN). La idea principal es predecir el ciclo de conducción completo para tener un conocimiento previo de todos los parámetros antes de empezar la conducción. Como resultado de este enfoque, el vehículo puede acondicionar el sistema para entregar el aumento de potencia en el momento preciso en que se requiera, ya que se dispone de un conocimiento completo del entorno. Esto optimiza el consumo de energía del sistema de refrigeración y mejora la disponibilidad de la función *Power Boost*. Para garantizar el correcto funcionamiento de la función, el algoritmo de aprendizaje automático que predice la velocidad de conducción se combina con un algoritmo en línea. El algoritmo en línea funciona en tiempo real en el vehículo y está a cargo de adquirir datos del conductor individual para realizar el llamado

fine-tuning del modelo ML. Debido a la individualización, la predicción de velocidad no será genérica, sino ajustada a cada conductor o vehículo, dependiendo de si el vehículo cuenta con reconocimiento de conductor o no. Paralelamente al predictor, el optimizador utiliza la información de la velocidad prevista y la pendiente del ciclo de conducción para mantener la batería y el motor siempre por debajo de la temperatura de reducción de potencia. Si la temperatura de un componente es más baja que su temperatura de reducción de potencia, se puede garantizar la máxima entrega de potencia y un funcionamiento seguro, proporcionando así la llamada función *Power Boost*. Además, el optimizador garantiza que se seleccione el nivel mínimo de enfriamiento para brindar mayor eficiencia de forma simultánea. Los métodos se han probado tanto en el sistema de refrigeración del motor eléctrico, accionando la bomba de refrigeración, como en el sistema de templado de la batería, accionando tanto el enfriador como el calentador PTC. Los resultados de la optimización realizada han mostrado una energía de templado reducida y, en consecuencia, una autonomía kilométrica aumentada. Un beneficio adicional de la estrategia de operación optimizada, junto con un aumento de potencia temporal y un sistema de templado más eficiente, es un mejor seguimiento de la vida útil de los componentes. Esto permite realizar un seguimiento individual de la tasa de degradación de los componentes para aumentar el valor del vehículo al conocer su estado actual. En comparación con la función actual del vehículo, la predicción también permite minimizar el envejecimiento de los componentes del vehículo. Las propuestas planteadas en esta tesis tienen como objetivo mejorar el rendimiento de los vehículos eléctricos aprovechando la conectividad de los vehículos para optimizar un gran número de parámetros.

Resum

En els darrers anys, els vehicles elèctrics han anat incrementant la seva quota de mercat. Aquests vehicles són vistos progressivament com una opció viable per clients de diversos perfils. Tot i això, encara que els fabricants i institucions de recerca s'esforcen per millorar la capacitat de la bateria, la reduïda autonomia quilomètrica del vehicle és el principal inconvenient i el que preocupa els clients actualment. Per resoldre aquest problema, la investigació està intentant innovar en els materials que s'utilitzaran a les bateries i els components, així com tractant de reduir el pes del vehicle per augmentar l'autonomia. Una altra manera de millorar el rendiment daquests vehicles és mitjançant la optimització del *software*. Tenint una estratègia d'operació de *software*, el vehicle pot millorar la seva operació sense cap canvi de *hardware*, cosa que és un gran benefici tant per al fabricant com per al client. Aquesta tesi tracta el tema de l'estratègia d'operació de *software* que, amb el *hardware* ja disponible en un vehicle, té la capacitat d'optimitzar diversos paràmetres com la potència de refrigeració. Investigacions anteriors han demostrat que la Programació Dinàmica proporciona una solució òptima, però requereix un alt rendiment computacional i no és factible en temps real. En aquest projecte, es proporcionarà una funció d'augment de potència (*Power Boost*). Aquesta funció permet que el vehicle lliuri un augment de potència temporal quan sigui requerida. El principal problema amb aquesta funció i la raó per la qual no es pot lliurar en tot moment és el control de temperatura. La temperatura afecta en gran mesura el comportament dels components, en redueix la vida útil i s'ha de controlar. Per fer front a aquest problema, aquesta tesi proposa la predicció de la velocitat del cicle de conducció utilitzant xarxes neuronals artificials (ANN). La idea principal és predir el cicle de conducció complet per tenir un coneixement previ de tots els paràmetres abans de començar la conducció. Com a resultat d'aquest enfocament, el vehicle pot condicionar el sistema per lliurar l'augment de potència en el moment precís en què es requereixi, ja que es disposa d'un coneixement complet de l'entorn. Això optimitza el consum d'energia del sistema de refrigeració i millora la disponibilitat de la funció *Power Boost*. Per garantir el funcionament correcte de la funció, l'algorisme d'aprenentatge automàtic que prediu la velocitat de conducció es combina amb un algorisme en línia. Aquest, funciona en temps real al vehicle i està a càrrec d'adquirir dades del conductor per realitzar l'anomenat *fine-tuning* del model *Machine Learning* (ML). A causa de la individualització, la predicció de velocitat no serà

genèrica, sinó ajustada a cada conductor o vehicle, depenent de si el vehicle compta amb reconeixement de conductor o no. Paral·lelament al predictor, l'optimitzador utilitza la informació de la velocitat prevista i el pendent del cicle de conducció per mantenir la bateria i el motor sempre per sota de la temperatura de reducció de potència. Si la temperatura d'un component és més baixa que la temperatura de reducció de potència, es pot garantir el màxim lliurament de potència i un funcionament segur, proporcionant així l'anomenada funció *Power Boost*. A més, l'optimitzador garanteix que es seleccioni el nivell mínim de refredament per lliurar més eficiència de forma simultània. Els mètodes s'han provat en un vehicle Cupra Born, tant al sistema de refrigeració del motor elèctric, accionant la bomba de refrigeració, com al sistema de temperat de la bateria, accionant tant el refredador com l'escalfador de coeficient positiu de temperatura. Els resultats de la optimització realitzada han mostrat una energia de temperat reduïda i, en conseqüència, una autonomia quilomètrica augmentada. Un benefici addicional de l'estratègia d'operació optimitzada, juntament amb un augment de potència temporal i un sistema de temperat més eficient, és un millor seguiment de la vida útil dels components. Això permet fer un seguiment individual de la taxa de degradació dels components per augmentar el valor del vehicle en conèixer el seu estat actual. En comparació amb la funció actual del vehicle, la predicció també permet minimitzar l'envelliment dels components del vehicle. Les propostes plantejades en aquesta tesi tenen com a objectiu millorar el rendiment dels vehicles elèctrics aprofitant la seva connectivitat per optimitzar un gran nombre de paràmetres.

Contents

Glossary

AD Autonomous Driving.

ANN Artificial Neural Network.

BEV Battery-Electric Vehicle.

BMS Battery Management System.

CAN Controller Area Network.

CNG Compressed natural gas.

CNN Convolutional Neural Network.

DC Direct Current.

DL Deep Learning.

DoF Degree of Freedom.

DP Dynamic Programming.

ECU Electronic Control Unit.

EM Electric Motor.

EOL End Of Life.

EU European Union.

EV Eectric Vehicle.

FL Federated Learning.

FLOP Floating Point Operation.

FMU Functional Mock-Up.

GPS Global Positioning System.

GRU Gated Recurrent Unit.

GUI Graphic User Interface.

HMI Human-Machine Interface.

ICE Internal Combustion Engine.

ISO International Organization for Standardization.

LEZ Low-Emission Zone.

LSTM Long Short-Term Memory.

MAE Mean Absolute Error.

MC Markov Chain.

ML Machine Learning.

MLP Multi-Layer Perceptron.

MPC Model Predictive Control.

MSE Mean Square Error.

NARX Nonlinear Autoregressive exogenous model.

NEDC New European Driving Cycle.

NN Neural Network.

OEM Original Equipment Manufacturer.

OSM Open Street Maps.

OTA Over The Air.

PHEV Plug-in Hybrid-Electric Vehicle.

PTC Positive Temperature Coefficient.

PWM Pulse-Width Modulation.

RC Resistor-Capacitor.

RMSE Root Mean Square Error.

RNN Recurrent Neural Network.

SEI Solid Electrolyte Interphase.

SFE Sequence Feature Extractor.

SGD Stochastic Gradient Descent.

SOC State Of Charge.

UDDS Urban Dynamometer Driving Schedule.

UI User Interface.

UPC Universitat Politècnica de Catalunya.

WLTC Worldwide harmonized Light vehicles Test Cylce.

WLTP Worldwide harmonized Light vehicles Test Procedure.

Chapter 1

Introduction

In the past years, battery electric vehicles have been increasing popularity. These vehicles are seen as a viable option, not only because of the public interest in reducing the local emissions, but also because of the performance improvement that these vehicles bring. So as to accomplish with the Paris Agreement [UNF15], the European Union (EU) and country governments are fostering electrification of the vehicles via incentives and funding to both manufacturers and consumers, as stated in the Regulation (EU) 2019/631 [Com17]. The main goal is to achieve net-zero emissions by 2050, which presents a challenge in which industry, government and public are required to take part. Although manufacturers and research institutions are putting their effort on improving the capacity of the battery, the reduced kilometric range of the vehicle is a main drawback.

A solvent method is to increase the number of charging points for electric vehicles. Although it is still not regulated, a study by the European Federation for Transport and Environment (T&E) (https://www.transportenvironment.org) shows an investment plan for increasing the number of electric charging points by 3 million by 2030. This would suppose only a 3% of the annual road transport infrastructure investment [TE21]. This approach benefits both customers and carmakers, since having efficient and fast charging points solves the kilometric range problem. As another approach to solve this issue, research in the field of electric vehicle manufacturing is putting its effort on innovating on materials to be used on batteries and components, as well as trying to reduce the weight of the vehicle to increase the kilometric range. Besides, another way of improving the performance of these vehicles is via software optimization. By having a software operation strategy, the vehicle can improve its performance without any change of hardware, which is a big benefit for both the manufacturer and the customer. This doctoral thesis targets precisely the topic of software optimization for electric vehicles.

A typical application of the operation strategy is the so-called power split problem. Let us present a hybrid vehicle with two different power sources. Typically, these vehicles count with an electric machine and a combustion engine, but other forms of hybridization are present in the market, such as fuel cells or Compressed Natural Gas (CNG). The power split problem defines which is the amount of power that should be delivered by each power source in order to optimize a criteria, such as minimizing the fuel consumption, maximizing the kilometric range or reducing to zero the emissions while driving over Low Emission Zones (LEZs).

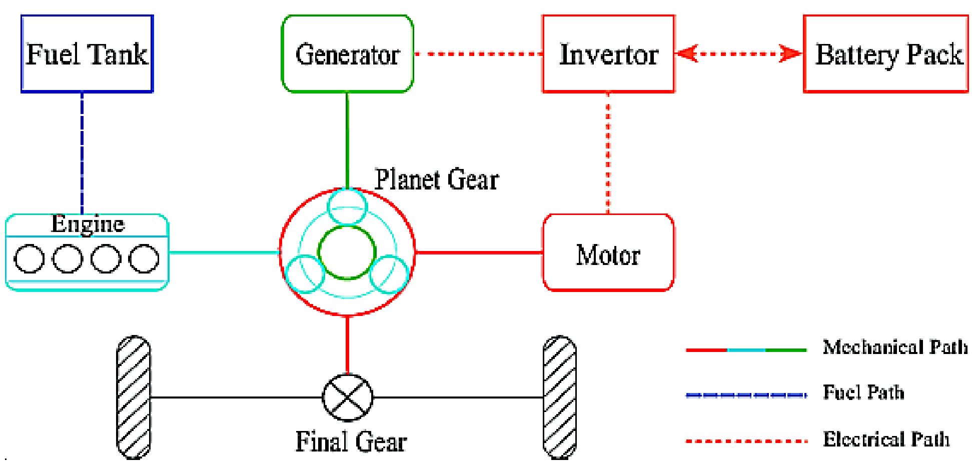

Figure 1.1: Hybrid-Electric powertrain scheme. Source: [Wan+17].

While several methods have been presented for implementing an operation strategy, Dynamic Programming (DP) has proven to achieve optimal performance [RBM12]. The main drawback, however, is that DP is not real-time feasible because of their high computational requirement. Moreover, Dynamic Programming needs to know the driving cycle in advance, even before driving. That means, to perform an optimal control of the vehicle, the complete velocity of the driving cycle has to be known. This fact introduces the need of prediction. If the vehicle is able to predict the driving speed, using vehicle dynamics models is sufficient to forecast all the vehicle parameters expected while driving. Naturally, the predicted driving parameters will differ from the recorded or actual parameters. However, if the prediction is sufficiently correct, applying Dynamic Programming with the predicted driving cycle can lead to a suboptimal solution which will be closer to the optimal solution achieved if the prediction performance would be completely accurate.

This kind of algorithm can as well be individualized for every driver and/or vehicle, if the vehicle counts with driver recognition, since the only values that need to be stored are the weights of the Neural Network, which signify a few bytes of memory allocation. The main drawback is that it is not real-time feasible. The training of the Neural Network has to be performed with as much representative data as possible and could take many hours to be completed. That is why solutions such as cloud computing or federated learning can be investigated further on, in order to apply this algorithm to road vehicles. An average driver tends to perform the same driving cycle daily, e.g. while driving to work. This is a great advantage for the algorithm, since new data will be available daily. The vehicle and/or driver will already count with a model pre-trained with generic data. After driving, the vehicle can send the recorded representative data, along with the weights of the previously pre-trained net, to the cloud computing server where the fine tuning can be performed.

1.1 Analysis of the customer benefits

The prediction of the route parameters can serve to deliver multiple customer benefits without a need of changing the vehicle hardware and just analyzing the driver behavior. Some of these benefits are summarized below:

1. **Providing increased power for a longer time**: If the temperature of the component is kept in the control, the power that can be delivered to the machine can be increased. A typical example would be fast charging. During fast charging the battery is supplied with high power constantly. This creates a faster increase of the battery cell temperature and consequently, of the coolant. If the temperature of the battery is decreased before reaching a fast charging station, the amount of power that can be delivered to the battery can be increased and therefore the charging operation can be completed within less time. As a parallel benefit, the function keeps the battery within its safe operational limit and aging is reduced.

2. **Efficient tempering system**: There might be scenarios in which the series vehicle cooling system is not efficient. This occurs when the vehicle cools down or heats up the battery or the electric machine in situations in which it is not necessary. That is because the vehicle works in an action-reaction scheme and powers up the cooling system when the temperature of the components is high. By anticipating the power request over the driving cycle, it can be in analyzed whether the temperature is going to be critical or not for the components. In case the component does not reach critical temperature values, the cooling or heating system power can be reduced and an amount of energy can be saved along time. This translates into a more efficient tempering system and an extended kilometric range.

3. **Ensuring maximum power for the complete trip**: The battery and electric machine derating temperature is the temperature at which its power input or output is limited. By restricting the power that can be delivered from the battery to electric machine, the delta temperature expected is reduced and does not surpass the

derating temperature. This is crucial for the components since derating temperature is the one at which their aging is accelerated. If the temperature of the component could be predicted, the cooling system could keep the temperature always below the derating threshold by anticipating future temperature increases. This means that the electric machine could be supplied with full power at any point of the driving cycle and experience of the driver would be improved.

1.2 Power boost function

One of the functions of interest, as described in the previous section, is the delivery of the maximum power from the battery to the electric machine. Both components have a derating temperature that limits the power that the components does admit. However, and as it will be presented in Chapter 6, the temperature of the EM presents a more dynamic behavior than the one of the temperature. That means, that the EM is typically the bottleneck when analyzing temperature evolution of the components and the first to apply a derating to the requested driving power. The *Power Boost* function is defined as the delivery of maximum power to the electric machine for allowing maximum acceleration. For this study case, the maximum electrical power of the electric machine is 170 kW. In order to provide this function, the temperature of both the battery and the EM must be kept under their corresponding derating limits. One of the main criteria for the design of algorithms, therefore, will be ensuring that this function is available at all times during a driving cycle.

1.3 Motivation of the thesis

The motivation of the thesis is to contribute to the research within the automobile industry and electric mobility, a field which is rapidly changing in the past years. Not only by the electrification of the powertrain, but by allowing connectivity in vehicles, a large number of parameters can be optimized with an operation strategy pursuing different objectives. A function that reduces the impact of the components aging will be delivered and thus, bring both social and economic benefit. It is inspiring realizing that connected vehicles with an electric powertrain (also accounting for hybrid-electric powertrain architectures) can improve its performance or efficiency by having a software update over the air (OTA). This feature is especially interesting for the customer, since the driving experience will be enhanced by just updating the vehicle for a few minutes, without any change of hardware. Moreover, this thesis work has been performed at Volkswagen, Wolfsburg (Germany) and participates directly in the development and implementation of methods within a Cupra Born vehicle [Cup22]. The ultimate objective is having an influence within the large automobile industry during the current times of mobility development.

1.4 Objectives and research questions

In this section, the objectives and functions to be delivered by this thesis work are described. As seen in previous sections, the described customer benefits take an action on the tempering system of the vehicle. As a summary of the three benefits, the power of the tempering system should be the minimum that accomplishes the condition that the maximum trip temperature does not reach the derating threshold. The main goal of the thesis would therefore be to design an optimized tempering system for the Cupra Born model, in order to provide the customer with multiple benefits such as extended kilometric range, increased power for a longer time and faster charging. Nonetheless, the developed methods are patented and can be used for multiple vehicle architectures within the Volkswagen Group.

However, this logic already poses the first challenge and research question. In order to know which is the optimal power to be used in the tempering system at each step, the future temperature increases should be anticipated. That means, that the complete behavior of the temperature must be calculated before the trip starts. If a prediction of the vehicle temperature is accomplished, an optimal tempering level will be selected at each time step and the terminal temperature of the components will be their derating temperature. By keeping the electric motor as close as possible to derating temperature, the cooling power is therefore reduced.
The choice after the terminal temperature being the derating temperature of the component is because it is the maximum temperature at which the electric machine can be supplied with the maximum power (170 kW). Moreover, if a prediction of the complete trip is available, it is known in advance which is the time at which the driving ends and the components temperature will be reduced passively, without any energy usage.

A second research question is the synthesis of a series vehicle simulator. By predicting the speed of the complete trip, vehicle simulators can be used to calculate all parameters related to that very same trip. Therefore, the prediction of the temperature is bound to the prediction of the speed of the driving cycle. That information can then serve for optimizing the tempering behavior, as it is possible to perform a comparison with the series vehicle.

One of the main objectives of this thesis, therefore, is to predict the velocity of the driving route. The premise is that the user selects a destination from its current origin. The GPS coordinates of the route are exported and, using map data, the speed can be predicted. This information, together with the slope profile of the route, are the only required inputs to calculate what is the required mechanical power that the electric machine needs to generate to drive that driving cycle. As previously introduced, after the prediction of the speed, this information, together with the slope profile and the characteristics of the vehicle, is used to calculate all the required signals that have an influence in the thermal behavior of the components. This requires a complete and exhaustive analysis of the series vehicle to understand the logic for controlling the different components of the tempering system.

Once that information is available, as a third research question, additional cooling or heating strategies can be presented to deliver an optimal tempering system and deliver several customer benefits. Dynamic Programming performs a calculation in a backwards motion and delivers an optimal result. The main boundary condition of dynamic programming, however, is that the complete trip has to be known in advance. This is the reason after the prediction of the speed bringing a great benefit, since it allows to accurately calculate all signals of a vehicle before the trip has started. With that, the boundary condition to apply dynamic programming and find an optimal tempering strategy is fulfilled. Let us summarize the main objectives in the following points:

1. Understanding the series vehicle tempering system and the different tempering scenarios depending on the individual component temperatures.

2. Predicting the velocity of the driving cycle with the boundary condition that the route is known.

3. Building a series vehicle simulator to calculate all signals related to the tempering system before the trip has started, from the speed prediction and the slope profile of the route.

4. Perform an optimization of the tempering system and compare it to the series vehicle behavior.

5. Analyzing results in terms of efficiency, while ensuring that the temperature remains below the derating temperature.

6. Establishing a communication with a series vehicle and perform real driving tests in order to assess the performance of the function with a real vehicle, parallel to the comparison with the simulations.

For the prediction stage, Artificial Neural Networks (ANN) will be trained with a data set owned by Volkswagen of approximate size of 2.8 terabytes, which counts with 40.000 kilometers, 450 recordings and 1424 trips. In order to compare how the function works and compare it to a series vehicle, measurements and recordings from the vehicle Controller Area Network (CAN) are required. A further step and objective of this thesis will be to implement the methods in order to read, clean, process and plot signals coming from the vehicle controllers. The signals of interest would be those of the tempering systems. As an example, a comparison of the optimized pump power with the vehicle requested pump power will be specially of interest to assess if the optimized strategy is more efficient.

After analyzing the optimized results and comparing them to the series vehicle, a possible deployment of the functions to the vehicle will be evaluated. This deployment, however, is not real-time possible in a vehicle because of the usage of dynamic programming as optimization algorithm. Taking advantage of the connected-car functions, the functions can be deployed in the cloud and use the car communication to send and retrieve data to or from the vehicle.

All of the described objectives have been elaborated according to the research and state of the art review. The state of the art chapter summarizes all the relevant outcomes and act as a basis for the development of this thesis. Moreover, taking advantage of the company knowledge, advise from experts in the series vehicle tempering system has been requested. During the development of the methods, an extensive review of the literature has additionally been performed to find novel methods in the same research direction.

1.4.1 Contents and organization

The contents of this thesis are organized as follows. Chapter 2 presents an extensive literature review on the topics of vehicle dynamics, optimization algorithms, Machine Learning and vehicle thermal behavior and tempering systems. Chapter 3 analyzes and implements the main concepts of the series vehicle cooling and heating systems. Chapter 4 introduces the methodology followed to synthesize a series vehicle simulator. Chapter 5 presents the methods, architectures and process followed in order to achieve a prediction of the speed and motor power of a route, as well as introducing some metrics and results. Chapter 6 aims at developing an optimal control strategy for the tempering system of a vehicle, while introducing results and metrics in comparison with the series vehicle. An overview of a possible industry application can be found in Chapter 7. Lastly, Chapter 8 introduces the main results from the research performed. As appendices, individual route results from the prediction and optimization algorithms are presented in Appendix 1 and 2, respectively.

Chapter 2

State of the art

This chapter is under a confidentiality agreement and its access is restricted.

Chapter 3

Vehicle tempering system

This chapter is under a confidentiality agreement and its access is restricted.

Chapter 4

Synthesis of a vehicle simulator

This chapter is under a confidentiality agreement and its access is restricted.

Chapter 5

Prediction of the velocity

This chapter is under a confidentiality agreement and its access is restricted.

Chapter 6

Tempering system optimization

This chapter is under a confidentiality agreement and its access is restricted.

Chapter 7

Industrial validation of the system

This chapter is under a confidentiality agreement and its access is restricted.

Chapter 8

Research results and conclusions

This chapter is under a confidentiality agreement and its access is restricted.

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Appendices

Appendix 1: Prediction results

This chapter is under a confidentiality agreement and its access is restricted.

Appendix 2: Optimization results

This chapter is under a confidentiality agreement and its access is restricted.