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Simultaneous Optimization of Energy Management for Heating and Driving Strategy of a Battery Electric Vehicle

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For my husband Pascal
and my children Leander, Adrian and Felina.

Abstract

Currently, the automotive sector focuses on three trends: battery electric vehicles, autonomous driving and connected drive functionalities. Energy management systems can profit from all three trends. The aim of an energy management system for battery electric vehicles is to maximize the range. This must be done using the limited computation capacity available during a trip without knowing the whole trip in advance with certainty. This thesis presents an energy management system that fulfills these criteria. It is developed and evaluated in a validated simulation environment. It influences three parameters: the velocity, the heater power, and the air mass flow to the cabin. These parameters are optimized for one trip and the optimized parameters are applied to other trips on the same route. To enable this transfer, various adjustments are made to the representation of the variables and to their integration into the vehicle. Various implementations are compared, for example different optimization strategies. The results are analyzed in detail. It is found that the approach leads to a considerable reduction in the energy consumption compared to state-of-the-art energy management systems. In particular, the transfer to other trips works. This means that the energy management system works with little data and requires little computation capacity during the trip. Lastly, the holistic approach, which optimizes all parameters at once, outperforms a serial optimization of the parameters. In summary, a novel concept has been developed, which shows promising results in a simulated vehicle.

Zusammenfassung

Derzeit konzentriert sich der Automobilsektor auf drei Trends: elektrisches, autonomes und vernetztes Fahren. Energiemanagementsysteme können von allen drei Trends profitieren. Das Ziel eines Energiemanagementsystems für batterieelektrische Fahrzeuge ist es, die Reichweite zu maximieren. Dies muss mit der begrenzten Rechenkapazität, die während einer Fahrt zur Verfügung steht, erreicht werden, ohne dass die gesamte Fahrt im Voraus mit Sicherheit bekannt ist. In dieser Arbeit wird ein Energiemanagementsystem vorgestellt, das diese Kriterien erfüllt. Es wird in einer validierten Simulationsumgebung entwickelt und bewertet. Drei Parameter werden beeinflusst: die Geschwindigkeit, die Heizleistung und der Luftmassenstrom in den Fahrzeuginnenraum. Diese Parameter werden für eine Fahrt optimiert und die optimierten Parameter werden auf andere Fahrten derselben Strecke übertragen. Um diese Übertragung zu ermöglichen, werden verschiedene Anpassungen an der Darstellung der Variablen und an ihrer Integration in das Fahrzeug vorgenommen. Es werden verschiedene Umsetzungen verglichen, zum Beispiel unterschiedliche Optimierungsalgorithmen. Die Ergebnisse werden detailliert analysiert. Es zeigt sich, dass der Ansatz zu einer erheblichen Energiereduktion im Vergleich zu einem Energiemanagementsystem aus dem Stand der Technik führt. Insbesondere die Übertragung auf andere Fahrten bringt einen erheblichen Vorteil. Dies bedeutet, dass das Energiemanagementsystem mit wenigen Daten arbeitet und wenig Rechenkapazität während der Fahrt benötigt. Schließlich übertrifft der ganzheitliche Ansatz, der alle Parameter auf einmal optimiert, eine serielle Optimierung der Parameter. Zusammenfassend wird ein neuartiges Konzept entwickelt, das in einem simulierten Fahrzeug vielversprechende Ergebnisse zeigt.

Contents

Abbreviations

ACC	Adaptive Cruise Control	1
BEV	Battery Electric Vehicle	1
BFGS	Broyden–Fletcher-Goldfarb-Shanno	54
BMS	Battery Management System	19
BMW	Bayerische Motoren Werke	38
CCM	Commuters' Cycle Monitoring	35
CVT	Continuously Variable Transmission	27
DC	Driving Cycle	17
DM	Decision Maker	4
DP	Dynamic Programming	5
EMS	Energy Management System	1
FC	Fuel Cell	22
FLC	Fuzzy Logic Controller	19
GA	Genetic Algorithm	5
GPS	Global Positioning System	57
HESS	Hybrid Energy Storage System	22
HEV	Hybrid Electric Vehicle	18
HVAC	Heating, Ventilation and Air Conditioning	19
HVH	High Voltage Heater	31
HiL	Hardware in the Loop	32
ICEV	Internal Combustion Engine Vehicle	1
KKT	Karush-Kuhn-Tucker	11
LIB	Lithium Ion Battery	2
ML	Machine Learning	79
MOOP	Multi–objective Optimization Problem	3
MOO	Multi–Objective Optimization	3
MORE	Mixed Optimization- and Rule-Based Energy Management System	2
MPC	Model Predictive Control	26
MSE	Mean Squared Error	47
NEDC	New European Driving Cycle	38
NLP	Non-linear Programming	22
NN	Neural Network	25
OEM	Original Equipment Manufacturer	2
PMP	Pontryagin's Minimum Principle	20
PSM	Permanent Magnet Synchronous Machine	27
PSO	Particle Swarm Optimization	23
PTC	Positive Temperature Coefficient	31
QP	Quadratic Programming	11
RMS	Root Mean Square	23

List of Symbols

a	$[1\,\frac{\mathrm{m}}{\mathrm{s}^2}]$	acceleration
A_f	$[1\,\mathrm{m}^2]$	frontal area of vehicle
c_d	[1]	aerodynamic drag coefficient
d_y	[1]	direction of step in gradient based optimization method
$\boldsymbol{e}$	[1]	function represented by vehicle model
E_bat	$[1\,\mathrm{W\,h}]$	total energy taken from battery
$E_\mathrm{bat,loss}$	$[1\,\mathrm{W\,h}]$	total energy dissipated during charging and discharging of battery
$E_\mathrm{bat,eff}$	$[1\,\mathrm{W\,h}]$	electric energy needed for the trip, energy taken from battery minus the battery losses
E_heat	$[1\,\mathrm{W\,h}]$	electric energy used for heating the cabin
$E_\mathrm{motor,loss}$	$[1\,\mathrm{W\,h}]$	losses occurring in the electric machine
E_tract	$[1\,\mathrm{W\,h}]$	energy used for traction
E_acc	$[1\,\mathrm{W\,h}]$	mechanical energy needed for accelerating the vehicle
E_recu	$[1\,\mathrm{W\,h}]$	recuperated energy
E_brake	$[1\,\mathrm{W\,h}]$	total energy dissipated and recuperated during braking
$E_\mathrm{brake,mech}$	$[1\,\mathrm{W\,h}]$	mechanical energy dissipated during braking
E_roll	$[1\,\mathrm{W\,h}]$	mechanical energy needed to overcome the roll resistance
E_air	$[1\,\mathrm{W\,h}]$	mechanical energy needed to overcome the air resistance
E_sail	$[1\,\mathrm{W\,h}]$	mechanical energy needed to overcome the roll resistance during deceleration of the vehicle
$E_\mathrm{cabin,loss}$	$[1\,\mathrm{W\,h}]$	thermal energy lost through the cabin
$E_\mathrm{coolant,loss}$	$[1\,\mathrm{W\,h}]$	thermal energy lost through the coolant
$E_\mathrm{air,loss}$	$[1\,\mathrm{W\,h}]$	thermal energy lost through the air streaming out of the cabin
$\boldsymbol{f}$	[1]	function to be optimized
f_i	[1]	i-th component of the optimized function
f_energy	[1]	objective function energy consumption
$f_\mathrm{temperature}$	[1]	objective function cabin temperature
f_time	[1]	travel time
f_Nadir	[1]	Nadir value of individual objective function
f_Utopia	[1]	Utopia value of individual objective function
$\bar{f}$	[1]	normalized individual objective function

F_d	$[1\,\mathrm{N}]$	aerodynamic friction losses
F_g	$[1\,\mathrm{N}]$	uphill driving force
F_i	$[1\,\mathrm{N}]$	inertial force
F_r	$[1\,\mathrm{N}]$	rolling friction losses
F_t	$[1\,\mathrm{N}]$	traction force
F	$[1\,\mathrm{N}]$	force
$\boldsymbol{g}$	[1]	inequality constraints
g	$[9{,}81\,\frac{\mathrm{m}}{\mathrm{s}^2}]$	gravitational acceleration
$\boldsymbol{h}$	[1]	equality constraints
I	$[1\,\mathrm{A}]$	current
k	[1]	counter
M	$[1\,\mathrm{N\,m}]$	torque
$\boldsymbol{o}$	[1]	objective function
$p(t)$	$[1\,\mathrm{W}]$	electrical heater power for one time step
P	$[1\,\mathrm{W}]$	power
P_heater	$[1\,\mathrm{W}]$	electrical heater power
$P_\mathrm{heater,OptimVar}$	$[1\,\mathrm{W}]$	electrical heater power as contained in the optimization variables
$P_\mathrm{heater,norm}$	$[1\,\mathrm{W}]$	electrical heater power as normalized by the heater controller
$P_\mathrm{heater,controlled}$	$[1\,\mathrm{W}]$	electrical heater power as outputted by the heater controller
P_recu	$[1\,\mathrm{W}]$	recuperated electrical power
m_air	$[1\,\frac{\mathrm{kg}}{\mathrm{s}}]$	air mass flow
m_v	$[1\,\mathrm{kg}]$	vehicle mass
t	$[1\,\mathrm{s}]$	time
t_travel	$[1\,\mathrm{s}]$	travel time
T_coolant	$[1\,\mathrm{K}]$	coolant temperature
$T_\mathrm{coolant,target}$	$[1\,\mathrm{K}]$	target coolant temperature
$\Delta T_\mathrm{coolant}$	$[1\,\mathrm{K}]$	difference between target coolant temperature and actual coolant temperature
T_cab	$[1\,\mathrm{K}]$	cabin temperature
$T_\mathrm{cab,target}$	$[1\,\mathrm{K}]$	target cabin temperature
$T_\mathrm{cab,Utopia}$	$[1\,\mathrm{K}]$	Utopia cabin temperature
ΔT_cabin	$[1\,\mathrm{K}]$	difference between target cabin temperature and actual cabin temperature

U	$[1\,\mathrm{V}]$	voltage
$v(t)$	$[1\,\frac{\mathrm{m}}{\mathrm{s}}]$	velocity for one time step
w_k	[1]	random disturbance at step k
x	$[1\,\mathrm{m}]$	distance
y	[1]	decision variable
λ_q	[1]	slope
$\boldsymbol{y}$	[1]	decision vector
$\boldsymbol{y^*}$	[1]	solution
$\boldsymbol{y^0}$	[1]	initial value
α	[1]	step length
$\mathcal{L}$	[1]	Lagrange function
π	[1]	control policy
ρ_a	$[1\,\frac{\mathrm{kg}}{\mathrm{m}^3}]$	air density
$\boldsymbol{\theta}$	[1]	DM priority vector
θ_i	[1]	i-th component of the DM priority vector
θ_energy	[1]	weight of the energy fitness value
$\theta_\mathrm{temperature}$	[1]	weight of the cabin temperature fitness value
θ_time	[1]	weight of the travel time fitness value
ϕ	[1]	merit function
ω	$[1\,\frac{1}{\mathrm{s}}]$	angular velocity

1 Introduction

Currently, three main trends in the automotive industry can be identified [1, p. 99] [2] [3, p. 141] [4]: Firstly, the spread of electric vehicles, in particular Battery Electric Vehicle (BEV) [5, p. 12]; Secondly, the development of autonomous vehicles [6]; Thirdly, the rise of connected drive functionality [7].

The increasing number of BEVs is the most important trend in the context of this thesis, as the topic is an Energy Management System (EMS) for BEVs. During the last years, world-wide sales of BEVs have increased drastically [8] [9] [10]. Electric vehicles are an answer to some of the world's most pressing problems [5, p. 1-19]:

- *Climate change*: Climate change is turning out to be one of humanity's main challenges [11] [12] [13, p. 6]. Headlines of a single German newspaper (Die Zeit) in August 2021 reveal the prevalence of the topic [14] [15] [16]. To limit the world-wide temperature increase, rapid and determined actions must be taken on a global scale [11]. One of the necessary measures is to achieve mobility that does not rely on fossil fuels and does not emit carbon dioxide into the atmosphere [5, p. 2] [13, p.6, 17]. BEVs are not inherently carbon neutral [5, p. 4] [17]. However, as they run on the electricity mix of the country they are used in, they enable shifting the problem to the electric power generation, where it can be handled more easily [17].

- *Bad air quality in urban areas*: More and more people live in cities [18] [19] [20]. This higher population density means that the problem of pollution becomes more pressing [20]. Moore et al. ([20]) identify Internal Combustion Engine Vehicles (ICEVs) as one of the primary sources of air pollution in cities. They cite that in Mexico City $75\ \%$ of the total pollution is caused by vehicles. Currently, even German cities have problems with air quality [21]. This is mostly due to the traffic sector, too [21]. Low air quality leads to an increase in lung diseases and cardio-vascular diseases [22]. Even the risk to die of Covid-19 is increased for people who live in an area with low air quality [23]. Electric vehicles solve this problem as the engine emission is zero [24]. The total emission depends on the source of the electric power used by the vehicle [24]. But even a conventional power plant can be equipped with a better filtering system and can be built outside densely populated areas [24]. Consequently, the health of city residents can be improved by using BEVs.

- *Noise exposure in urban areas*: Residents of cities are not only exposed to pollutants due to ICEVs but also to noise [24]. The constant exposure to high noise levels can lead to increased stress and, therefore, negative effects on the health [25]. As the electric machine is far quieter than a combustion engine, electric vehicles can help to alleviate this problem [24].

- *Lack of mobility in poor, rural areas*: Many rural areas of developing countries suffer from a lack of mobility options [26]. People cannot rely on public transport in these sparsely populated areas. However, personal transport is too expensive for most inhabitants [26]. The existing vehicles are often not sufficiently adapted to the needs of these areas and are additionally too expensive [26]. Combined with solar power plants and micro-grids, BEVs can help to alleviate these problems [26].

The second trend mentioned above is the increase of autonomous driving functions in all types of vehicles. Autonomous driving systems encompass low-level functionalities such as a parking assistant or an Adaptive Cruise Control (ACC) as well as more complex functions allowing driverless vehicles [27] [28]. The first class of functions is already part of commercially available vehicles, while the second class is still under development. One purpose of autonomous driving functions is to enhance the safety of traffic participants. Another important aspect is the convenience of the driver and the passengers [27]. However, there are also systems which aim to improve the overall efficiency of the vehicle [29] [30].

The last-mentioned trend is the growth of connected drive functionalities [3, p.108, 121]. Connected drive means that vehicles communicate among each other, with the infrastructure or the cloud [31] [32]. The idea is that this interconnectedness makes the driving experience for the user more enjoyable, and the services can therefore create revenue for the Original Equipment Manufacturer (OEM) [3, p.108, 121]. In the context of BEVs, it is also possible to use connected drive functionality to enhance the driving experience [33]. Exploiting these potentials can significantly improve individual mobility.

1.1 Current Challenges for EMSs in BEVs

While the previous section shows the advantages of BEVs, this type of vehicle is also faced with challenges. In the following, those challenges that can be addressed by an EMS are investigated. One of the major drawbacks is the limited range compared to an ICEV [34]. Additionally, BEVs face even more severe range limitations in cold ambient temperatures [35] [36]. Under these conditions ICEVs have the advantage that the waste heat of the engine can be used for heating. As BEVs are more efficient, not enough waste heat is available [36]. Moreover, the range is less of an issue for ICEVs than for BEVs. An EMS can help by synchronizing the heating and the recuperated energy to achieve maximum overall efficiency [36] [178]. Another challenge for BEVs is the low lifetime of the Lithium Ion Battery (LIB) [37]. The aging process of the LIB is heavily influenced by the stress-factors during the operation of the vehicle [38]. Therefore, an EMS can be configured to alleviate the stress factors and thus influence the endurance of the battery positively [36].

The main aim of an EMS is therefore to increase the range by maximizing the overall efficiency. Additionally, an EMS can take into account the aging of the LIB. These objectives must be attained without impacting negatively on those parameters that are directly linked to the user satisfaction. One of the main challenges for an EMS is therefore to define and resolve the objectives. Moreover, the scope of the EMS must be defined. This encompasses the definition of the subsystems and parameters that are influenced by the EMS. These targets must be attained with the available resources. The limited resources are forecast data and computing capacity.

The EMS designed for this thesis meets these challenges: The Mixed Optimization- and Rule-Based Energy Management System (MORE) works with little onboard computing power and does not rely on forecast data. It encompasses the driving strategy as well as the heating system to facilitate an optimal trade-off between different objectives.

1.2 Composition

The main part of this thesis is structured as follows: First, the *Theoretical Foundation (Chapter 2)* gives the reader the necessary background knowledge to understand and assess the presented EMS. The focus lies on the description and classification of the optimization methods as well as the tools for modeling BEVs. The topics are selected to be relevant for the thesis but are areas on which it supplies no original research. Second, in the *State of the Art (Chapter 3)* the focus lies on EMSs for BEVs. Moreover, a classification for EMSs is drawn up. The chapter also contains a criticism of the state of the art that illustrate the weaknesses of the existing literature. Third, the *Scientific Objective (Chapter 4)* identifies the research questions and highlights the mission statement for this thesis. Next, the *Approach (Chapter 5)* presents how the MORE works. The chapter also explains how the results needed for this thesis are generated and what tools are used. The highlight is the description of the optimization problem and the concept for the online application. Subsequently, the *Results (Chapter 6)* demonstrate that the concept is feasible and leads to promising results. The results of selected experiments are presented and discussed in detail. Finally, the *Discussion (Chapter 7)* highlights the advantages and disadvantages of the chosen concept and gives an outlook to possible future work.

2 Theoretical Foundation

This chapter aims to provide the reader with the necessary background information to understand the Mixed Optimization- and Rule-Based Energy Management System (MORE). It focuses on Multi–Objective Optimization (MOO) (Section 2.1) and on modeling of BEVs (Section 2.3).

2.1 Basics of Multi-objective Optimization

This section describes the basics of MOO. It concentrates on information that is used for implementing the MORE.

2.1.1 Definition of Multi-objective Optimization

Many real-world optimization problems require MOO, because conflicting objectives must be considered [39, p. 1] [40, p. 517-518]. Examples for Multi–objective Optimization Problems (MOOPs) can be found in the optimization of the powertrain in vehicles, in EMSs for different applications, in the scheduling of power plants and in production planning.

The aim of MOO is to optimize more than one objective at the same time [39, p. 5]. The basic MOOP without constraints is shown in Equation 2.1 [40, p. 518]. In the following, all notations are given for minimization problems. According to the duality principle, maximization problems can be reformulated to minimization problems [39, p. 5][40, p. 13][41, p. 14].

$$\underset{\boldsymbol{y}}{min} f(\boldsymbol{y}) = \underset{\boldsymbol{y}}{min}[f_1(\boldsymbol{y}), f_2(\boldsymbol{y}) \dots f_k(\boldsymbol{y})], \boldsymbol{y} \in \mathbb{R}^n \tag{2.1}$$

The vector $\boldsymbol{y}$ is called decision vector and consists of the decision variables, shown in Equation 2.2 [39, p. 5].

$$\boldsymbol{y} = [y_1, y_2, \dots y_n]^T \tag{2.2}$$

In contrast to that, single objective optimization only optimizes one objective. Consequently, the basic formulation for a single objective optimization problem is as shown in Equation 2.3 [40, p. 13]. In this case only one objective function exists.

$$\underset{y}{min} f(y), y \in \mathbb{R} \tag{2.3}$$

Most real-world problems are constrained [40, p. 481]. For these problems, the constraints must be added to the formulation of the MOOP in Equation 2.2. This is done in accordance with [41, p. 13].

$$\boldsymbol{h}(\boldsymbol{y}) = [h_1(\boldsymbol{y}), h_2(\boldsymbol{y}) \dots h_l(\boldsymbol{y})] = 0 \tag{2.4}$$

$$\boldsymbol{g}(\boldsymbol{y}) = [g_1(\boldsymbol{y}), g_2(\boldsymbol{y}) \dots g_m(\boldsymbol{y})] \geq 0 \tag{2.5}$$

Equation 2.4 expresses the equality constraints, while Equation 2.5 expresses the inequality constraints [41, p. 13]. A vector $\boldsymbol{y}$ must satisfy Equations 2.4 and 2.5 to be a solution to the minimization problem formulated in Equation 2.1 [41, p. 14]. The functions $g_i(\boldsymbol{y})$ and $h_j(\boldsymbol{y})$ are called constraint functions [41, p. 14]. The constraint functions define the feasible region or the search space of the optimization [41, p. 14].

2.1.2 Problem Formulation for Multi-objective Optimization Problems

For a single objective optimization problem, a global or local optimum can be found. The optimum is the vector minimizing the objective function $f(y)$. For MOOPs, no universal definition for an optimum exists [43, p. 1]. Which vector or vectors $\boldsymbol{y}$ solve the MOOP depends on the individual user who applies the optimization procedure. It is assumed that this user is an expert in the problem domain and therefore knows which solution is satisfying for them. In the following, the user is referred to

No Involvement of DM	Rising Involvement of DM		High Involvement of DM
No Preference	**A priori**	**A posteriori**	**Interactive**
Description			
No involvement of DM	DM decides before optimization is run	DM picks one solution after optimization is run	DM interacts with optimization
Examples			
Neutral Compromise Method [42, p.14]	Weighting Method [42, p.10] ϵ-constraint Method [42, p.13]	Weighting Method [42, p.10]	Reference Point Approaches [42, p.29]

Figure 2.1 : Classification of optimization methods according to the involvement of the DM [42]

as Decision Maker (DM). The MOOP is formulated to allow the DM to interact with the optimization algorithm. As a result, four different approaches can be chosen.

Figure 2.1 gives an overview of the approaches sorted by the involvement of the DM. The first possibility is to cut out the DM completely. This method is called *no preference*. However, the DM usually formulates the optimization problem in a way that their preferences still shape the outcome of the optimization. The second approach is called an *a priori* approach. In this case the DM states their wishes before the optimization is run. This means the MOOP is transformed into a single objective problem for which a global or local optimum can be found. One possibility to do that is to use an aggregating method. The most straight-forward method to transform a MOO into a single objective problem is the weighted sum method. Equation 2.6 showcases this approach. [42]

$$\underset{\boldsymbol{y}}{min} f(\boldsymbol{y}) \Rightarrow \underset{\boldsymbol{y}}{min} \sum_{i=1}^{n} \theta_i \cdot f_i, \text{ where } \sum_{i=1}^{n} \theta_i = 1 \tag{2.6}$$

The vector $\boldsymbol{\theta}$ is called DM priority vector, as it expresses how the DM prioritizes the objectives. To obtain better results, it is possible to normalize the objective function using the Nadir and Utopia values [42, p. 7]. The Nadir value $f_i^N(\boldsymbol{y})$ is the worst possible outcome of $f_i(\boldsymbol{y})$. The Utopia value f_i^0, on the other hand, is the optimum of $f_i(\boldsymbol{y})$, if it is optimized separately. The computation of the Utopia values is straightforward, while the Nadir values often necessitate problem specific knowledge or cannot be computed at all. How the objective functions $f_i(\boldsymbol{y})$ can be normalized is shown in Equation 2.7 [42, p. 14-15].

$$f_i^{norm}(\boldsymbol{y}) = \frac{f_i(\boldsymbol{y}) - f_i^N(\boldsymbol{y})}{f_i^0(\boldsymbol{y}) - f_i^N(\boldsymbol{y})} \tag{2.7}$$

A posteriori means that the DM decides which solution is used after the optimization is done. The optimization comes up with a selection of equally good solutions and the DM decides which of these solutions is acceptable for them. As shown in Figure 2.1, *a posteriori* approaches require a higher involvement of the DM than *a priori* approaches. In particular, the DM must interact with the optimization after every run of the algorithm. For an *a priori* approach the preferences of the DM must be stated only once, even if the algorithm is run multiple times. The concept of these equally good solutions is called Pareto optimality. A solution is Pareto optimal if no objective can be enhanced without deteriorating another [39, p. 10]. In the following, the most important definitions concerning Pareto optimality are given. These definitions are in accordance with [39] and [40].

1. **Domination**: A point $\boldsymbol{y}^*$ dominates $\boldsymbol{y} \in \mathbb{R}^n$ if Equation 2.8 and 2.9 are fulfilled [39, p. 11] [40, p. 519].

$$f_i(\boldsymbol{y}^*) \leq f_i(\boldsymbol{y}) \text{ for all } i \in [1, n] \tag{2.8}$$

$$f_j(\boldsymbol{y}^*) \leq f_j(\boldsymbol{y}) \text{ for one or more } j \in [1, n] \tag{2.9}$$

2. **Non-dominated**: A point $\boldsymbol{y}^*$ is non-dominated in $\boldsymbol{y}$, if no point $\boldsymbol{y}$ exists that dominates $\boldsymbol{x}^*$ [40, p. 519].

3. **Pareto point**: A point $\boldsymbol{y}^*$ is called Pareto point, if it is non-dominated within the search space [40, p. 519].

4. **Pareto set**: The set containing all Pareto points $\boldsymbol{y}^*$ is called Pareto set [39, p. 11] [40, p. 519].

5. **Pareto front**: The Pareto front contains the function vectors $f(\boldsymbol{y}^*)$ of all Pareto points $\boldsymbol{y}^*$ in the Pareto set [39, p. 11] [40, p. 519].

Typically, the result of an *a posteriori* method is the Pareto set and the resulting Pareto front. The DM considers these results and chooses the solution that fits their needs best. Many different *a posteriori* methods exist. Here, only one example is given: The weighted sum method shown in Equation 2.6 can also be adapted to be used as an *a posteriori* method. In this case, the weights $\theta_1, \theta_2 \ldots \theta_n$ are varied to obtain a Pareto set of solutions. Afterwards the DM chooses one solution.

In the context of EMSs, the DM often cannot influence the results after the optimization. For example, if the EMS is used during the operation of a vehicle, the DM being the engineer who designed the EMS has no opportunity to interact with the algorithm after the optimization. However, they can use an *a priori* method to state their preferences before the algorithm is implemented in the vehicle.

The rightmost approach in Figure 2.1, demands the highest involvement of the DM. This approach is referred to as *interactive* because the DM continuously interacts with the algorithm during the optimization procedure.

2.2 Overview of Optimization Methods

In the previous section (Section 2.1.1), a basic MOOP is introduced. Based on the explanations regarding the MOOP, this section provides an overview of optimization methods. First, a categorization of optimization methods is given. Second, the three algorithms used in this thesis are introduced. These are Genetic Algorithms (GAs), Sequential Quadratic Programming (SQP) and Dynamic Programming (DP).

2.2.1 Categorization of Optimization Methods

Figure 2.2 shows how global optimization methods can be categorized. The figure shows a small excerpt of methods; for a more detailed overview refer to [39]. For enumerative methods, each possible solution is evaluated, the results are then compared, and the best result is chosen as the optimum [39, p. 21]. This strategy can only be applied if the number of possible solutions is very limited [39, p. 21].

Stochastic optimization methods were devised to solve irregular optimization problems [39, p. 22]. For most stochastic optimization procedures, no guarantee is given that they find the global optimum [39, p. 22-23]. Typically, no domain knowledge is integrated into the approach [39, p. 22]. Basically, the objective functions $f_j(\boldsymbol{y})$ are used to assign a fitness value to the possible solutions $\boldsymbol{y}$ [39, p. 22]. The optimization algorithm uses these fitness values to find the optimum [39, p. 22]. The most straightforward stochastic optimization algorithm is the random walk [39, p. 22]: In each iteration a randomly selected $\boldsymbol{y}^i$ is evaluated. The value $f(\boldsymbol{y}^i)$ is stored. Then a new $\boldsymbol{y}^{i+1}$ is chosen by adding

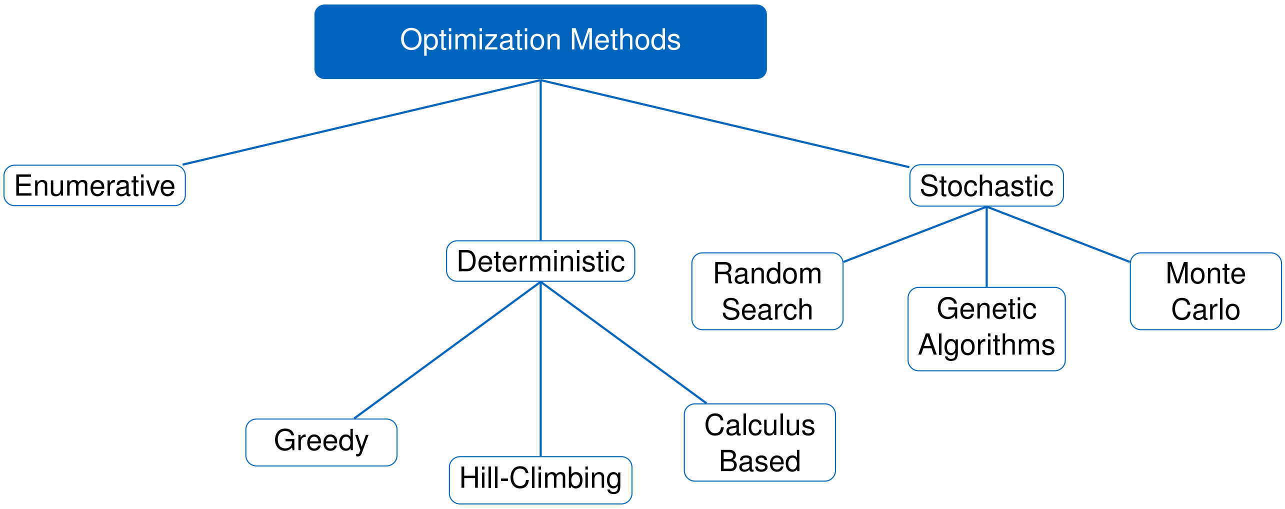


Figure 2.2 : Overview of the Classification for Global Optimization Methods according to [39, p. 21]

a random vector $\boldsymbol{d}$ to the vector $\boldsymbol{y}^i$. The new value of the objective function $f(\boldsymbol{y}^{i+1})$ is computed and compared to $f(\boldsymbol{y}^i)$. If $f(\boldsymbol{y}^{i+1})$ is better than $f(\boldsymbol{y}^i)$, $\boldsymbol{y}^{i+1}$ is taken as the starting point for the next step. Otherwise, it is discarded and $\boldsymbol{y}^i$ remains the starting point for the next step. For most MOOPs, the random walk is not efficient [39, p. 23]. Over the years several more complex stochastic optimization algorithms have been developed. One of the most important classes are GAs.

2.2.2 Genetic Algorithm

In the following, an introduction to GAs is given. As shown in Figure 2.2, GAs are a heuristic optimization method. Their strength is, as with other heuristic approaches, that they can be applied to a wide variety of optimization problems [41, p. 82]. Two aspects should be noted: Firstly, while GAs can be applied to a wide variety of optimization problems, this does not mean that they are necessarily the most efficient approach or that they yield the best possible results. Secondly, not every GA can be directly applied to every problem.

As already motivated in Section 2.1.2, this thesis focuses on an *a priori* approach. In this case a GA for a single objective problem can be used. In the following, the basic working principle of such a GA is described.

Figure 2.3 exemplifies the sequence of a GA. The terminology for GAs is inspired by the terminology used to describe evolution in nature. Table 1 defines the key terms.

As shown in Figure 2.3, in the first step the initial population is created. This means that an initial set of candidate solutions is generated. Next, each of the individuals is evaluated and assigned a fitness value. This evaluation can be done using a model. The model takes the individuals as input and returns the fitness value. In the next step, it is checked whether one or more termination criteria are met. If this is the case, the individual with the highest fitness value is returned and the algorithm terminates. If no termination criterion is met, the algorithm continues with the selection. In this step the individuals for the next population are selected. In general, the aim is to discard the worst individuals and keep the best, while at the same time maintaining the diversity of the population. A diverse population helps to prevent getting stuck in a local minimum. After the selection, the individuals recombine. This means that the information of two individuals is blended. The final step is the mutation. Mutation means that random changes are applied to selected individuals. After the mutation, the next iteration of the GA starts with the evaluation. One iteration of the GA is referred to as generation. [40, p. 50]

The GA contains deterministic as well as random operators. The evaluation of the individuals, the check for the termination criteria and some variations of the selection are deterministic, while

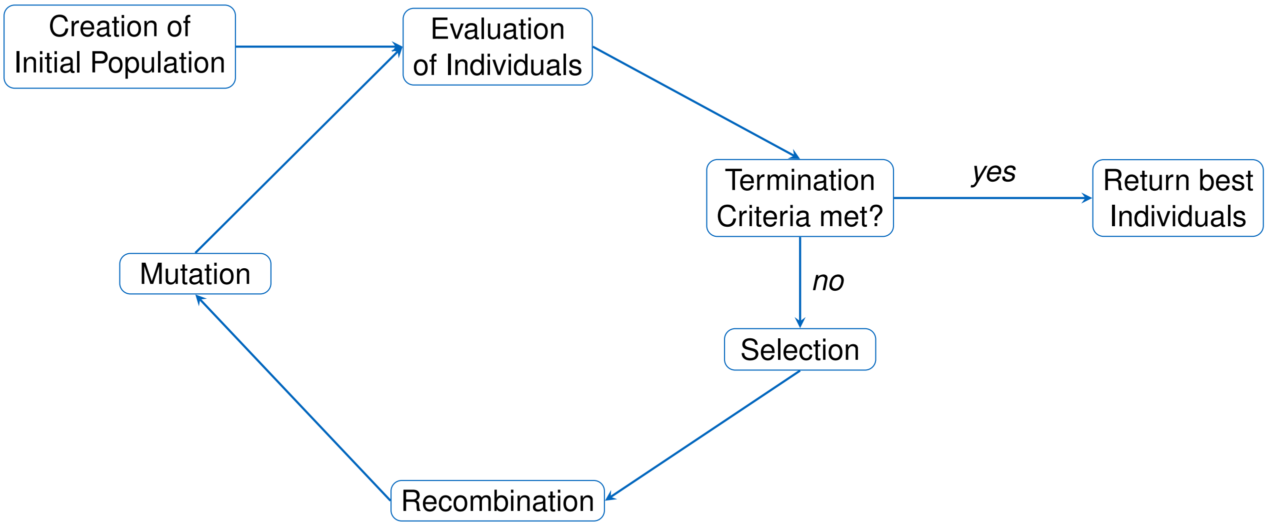


Figure 2.3 : Basic sequence of a GA (refer to [40, p. 50])

Table 1 Terminology for GAs (refer for example to [40] [41])

Term	Definition in context of GAs
Individual	Possible solution in search space; can either be continuous or binary coded
Population	Set of individuals
Generation	Iteration of GA; population during one iteration
Child	Individual of following generation
Parent	Individual of current generation
Fitness value	Value assigned to individual indicating how well it solves the optimization problem
Selection	Process of choosing the individuals for cross-over
Recombination	Transfer of information between individuals; contains random elements
Mutation	Random changes made to individuals

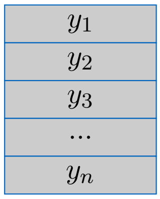


Figure 2.4 : Example of an un-encoded individual

the mutation, the recombination and sometimes the creation of the initial population contain random elements.

In the following, different ways to implement the individual steps of a GA can be implemented are introduced. The focus lies on option used in this thesis.

Representation of Individuals: The individuals can either be represented with real values or be encoded. In this thesis, the individuals are represented with real values. Figure 2.4 shows a schematic example of an individual consisting of real valued variables. Real valued individuals have the advantage that they facilitate faster computation because they do not have to be decoded before evaluation [40, p. 50] [41, p. 86]. Additionally, they are more accurate, and the required accuracy and range does not have to be defined prior to computation [41, p. 110]. The main disadvantage of real-valued individuals is that they differ more from the biological model [41, p. 86]. This means that it is more difficult to draw up meaningful recombination and mutation operators [41, p. 110].

Initialization: Typically, the initialization of the population is done by generating the individuals randomly [40, p. 180]. The user defines the range in which the individuals are created [40, p. 180]. However, sometimes the convergence of the GA can be improved if the creation of the initial population is modified. Firstly, more individuals than necessary can be created and only the best individuals are kept for the initial population [40, p. 180]. Secondly, the initial population can be enhanced by introducing expert solutions as individuals [40, p. 180].

Mutation: Mutation describes the process of randomly making changes to an individual [41, p. 95]. The mutation rate specifies how likely such a change is [40, p. 49]. Typically, the mutation rate in GAs is low (about 1-2 %) [40, p. 49]. However, no general rule exists how the mutation rate should be set [40, p. 49]. Both, a too high and a too low mutation rate, have an adverse impact on the results of the GA [40, p. 49].

In a GA with encoded individuals, the most straightforward implementation of mutation is that each bit of each individual has a probability to be switched [40, p. 49]. However, this does not work for real-valued individuals. The simplest approach to mutation for real-valued GAs is the random mutation [40, p. 56] [41, p. 122]: With a certain probability each parameter y_i is replaced with a random number within the search space. A more popular method is the normally distributed or Gaussian mutation [40, p. 215] [41, p. 122]: Each parameter of each individual is replaced by a random number with a certain probability. This random number is normally distributed around the original value of the parameter in the parent individual.

Crossover: Crossover describes the combination of the information of two individuals. In general, it is the dominant factor for change in the population from one generation to the next [41, p. 112]. The different implementations of crossover operators can be categorized into two classes [41, p. 112-113]: Naive and blended crossover.

The simplest implementation of naive crossover is the single-point crossover [41, p. 112-113] [40, p. 209]: A random position within the individuals is chosen. The child receives all information before this point from one parent, and all information after this point from the other. This concept can be expanded to multiple-point crossover [40, p. 210] and to uniform crossover [41, p. 112] [40, p. 210]. In the case of uniform crossover, a separate decision for each parameter is made. Either the information from the first or the second parent is chosen for the child [40, p. 210-211]. All variations of naive crossover can be used with encoded and real-valued individuals [40, p. 209-211][41, p.93-94, 111].

In contrast to that, blended crossover can only be used with real valued individuals [41, p. 113]. The idea is that the two parents are connected by a straight multidimensional line and the children lie on that line. The exact position of the children is determined by the specific implementation. For example, a parameter β can be used to compute the children using the following set of equations [40, p. 213].

$$\begin{aligned} \boldsymbol{y_{min}}(i) &= min(\boldsymbol{y_a}(i), \boldsymbol{y_b}(i)) \\ \boldsymbol{y_{max}}(i) &= max(\boldsymbol{y_a}(i), \boldsymbol{y_b}(i)) \\ \Delta\boldsymbol{y}(i) &= \boldsymbol{y_{max}}(i) - \boldsymbol{y_{min}}(i) \\ \boldsymbol{y_{child}}(i) &= U(\boldsymbol{y_{min}}(i) - \beta\Delta\boldsymbol{y}(i), \boldsymbol{y_{max}}(i) + \beta\Delta\boldsymbol{y}(i)) \end{aligned} \tag{2.10}$$

In Equations 2.10, $\boldsymbol{y_a}$ and $\boldsymbol{y_b}$ denote the chosen parents and $\boldsymbol{y}$ the resulting children. The index i indicates that the i-th feature of the vector is regarded. The children are determined by the uniform distribution in the area defined by the parents and the parameter β. The parameter β is defined by the user. For $\beta < 0$ the children lie between the parents, for $\beta > 0$ the children lie outside the range defined by the parents. Both configurations are used. This type of crossover is referred to as heuristic crossover. A related approach is the arithmetic crossover [40, p. 212-213] [41, p. 113]: For this method the weighted arithmetic mean of the parents is used to create the children.

Selection: The aim of selection is to choose the individuals for crossover and therefore those individuals whose information is transferred to the next generation [40, p. 45-46]. The most common approach is the roulette wheel selection [40, p.46-49, 199]: Each individual is assigned a section of an imaginary roulette wheel according to its fitness value. In the next step a pointer is spun, stopping randomly in one position of the wheel. The individual that is assigned this section is chosen. Because individuals with a higher fitness value are assigned a larger section of the wheel, they have a higher probability of being chosen. The process is repeated until sufficient parent individuals are selected.

The problem with roulette wheel selection is that the fittest individual might not be chosen [40, p. 200]. Consequently, the information of this individual is lost, and the algorithm might move further away from the optimum [40, p. 200]. To avoid this, the roulette wheel selection can be modified to stochastic universal sampling [40, p. 199-201]: Again, the sections of the roulette wheel are allocated according to the fitness value of the individuals. However, the pointer is modified. Instead of spinning a single pointer multiple times, as many pointers as selected individuals are used. The pointers are equally spaced and spun only once to select the individuals. This reduces the risk of not choosing the fittest individual.

Besides roulette wheel selection and its variations, another popular selection method exists: the tournament selection [40, p. 207] [41, p. 88-89]. Tournament selection means that two or more individuals are chosen randomly to compete against each other [40, p. 207]. Each of these competitions is called a tournament. The individuals in one tournament are compared to each other and the fittest individual is selected. Two variations exist [40, p. 207-208]: Strict and soft tournament. In a strict tournament the fittest individual is chosen with a likelihood of 1. In a soft tournament the fittest individual only wins with a likelihood smaller than 1. This introduces another stochastic element into the selection process.

Elitism: Elitism means that not all individuals from one generation are created by crossover of the parent individuals, but that the best parents survive into the next generation [40, p. 188]. This is done to avoid losing good solutions [40, p. 188]. According to Simon [40, p. 190] elitism should always be used because it significantly improves the algorithm at low computational costs. Mainly two implementation options exist [40, p. 188]: Firstly, less children can be produced by crossover. The missing children are the best individuals from the parent generation. Secondly, the full number of children can be generated by crossover. The worst children are replaced by the best parents. The second option has the disadvantage that it requires more function evaluations and sorting, but it usually yields the better results [40, p. 188].

Termination: A variety of termination criteria for GAs exist, which can either be used separately or be combined [40, p. 181-182]: Firstly, it is possible to stop after a predefined number of generations or evaluations of the fitness function. The advantage of this approach is that the run-time is predictable. Secondly, the algorithm can terminate if the solution is satisfactory. The difficulty is to decide when a solution is satisfactory. Moreover, the change of the fitness values can be used as an indicator. Either the algorithm stops if the fitness value of the best individual does not change significantly anymore, or it can terminate if the average fitness value of the population remains more or less constant. Lastly, the standard deviation of the population can be used as an indicator as when to stop. A low standard deviation means that the population is uniform.

Constraint Handling: To solve problems that are constrained, as defined in Equations 2.4 and 2.5, the GA must be adapted [40, p. 481]. In this thesis only linear constraints are considered because they suffice to define the MOOP. Three main approaches for constrained problems exist [40, p. 481]: Penalty function approach, special representation of the individuals or special implementations of the operators and repair algorithms. Additionally, hybrid approaches can be used [40, p. 481].

According to Simon ([40, p. 483]) penalty approaches are the most popular approaches. These approaches work by adding a penalty term to the fitness function which penalizes infeasible solutions [40, p. 483]. Alternatively, these solutions can also be eliminated [40, p. 485]. Two kinds of penalty algorithms exist [40, p. 483-485]: Interior and exterior point methods. While exterior point methods allow infeasible individuals, interior point methods only permit feasible individuals. Exterior point methods are more common because the infeasible individuals might still contain valuable information [40, p. 484].

The special representation of the individuals or special implementations of the operators is specific to the optimization problems [40, p. 482]. It means that either the individuals are represented in a way to make infeasible solutions impossible or that the operators (initialization, selection, mutation, crossover) are implemented so that infeasible individuals are not created [40, p. 482]. Because these methods are specific to the optimization problem, they must be developed specifically for every problem and are therefore harder to implement [40, p. 499]. However, they often also lead to the best results [40, p. 499].

Repair algorithms are used in GAs to repair infeasible individuals so that they become feasible again [40, p. 482]. Typically, some infeasible individuals remain to preserve the diversity of the population [40, p. 482].

2.2.3 Sequential Quadratic Programming

SQP is a gradient based optimization method [44, p. 529]. It differs from GAs insofar as it requires a more precise mathematical description. In the context of this thesis, only the basic concept of SQP is presented. The aim is to explain the different behavior of the algorithms in the practical application.

The term SQP describes a class of algorithms that all follow the same pattern for solving optimization problems but differ in the implementation. SQP algorithms are efficient on small as well as on large scale problems. Variations exist for unconstrained and constrained problems [44, p. 530]. SQP optimization works under inequality constraints as well as equality constraints [45, p. 1]. Moreover, the constraints may be non-linear [45, p. 2]. Like all gradient based optimization methods, SQP can only guarantee a local optimum [45, p. 6]. As mentioned above, gradient based methods and consequently SQP take the structure of the problem into account and the problem must fulfill certain requirements for gradient based methods to be applicable. In general, SQP methods pose rather weak requirements on the problem, as the gradient is typically approximated.

SQP solves a constrained nonlinear optimization problem of the form described in Section 2.1.1 in Equation 2.3. $f(y)$ as well as $g(y)$ and $h(y)$ can be nonlinear [45, p. 2].

For constrained optimization problems, the first order optimality conditions are more difficult to formulate than for the unconstrained case [44, p. 320]. In the unconstrained case the first order optimality condition is that the gradient of the objective function is zero [44, p. 14-15]: $\nabla f(y^*) = 0$. For an exhaustive treatment of all optimality conditions for unconstrained optimization refer to [44, p. 14-17]. For constrained optimization the first order optimality condition is expanded to the Karush-Kuhn-Tucker (KKT) conditions [44, p. 320-321].

The basic principle of SQP methods is to model the original optimization problem at the current step k with a Quadratic Programming (QP) subproblem [44, p. 530] [45, p. 2]. This subproblem is minimized to find the next iterate y_{k+1} [44, p. 530][45, p. 2]. The subproblem is chosen to be quadratic because a QP problem reflects the non-linearity of the original problem and can still be solved efficiently [45, p. 7].

It follows that for the implementation of a SQP method three separate issues must be addressed: Firstly, how can the QP be formulated [45, p. 10]? Secondly, how can the QP be solved [45, p. 10]? Thirdly, how can global convergence be ensured [45, p. 27]? These are also the main points in which SQP methods differ. Moreover, this structure allows to break down the analysis of SQP into smaller problems [45, p. 10]: For the algorithm to converge the QP subproblem must be solvable and the resulting steps must lead into the right direction.

First, the formulation of the QP subproblem is looked at. The general form of a QP problem is [45, p. 7]:

$$\begin{aligned} \underset{\boldsymbol{d}_{\mathbf{y}}}{min} (r^k)^T \boldsymbol{d}_{\mathbf{y}} + \frac{1}{2} \boldsymbol{d}_{\mathbf{y}}{}^T B_k \boldsymbol{d}_{\mathbf{y}} \\ \text{subject to } \nabla h(y^k)^T \boldsymbol{d}_{\mathbf{y}} + h(y^k) = 0 \\ \nabla g(y^k)^T \boldsymbol{d}_{\mathbf{y}} + g(y^k) \leq 0 \end{aligned} \tag{2.11}$$

$\boldsymbol{d}_{\mathbf{y}}$ is defined as $\boldsymbol{d}_{\mathbf{y}} = y - y^k$ [45, p. 7]. To define a QP for a SQP method r^k and B_k must be suitably defined [45, p. 7]. The most obvious choice for the QP would be the local approximation to $f(y)$ at y^k [45, p. 7]. This approach works only with linear constraints. The QP can be expanded to work with non-linear constraints [45, p. 7].

The solution of Equation 2.11 is used to update the iterate of the original optimization problem: $y^{k+1} = y^k + d_{\mathrm{y}}$ [45, p. 9]. How the QP problem is solved is one of the design parameters of a SQP method [45, p. 7]. A possible approach is the Newton method [45, p. 13-15]. One challenge is that the solution for the QP problem can only be found if the Hessian matrix $\nabla^2_{yy}\mathcal{L}(y^k, u^k, v^k)$ fulfills certain conditions. For a discussion of these conditions refer to [45, p. 16-26]. Here, Boggs et al. also discuss different approaches how the approximation of the Hessian matrix can be adapted to fulfill these conditions. SQP can be combined with line search as well as with trust region methods [44, p. 545-546].

The local convergence of SQP methods designed by the above principles can be shown [45, p. 12]. However, for practical applications local convergence is not enough and global convergence is required [45, p. 10]. To gain a clear understanding of the terms, a short definition is given [45, p. 10]: If an optimization method converges locally, this means that the optimum y^* can be found from a starting point y^0 that is 'close enough' to y^*. For real-world problems it is usually not possible to tell whether y^0 is close enough to y^*, because y^* is of course not known when y^0 is chosen. Therefore, the aim is to develop globally convergent methods. These methods also converge to y^* from remote starting points y^0. It is important to note that global convergence is different to convergence toward a global optimum.

To facilitate global convergence, a merit function approach can be used [44, p. 540] [45, p. 27]. The merit function ϕ tracks the process of the optimization over the iterations [45, p. 27]. Every step d_{y} must not only solve the QP sub-problem, but also lead to a minimization of the merit function ϕ [45, p. 27]. The step length can be adapted, but the direction of the step remains unchanged [45, p. 27]. For a detailed discussion of merit function approaches and their theoretical background refer to [44, p. 540-543] [45, p. 27-39].

In accordance with [45, p. 11], a description of the basic SQP algorithm is given in the following. The approximations (y^0, u^0, v^0), B_0 and the merit function ϕ are given. At the beginning the iterate counter is set to zero: $k = 0$.

1. Formulate and solve QP subproblem from Equation 2.11 to obtain $(d_{\mathrm{y}}, d_u, d_v)$.

2. Choose step length α to satisfy:
$$\phi(y^k + \alpha d_{\mathrm{y}}) < \phi(y^k) \tag{2.12}$$

3. Set
$$\begin{aligned} y^{k+1} &= y^k + \alpha d_{\mathrm{y}} \\ u^{k+1} &= u^k + \alpha d_u \\ v^{k+1} &= v^k + \alpha d_v \end{aligned} \tag{2.13}$$

4. Stop if converged.

5. Compute B_{k+1}.

6. Set k to $k+1$ and go to step 1.

The above algorithm leaves many implementation details open but highlights the basic concept of SQP. For implementation details both [44] and [45] can be referred to.

2.2.4 Dynamic Programming

DP is a deterministic optimization technique [46, p. 23]. Unlike GA and SQP, it can theoretically determine the global optimum e.g. the minimal costs of a process [46, p. 23].

To describe DP, the technique is decomposed into two steps: First, the problem at hand must be reformulated to have the required structure for DP. Second, the reformulated problem is optimized.

At the core of DP lies Bellmann's principle of optimality [46, p. 18]. It states that, if a problem can be decomposed into sub-problems, these problems can be optimized separately and be put together at the end to form an optimal solution [46, p. 18].

According to [47, p. 14] the optimization problem in its most general form can be written as follows:

$$Problem\ P^0 : p^* = \underset{y \epsilon Y}{opt}\, f(y) \tag{2.14}$$

In Equation 2.14, y denotes the decision variable that is taken from Y and $f(y)$ the objective function. The decomposition means that each state is expressed as a function of the preceding state [46, p. 2-3]:

$$s_{k+1} = q_k(s_k, y_k, w_k) \tag{2.15}$$

In Equation 2.15, s_k denotes the state, y_k is the decision variable and w_k the noise or disturbance. The index k denotes the discrete time. k lies between 0 and $N-1$, with N being the horizon or number of time-steps in which the control is applied.

This formulation is sometimes referred to as multistage decision model [47, p. 36]. For DP the model must be Markovian [47, p. 52]. Markovian means that it satisfies the Markov condition [47,

p. 52]: Every state only depends on the previous state and the transition function. The formulation in Equation 2.15 shows a Markovian model, because x_{k+1} is only a function of x_k and no previous states.

Moreover, the objective function must be cumulative [46, p. 3]. The total costs with a cumulative objective function can be written as follows [46, p. 3]:

$$f_N(s_N) + \sum_{k=0}^{N-1} f_k(s_k, y_k, w_k) \tag{2.16}$$

In Equations 2.15 and 2.16, the random disturbance w_k cannot be influenced and therefore not be optimized [46, p. 3]. The objective function can therefore be more meaningfully expressed as the expected costs [46, p. 3]:

$$J(s_0) = E\left\{ f_N(s_N) + \sum_{k=0}^{N-1} f_k(s_k, y_k, w_k) \right\} \tag{2.17}$$

In Equation 2.17, $J(s_0)$ denotes the expected total costs for the initial state s_0 [46, p. 13].

The parameters that can primarily be influenced are the controls y_k. A series of functions for the control parameters is called policy. A policy can be defined as follows [46, p. 13]:

$$\pi = \{\mu_0, \ldots, \mu_{N-1}\} \tag{2.18}$$

Each control parameter can be expressed as a function of the current state [46, p. 13]:

$$y_k = \mu_k(s_k) \tag{2.19}$$

The expected costs from Equation 2.17 can be rewritten as follows [46, p. 13-14]:

$$J_\pi(s_0) = E\left\{ f_N(s_N) + \sum_{k=0}^{N-1} f_k(s_k, \mu_k(s_k), w_k) \right\} \tag{2.20}$$

The aim of DP is therefore to find the optimal policy π^*, which minimizes the costs [46, p. 14]. This can thus be expressed as [46, p. 14]:

$$J_{\pi^*}(s_0) = \underset{\pi \epsilon \Pi}{min} J_\pi(s_0) \tag{2.21}$$

In Equation 2.21, Π denotes the set of all admissible policies.

Figure 2.5 shows the representation of a deterministic multistage model with a transition graph. Each circle represents one state. The system can transition between the states depending on the control variables u_k and the current state s_k. A time-step is referred to as *stage*. The numbering of the stages is given beneath Figure 2.5. In the figure each arrow is associated with a cost function $f_k(s_k, y_k)$. It is important to note that the transition can only go from one stage to the next and never backwards or within one stage.

After the DP problem is formulated, the DP approach is used to solve the problem. First, the objective function for every state is computed. This is done in accordance with Equation 2.17 by taking the costs from the previous state and adding the costs for the transition [48, p. 359]. This process is shown in Figure 2.6. The notation introduced in Equations 2.16 to 2.21 is used. It represents a detailed example taken out of Figure 2.5. In the example, state $s_{2,1}$ can be reached by two ways from the previous state $s_{1,1}$. One way incurs the costs f_{1a}, the other the costs f_{1b}. Which of the two possibilities is used depends on the decision variable y_1. According to Equation 2.17 the cumulative

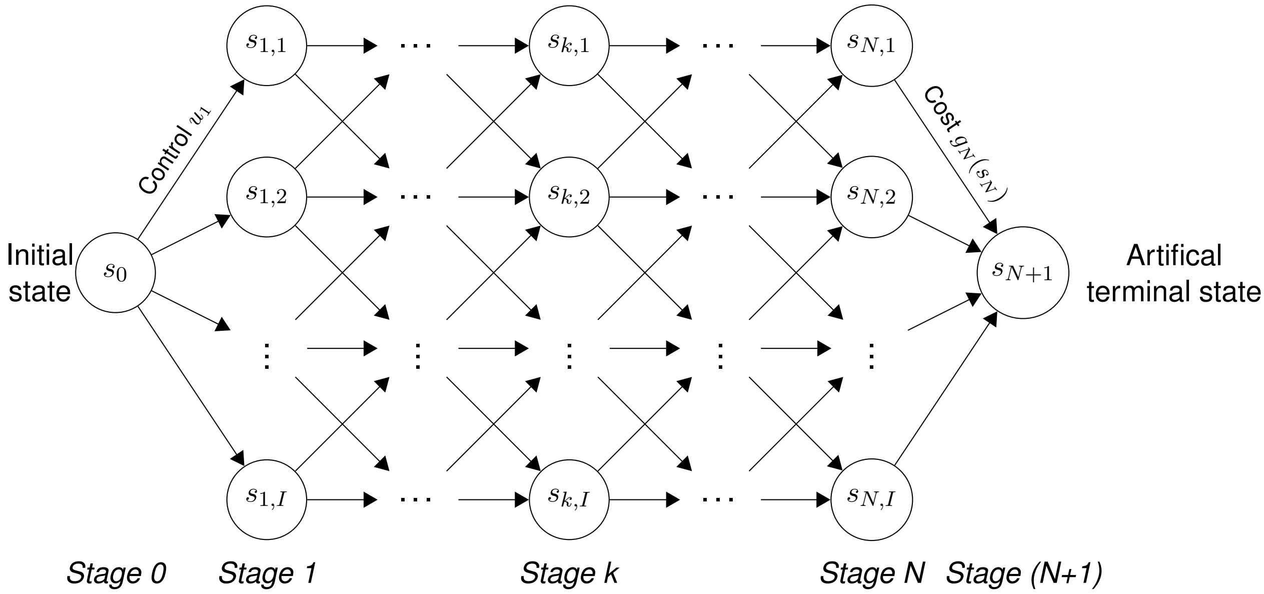


Figure 2.5 : Transition graph for deterministic multistage decision model (refer to [46, p. 65])

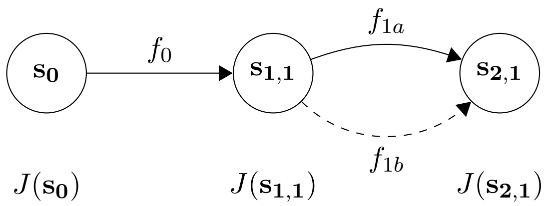


Figure 2.6 : Decomposition of optimization problem, transition between two states

objective function $J(s_{2,1})$ can be expressed as:

$$J(s_{2,1}) = J(s_{1,1}) + f_1 \tag{2.22}$$

If $f_{1a} < f_{1b}$ the transition from $s_1, 1$ to $s_2, 1$ via f_{1a} is the optimum for this sub-problem. These costs are stored by the algorithm [48, p. 359]. Therefore, the computation for every state must be done only once [48, p. 359]. The least expensive path represents the optimal control policy [46, p. 14]. In this example the sub-problem is solved by direct enumeration. This is the common DP approach [47, p. 21-22].

It is evident that this strategy is less computationally expensive than a naive enumerative approach [48, p. 365]. However, the trade-off for this are higher memory demands [48, p. 365].

Theoretically, DP finds the global optimum [46, p. 18]. In practical applications this is not always the case. When the problem is formulated for DP, the optimum for this problem can be guaranteed. However, the challenge is to cast a real-life problem into the correct formulation for DP. If the problem is not discrete in the first place, discrete states must be defined artificially [46, p. 25]. This might mean that the optimum found by the DP algorithm is not the optimum for the original continuous optimization problem [46, p. 18]. Reformulating the problem to satisfy the Markov condition might also not always be possible or lead to suboptimal solutions [47, p. 56].

An additional challenge for using DP is the curse of dimensionality [47, p. 170] [49, p. 3]. It is important to note that the curse of dimensionality impacts other optimization methods as well [47, p. 170]. However, in the following it is considered only in connection with DP. Powell [49] describes three curses of dimensionality [49, p. 5-6]:

- *State Space:* The computation time grows exponentially with the number of dimensions of the state variable s. This can be written as $\mathcal{O}(L^I)$, with L being the number of values the state variable can assume and with I being the dimensionality of the state variable.

- *Outcome Space:* The computation time grows exponentially with the number of dimensions of the random disturbance w. This can be written as: $\mathcal{O}(M^J)$, with M being the number of values the disturbance can assume and with J being the dimensionality of the random disturbance.

- *Action Space:* The computation time grows exponentially with the number of dimensions of the decision variable u. This can be written as: $\mathcal{O}(N^K)$, with N being the number of values the decision variable can assume and with K being the dimensionality of the decision variable.

The three curses of dimensionality imply that DP becomes infeasible for many real-world problems due to the high computation time [47, p. 180].

2.3 Modeling of BEVs

In this section an introduction to the modeling of BEVs is given. This is relevant for the thesis because the developed EMS is based on a vehicle model.

Models are essential for the development process of all types of vehicles [50, p. 5-6] [51]. They can facilitate faster and cheaper development, as they can reduce the need for physical prototypes. On the one hand the components of the vehicle can be modeled individually, on the other hand the entire powertrain can be modeled [52, p. 3]. This thesis focuses on the latter. Powertrain models often only model the longitudinal dynamics of the vehicle. Thus, they focus on the energy transformations done between the power source and the road. Powertrain models are used in combination with optimization methods [52, p. 42]. Three distinct areas in which optimization methods and models are combined can be differentiated [52, p. 42]:

- Structural Optimization: The structure of the powertrain is not yet defined. The model needs to be flexible to compare different powertrain structures [52, p. 44]. An example for this can be found in Pesce [53].

- Parametric Optimization: The powertrain structure remains fixed and only the parameters are adapted. This was also done by Pesce [53] and by Tschochner [50].

- Control System Optimization: The supervisory control algorithm is optimized. This is the focus of the thesis and examples can be found in Chapter 3.

The different applications lead to different requirements for the respective models [52, p. 42]. In particular, the trade-off between computation time and accuracy needs to be considered [53, p. 20] [54]: In general, higher accuracy leads to higher computation times.

2.3.1 Energy Conversion Scheme

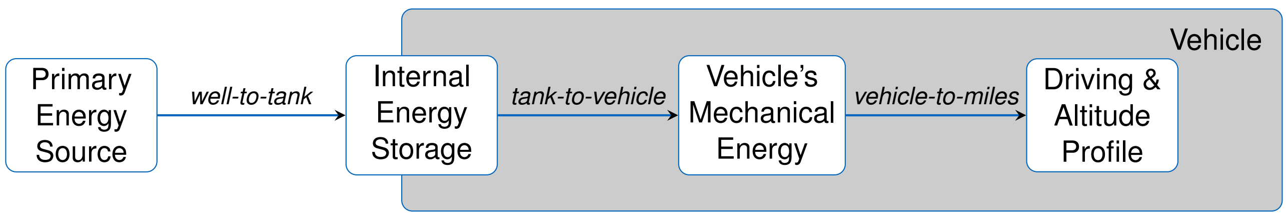


Figure 2.7 : Energy conversions to move a vehicle (refer to [52, p. 4])

For modeling vehicles, it must be considered how the energy is converted. Figure 2.7 shows the energy conversions necessary for driving. Three energy conversions can be identified and are explained in the following [52, p. 4]: Firstly, the *Well-to-Tank* energy conversion is done. Here, the energy from the primary source is transformed to facilitate storing the energy within the vehicle [52, p. 4]. For BEVs the primary energy source can be any source of electrical energy, which is transported to the vehicle and stored in the LIB [52, p. 6]. This upstream energy conversion is not part of the powertrain simulation as it is performed outside the vehicle [52, p. 5]. Secondly, *Tank-to-Vehicle* energy conversion is performed: The energy from the on-board energy storage is converted into the mechanical energy of the vehicle [52, p. 4]. This mechanical energy is kinetic energy stored in the movement of the vehicle and potential energy if the vehicle moves up a slope. This conversion is the core part of powertrain simulation because the powertrain affects the energy conversion [52, p. 12]. The efficiency of this conversion can be optimized by design decisions regarding the powertrain as well as the EMS [52, p. 12]. Lastly, the *Vehicle-to-Miles* energy conversion is performed. In this the mechanical energy stored in the movement and altitude of the vehicle is dissipated while the vehicle moves forward [52, p. 13]. The dissipation of energy is described by the elementary equation of longitudinal dynamics [52, p. 13]. It is not influenced by the powertrain. It is for example influenced by the driving strategy and the design of the vehicle body.

2.3.2 Elementary Equation of Longitudinal Dynamics

As mentioned in Section 2.3.1 the *Vehicle-to-Miles* energy conversion is described by the elementary equation of longitudinal dynamics. The equation can be written as follows [52, p. 14]:

$$m_{\mathrm{v}}a = F_{\mathrm{t}}(t) - (F_{\mathrm{d}}(t) + F_{\mathrm{r}}(t) + F_{\mathrm{g}}(t) + F_{\mathrm{i}}(t)) \tag{2.23}$$

In Equation 2.23 m_{v}, denotes the mass of the vehicle and a the acceleration. F_{t} is the traction force, F_{d} are the aerodynamic friction losses, F_{r} the rolling friction losses, F_{g} is the uphill driving force, and $F_{\mathrm{i}}(t)$ is the inertial force.

The aerodynamic friction losses F_a are the losses caused by the friction the vehicle experiences when moving through air [52, p. 14]. It can be expressed as follows [52, p. 14]:

$$F_{\mathrm{d}}(v) = \frac{1}{2}\rho_{\mathrm{a}}A_{\mathrm{f}}c_{\mathrm{d}}(v, ...)v^2 \tag{2.24}$$

With ρ_{a} being the air density, A_{f} the frontal area of the vehicle and $c_{\mathrm{d}}(v, ...)$ the aerodynamic drag coefficient. $c_{\mathrm{d}}(v, ...)$ must be approximated either mathematically or experimentally [52, p. 14]. It is evident that $F_d(v)$ can be influenced only by the velocity and design parameters of the vehicle's body.

The rolling friction is the friction that is caused by the interactions of the tires with the road [52, p. 15-16]. It can be written as [52, p. 15]:

$$F_{\mathrm{r}}(v, p, ..) = c_r(v, p, ...)m_{\mathrm{v}}gcos(\lambda_q) \tag{2.25}$$

In Equation 2.25 $c_r(v, p, ...)$ is the rolling friction coefficient [52, p. 15]. It depends on a variety of factors such as the tire pressure and the texture of the driving surface [52, p. 15]. The term $cos(\lambda_q)$ takes the influence of the slope into account [52, p. 15]. The rolling friction losses F_{r} can be influenced via the vehicle mass m_{v} or the rolling friction coefficient $c_r(v, p, ...)$ [52, p. 15]. Both parameters are independent of the powertrain.

The uphill driving force is the force needed for the vehicle to drive up a slope [52, p. 16]. It can be formulated as [52, p. 16]:

$$F_{\mathrm{g}}(\lambda_q a) = m_{\mathrm{v}}gsin(\lambda_q) \tag{2.26}$$

The only parameter in Equation 2.26 that can be influenced in the design process of the vehicle is the vehicle mass m_{v}.

The last term of Equation 2.23 is the lumped together term to approximate the inertial forces of the rotating parts of the powertrain [52, p. 16]. The inertia caused by the vehicle mass is already considered in the term $m_{\mathrm{v}}a$ [52, p. 16]. The inertial forces can either be modeled with the powertrain components or summarized in Equation 2.23 [52, p. 16].

2.3.3 Approaches to Vehicle Modeling

Two basic approaches to vehicle modeling exist [52, p. 37-41] [50, p. 11]: The quasistatic and the dynamic approach. In the following, both approaches are introduced and subsequently compared. The quasistatic approach is also called inverse approach [50, p. 11]. Figure 2.8 shows the information flow for this approach. The simulation starts at the wheels and the power required from the battery is computed in the powertrain [50, p. 11]. The components of the powertrain can for example be modeled using efficiency maps [50, p. 12]. The Driving Cycle (DC) is divided into sections in which the velocity is assumed to be constant [52, p. 38]. The choice of this interval influences the computing time and the accuracy of the simulation. The quasistatic approach is suited to model complex powertrains [52, p. 39]. The main drawback is that the model disregards the physical causality [52, p. 39]. Moreover, if the battery or another component of the drivetrain cannot supply the required power, the simulation must be repeated with an adjusted speed [50, p. 12]. This can also deteriorate the computation time. The dynamic approach takes the physical causality into account [52, p. 40]. Figure 2.9 shows the information flow in the dynamic approach. The dynamic approach is also referred as forward approach [50, p. 11]. The base of the dynamic approach is the mathematical description of the system [52, p. 40]. Typically, the model is based on the ordinary differential equations [52, p. 40]. The dynamic approach is computationally more expensive [52, p. 41]. However, some optimization problems can only be solved using the dynamic approach [52, p. 41]. Because the description is based on differential equations, the dynamic approach needs more in-depth knowledge of the modeled system [52, p. 40]. Both approaches can be used with different optimization problems. As mentioned above not all problems can be represented using the quasistatic approach. However, the higher computational effort might prevent the use of the dynamic approach. Moreover, the formulation of a dynamic powertrain model is more difficult because a higher knowledge about the system is required. For a thorough comparison of both approaches refer to [50, p. 13].

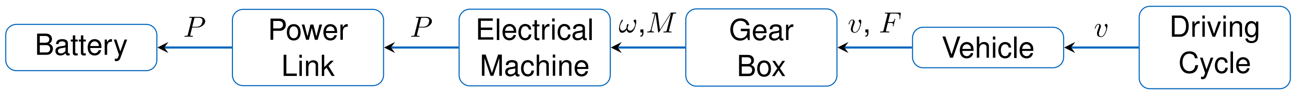


Figure 2.8 : Information flow in vehicle model with quasistatic approach (refer to [52, p. 69], [50, p. 11])

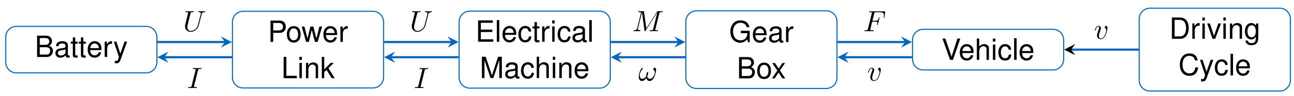


Figure 2.9 : Information flow in vehicle model with dynamic approach (refer to [52, p. 69], [50, p. 11]))

3 State of the Art

This chapter introduces the research relevant for assessing the Mixed Optimization- and Rule-Based Energy Management System (MORE). First, term "Energy Management System (EMS)" is explained (Section 3.1). Next, methods how EMS can be classified are introduced (Section 3.2). In the final section (Section 3.3) the current state of the art is reviewed and critiqued.

3.1 Terminology

The term EMS is used in different areas of engineering. For example, it is applied in the context of buildings and comprehensive home EMS [55–57]. Some sources also integrate BEVs in the EMS of buildings [58–61]. In the automotive sector the term is relatively new, as it is rarely found in the context of ICEVs. The term emerged in the context of Hybrid Electric Vehicles (HEVs) and is mostly used in this context [62–65]. Fewer references to EMS exist in literature on purely electric vehicles, for example [66, 67].

In all the above-named contexts an EMS can be defined as follows: It is the software that distributes the energy within the respective system. Energy refers to different forms of energy. Some EMS manage only electrical energy, while others also manage other forms of energy such as thermal or kinetic energy. An EMS can either manage the energy flows within one component, the whole system or a subsystem within the superordinate system. The EMS is often the link between other subsystems actively influencing the energy flows during the operation of the system. The EMS manipulates control variables to achieve one or more objectives. Typically, one of the aims is to minimize the energy consumption. Another might be to minimize the component aging. If multiple objectives are defined the EMS seeks a trade-off between these objectives.

Another term that is sometimes used in a similar context is the term *operation strategy* or infrequently *operational strategy*. Examples can be found in [68–73]. There is no comprehensive definition for operation strategies in the context of BEVs. However, in most publications it is used synonymously with the term EMS. As EMS is the more common term, it is used for this thesis.

Figure 3.1 shows an example for an EMS in a BEV. At the top of the figure possible objectives are listed. These include but are not limited to the vehicle dynamics, the range of the vehicle, the stress on

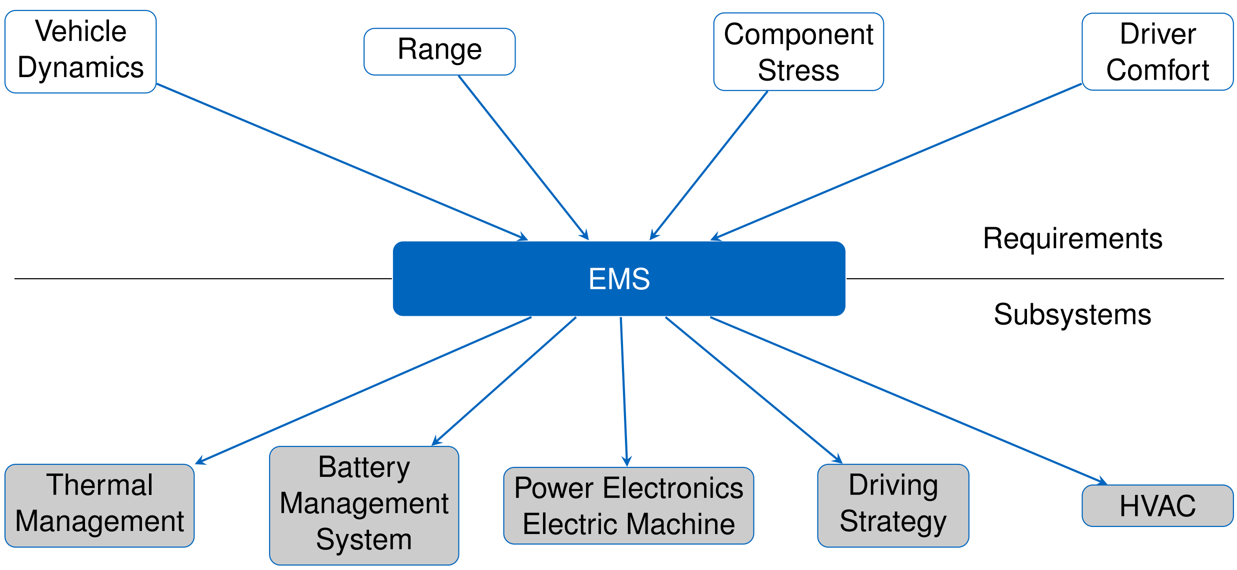


Figure 3.1 : Example for the requirements and the subsystems managed by an EMS in a BEV

the individual components and the comfort of the driver. A holistic EMS interacts with several subsystems to optimize these objectives. For example, the EMS can interact with the Thermal Management System (TMS), the Battery Management System (BMS), the software for the power electronics and the electric machine, a driving strategy, and the Heating, Ventilation and Air Conditioning (HVAC).

3.2 Classification of EMSs

An overview of the different criteria for classification of EMSs is given in Figure 3.2. The first distinc-

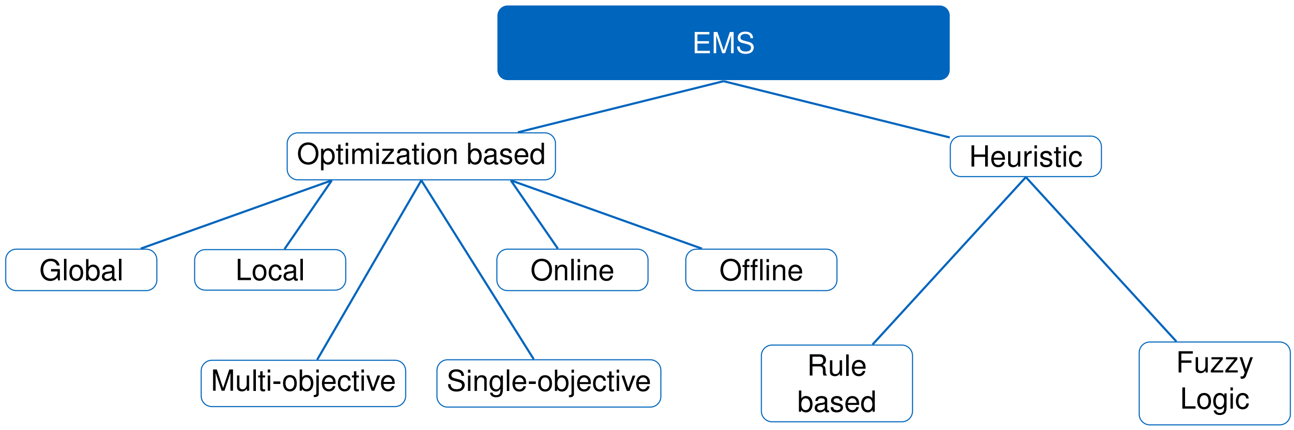


Figure 3.2 : Overview over the classification of EMS

tion can be made between holistic and component-wise EMSs. A component-wise EMS centers on one component of the vehicle. Component-wise EMS exist for example for the battery (e.g. [74–76]), the gear set (e.g. [77, 78]) and for the TMS (e.g. [79–81]). One advantage of these EMSs is that they are limited to one component and therefore their complexity can be low. However, in a BEV such systems must be implemented for several components to ensure a trouble-free operation. Because each of the systems has a limited sphere of influence, the solution that is found cannot be optimal for the overall system.

In contrast, holistic EMSs encompass all or at least several components of the drive train (e.g. [82–84]). Often a holistic EMSs has only limited influence over the components, as some of the energy management tasks remain with the EMS of the respective component. The advantage of a holistic EMS is the possibility to coordinate the operation to attain the optimal energy consumption.

EMSs can also be divided into optimization-based and heuristic systems [85]. An EMS is called optimization-based if it uses an optimization method to distribute the energy within the system [85]. These systems strive for the optimal solution. They can either search for the global or for a local optimum [86]. If the EMS searches for a global optimum, it cannot be used for real time optimization [85].

Heuristic strategies cannot find the optimal solution [85]. One important subcategory of heuristic strategies are rule-based strategies [85]. These work with a fixed set of rules deciding how the control variables are adapted to the changing conditions [85]. The second category of heuristic strategies are EMSs based on Fuzzy Logic Controllers (FLCs) [85]. The rules for heuristic EMSs can be devised using an optimization method [85].

The final way to categorize EMSs is by distinguishing whether they are applied online or offline [86]. Online means that the EMS can be used during a trip [86]. Offline strategies can generally not be used for real world scenarios but are applied to more theoretical questions during the development of the vehicle [86]. Moreover, they can be used as a point of reference [86]. Heuristic strategies are online, while optimization-based EMSs are divided between offline and online [86].

3.3 Review of the State of the Art

This section gives an overview of existing EMS. In Section 3.3.1, literature on component-wise EMSs is reviewed. Section 3.3.2 deals with holistic EMS. The final subsection (3.3.3) summarizes the section and provides a criticism of the state of the art.

3.3.1 Component-wise EMSs

In this subsection EMSs for the individual components of the vehicle are introduced. Even though this thesis focuses on a holistic EMSs, it is relevant to consider component-wise EMSs because they serve as a point of reference. Moreover, component-wise EMSs can be combined to form a holistic EMS. The parameters which can be influenced by a component-wise EMS for each component, can also be used by a holistic EMS. The subsection is organized by components.

Driving Strategies

Driving strategies are a component-wise EMS because one variable—the velocity—is adapted to improve the performance of the vehicle. For this thesis, only driving strategies that optimize the energy consumption are examined, as only these are directly related to the EMS. All the considered literature focuses on optimizing the velocity or the acceleration of the vehicle. The optimization objectives that can be found in the literature beside the energy consumption, are the comfort of the driver, the aging of the battery, and travel time.

In Table 2 an overview of the cited literature is given. The literature is categorized by whether it can be applied online, by the objectives of the optimization, and by the applied method.

Yi et al. [87] divide the route into small sections. For every subsection a constant speed is chosen that minimizes the roll and the air resistance. This simplified approach allows the authors to formulate a convex optimization problem. The optimization method is not specified in the publication. [87] is set apart from other publications because the authors consider the weather conditions, the road surface and especially the wind speed for their optimization.

[88] describes a strategy for autonomous vehicles. The GPS is used to find the most energy efficient route to reach the destination. This route is subdivided into prediction periods and the speed profile for every prediction period is optimized using the minimum principle. The authors tested their method only on a single prediction period. They model the drivetrain in detail including a non-constant internal resistance of the LIB.

In [89] the authors minimize the aging of the battery in addition to the energy demand. They use an aging model to compute the State of Health (SoH) of the battery and choose the velocity profile to maximize both State of Health (SoH) and State of Charge (SoC). For the optimization they use Pontryagin's Minimum Principle (PMP) and a Hamiltonian function.

The sources [90, 91, 99] are published by the same team and the research is interlinked. In [90] the authors optimize the acceleration of the vehicle, in [91] they focus on the deceleration and [99] places the findings into the context of a larger system. For [90] and [91] the authors employ a similar methodology: In both cases they only optimize part of the whole DC using GAs. Moreover, both papers optimize the time for acceleration or deceleration respectively as well as the total jerk. The jerk is used to measure the comfort of the passengers. For the acceleration they minimize the energy demand and for the deceleration they maximize the recuperation. In both cases the optimization variables are the acceleration as a function of time. In [90] the optimization problem is formulated in three different ways: Firstly, the jerk is only considered as a constraint. Secondly, the jerk is optimized alongside the other two objectives. Lastly, the jerk is a constraint as well as a part of the objective function. In both papers the authors choose an *a posteriori* method. They use GAs to create a Pareto front and the operator chooses their preferred solution. The authors aim for the online implementation of their system and only optimize a limited time ahead. However, it does not become clear how uncertainty in the prediction is handled. In [99] the approaches of [90, 91] are integrated

Table 2 Overview of literature on driving strategies

Source	offline or online	Objectives	Method
[87]	offline	minimize air and roll resistance	not specified
[88]	online	minimizes energy demand	minimum principle
[89]	online	SoH and SoC of the battery	Pontryagin Minimum Principle (with Hamiltonian function)
[90]	online	time for acceleration, jerk, energy demand	different GAs
[91]	online	time for deceleration, jerk, recovered energy	multi-objective GA
[92]	online	range of vehicle	rule-based approach and DP depending on driving situation
[93]	online	energy demand and time	rule-based derived from DP
[94]	online	energy demand and time	DP
[95]	online	energy demand	quadratic programming
[96]	offline	energy demand and time for acceleration	multi-objective GA
[30]	both implemented	energy demand	DP, NLP algorithm
[97], [98]	online and offline combined	energy demand, dynamic behavior	SQP, NLP algorithm

into a system assisting the driver. Here the objectives are the total energy consumption, the jerk, and the travel time.

Becker [92] details a driver assistance system that maximizes the range of a BEV. His EMS is based on a detailed vehicle model and an analysis of the factors influencing the energy consumption. He identifies three ways to minimize the energy consumption: Firstly, he dampens the velocity profile. Secondly, he evaluates recuperation. Thirdly, he tries reducing the losses of the components. For different driving situations he develops different approaches. For the acceleration and deceleration of the vehicle he optimizes the velocity profile using DP. For driving with a constant speed, he uses a heuristic strategy. The resulting driving strategy can be used online.

In [93], a so-called *Eco-ACC* designed by Bosch is discussed. The system was developed to work with a HEV as well as with a BEV. The classical ACC functionality is expanded to minimize the energy consumption. The energy consumption and the time needed for a maneuver are optimized using DP. This approach can only be applied offline. Therefore, the authors use the results from the optimization as basis to develop a rule-based strategy.

In [94] the authors suggest a driving strategy based on DP. They express the velocity as a function of the place and optimize it for the entire trip. To implement this global strategy, they use a prediction of the future route. They claim that their approach is applicable online in the vehicle.

The authors of [95] also develop an Eco-ACC like [93], which they call ECC for 'Efficient Cruise Control'. The system is designed with the Tesla Model S as an example. The approach is based on a vehicle model implemented in MATLAB/Simulink. The power train of the vehicle is not modeled in detail. This means that no efficiency maps of the individual components are used. The authors take the status of traffic lights into account to compute the optimum velocity profile. The minimization problem is formulated with a quadratic cost function consisting only of the energy consumption. The solution must observe speed limitations. If a preceding vehicle is detected, a minimal distance must be preserved. The optimization problem is solved using quadratic programming. The authors claim that the system can be applied online.

Vaz et al. [96] describe a driving strategy that adapts the acceleration of the vehicle. They use two approaches: Firstly, they use a fixed value for the acceleration for the whole maneuver. Secondly, the acceleration varies during the maneuver. However, for the changing acceleration there is also a limited number of different values. In the comparison of the two approaches the changing acceleration yields better results and is therefore investigated in more detail. The objective function consists of the energy demand and the time needed to reach the target velocity. The problem is solved using a multi-objective GA with an *a posteriori* approach. In the power train model, a direct current machine is modeled, making the scenario unrealistic. Moreover, the approach cannot be applied online.

In [30] Koch et al. investigate the combination of a driving strategy and the optimization of the drive-train topology. The authors consider two algorithms: Firstly, they approximate the solution for the driving strategy using a Non-linear Programming (NLP) algorithm. This algorithm can be applied online. Secondly, they use a DP to find the global optimum and compare the online solution obtained with it. They find that the NLP algorithm comes close to the global optimum. Koch et al investigate two scenarios: On the one hand, they model the case in which the vehicle follows another, and the velocity can only be varied in a small range. On the other hand, they model a scenario in which the velocity can be varied in a wider range.

One area in which a driving strategy that minimizes the energy consumption is crucial is racing with autonomous electric vehicles [97]. For this thesis only one such strategy is discussed as it focuses on passenger cars. Herrmann et al. [97] develop an energy strategy that interacts with the path planner and a friction estimation to find the optimal velocity. In [98] the optimization of the velocity using the subsystems is presented. The energy strategy is based on a model of the drive train including the thermal behavior of the components. It uses a NLP algorithm. The velocity optimization is solved using SQP. The velocity is first optimized offline with the information available at the start of the race. During the race it is updated to account for prediction errors as well as unforeseen events. What sets [97] and [98] apart from other work in this section is that the concept is integrated in a vehicle and issues as to the interaction with other controllers in the vehicle are resolved.

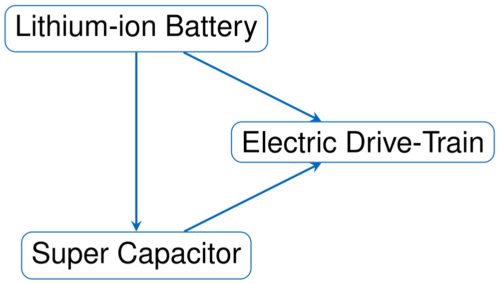
Hybrid Energy Storage System (HESS)

The battery is one of the core components of a BEV. Its safe operation is ensured by the BMS. As the battery supplies the energy requested by the other components, usually no EMS beyond the BMS is needed for the battery. This is different if a HESS is used.

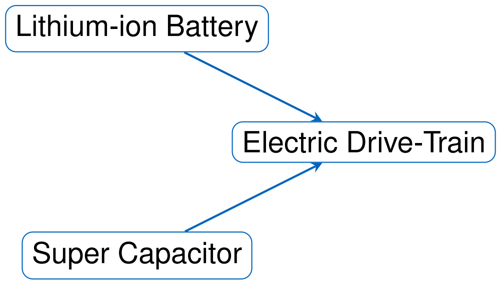
A HESS is an energy storage system that consists of more than one type of storage [100]. A HESS combines one storage type with a short response time and a high power density with a storage with a longer response time and a high energy density [100]. The storage system can for example consist of a LIB and a Super-Capacitor (SC) [101]. They can also encompass a Fuel Cell (FC) and a LIB [102] or a FC and a SC [103]. Two types of LIB are also possible [104].

The high power storage - e.g. the SC - supplies the power during dynamic driving situations [105]. However, its energy density is too low to ensure a sufficient range for the vehicle [105]. Therefore, the additional high energy storage is needed [105].

Two different configurations exist [105]: Firstly, the LIB and the SC are connected to the electric machine and with each other. This configuration is called fully connected or fully active [106]. Secondly, both storage systems are connected to the machine but not with each other. This is referred to as a partly connected or semi-active configuration [106]. In the fully connected configuration, the two systems can exchange energy among each other, in the partly connected that is not possible. The two configurations are shown in Figure 3.3. In this figure the possible energy flows are indicated by the arrows.



(a) Fully connected configuration



(b) Partly connected configuration

Figure 3.3 : Possible energy flows for a HESS

The task of the EMS in a HESS is to determine which storage is used to maximize the efficiency of the drive train. Some systems also include the lifetime of the components especially the LIB [107].

For organizing the literature on EMS for HESS, the system introduced in Section 3.2 is applied. Table 3 sums up the literature reviewed in this section. The table contains the type of HESS used as well as all relevant details on the EMS. Every EMS optimizes the power distribution between the energy sources.

Firstly, EMS for HESS that employ a rule-based strategy are discussed. The authors of [109] use a rule-based strategy for a system consisting of a SC and a LIB. The system is not fully connected. The authors develop three distinct strategies for acceleration, constant speed, and braking. The rules for these strategies are formulated in flow charts and derived from the basic equations governing the behavior of a vehicle.

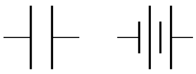
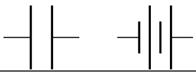
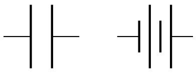
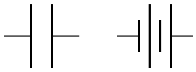
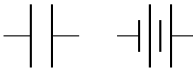
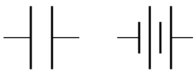
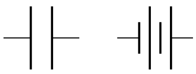
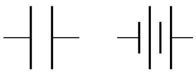
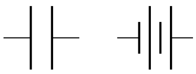
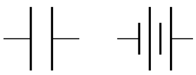
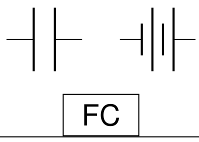
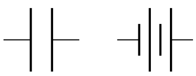
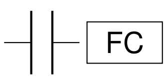
In [75] the authors also introduce a rule-based strategy for an urban BEV. The storage consists of a LIB and a SC, which are fully connected. Similar to [109], the rule-based strategy is expressed as a flow chart and the goal is to minimize the energy consumption.

The authors of [110] investigate a rule-based EMS, which derives the rules from an optimization run on a DC using Particle Swarm Optimization (PSO). The system consists of SC and LIB and is fully connected. Like the other publications, it focuses on minimizing the energy consumption, but the authors also strive to develop a strategy that minimizes the battery aging. They investigate the influence of the temperature on the EMS and the authors conclude that the temperature does not impact the EMS.

Hu et al. [76] also develop a rule-based EMS based on optimization. They use statistical analysis to define the rules. They express the power provided by the SC as a linear relationship of the power requested by the machine. This system is complemented with a FLC if traffic information is available. The aim of the publication is to minimize the energy consumption as well as the battery aging.

In [113], different rule-based strategies are compared with each other. This source also provides an overview of different approaches to an EMS for HESS and a classification. The strategy that is proposed is based on a dynamic limitation of the battery power. The considered system is a combination of a LIB and a SC. The aim of the optimization is to maximize the efficiency of the HESS and to minimize the battery aging. The battery aging is represented by the Root Mean Square (RMS) of the battery current. A lower RMS corresponds to less stress for the battery. This criterion ensures that the system uses the SC for high power demands and to store the recuperated energy. For the

Table 3 Overview of literature on HESS

Reference	Type of HESS	Vehicle Type	Type of EMS	Objective Function	Application
[108]		FCV	Optimization based using DP	Fuel consumption (FC)	Offline
[75, 109]		BEV	Rule-based	Energy consumption	Online
[110]		BEV	Rule-based derived from PSO	Energy consumption and Temperature	Online
[76]		BEV	Rule-based derived from DP, secondary FLC	Energy consumption and Aging	Online
[107]		HEV	Optimization based using DP	Drive train efficiency	Online
[111]		BEV	Optimization based using PMP	Energy consumption and aging	Offline
[112]		BEV	FLC	Energy consumption and aging	Online
[113]		BEV	Rule-based using dynamic power limitation of LIB	Efficiency and RMS	Online
[114]		BEV	Optimization based using k-nearest neighbor search	RMS of battery current	Online
[115, 116]		BEV	Rule-based derived from DP	Total costs of ownership	Online
[117]		BEV	Filtering based approach	Aging of FC and LIB	Online
[118]		BEV	Fuzzy Sliding Mode controller	Energy consumption	Online
[103]		BEV	Radial basis NNs	Hydrogen consumption	Online

evaluation of the strategy the range of the vehicle is fixed to 150 km and the size of the HESS is adapted to the strategy.

In [115], a partly connected HESS consisting of a LIB and a SC for an electric city bus is investigated. The authors propose a rule-based EMS derived from a DP algorithm. Most notably they employ an elaborate battery model to quantify the aging. This allows them to compute the total costs of ownership and use them as optimization target. The total costs of ownership are influenced by the battery aging, the configuration of the HESS and the efficiency. They also use the DP algorithm for sizing the HESS. In [116] the authors build on the results and consider the influence the battery pricing and the temperature has on the design of the EMS.

The authors of [117] introduce a HESS consisting of a FC, a LIB and a SC. Both the LIB and the SC are equipped to store the energy from regenerative braking. These two storage types cannot exchange energy. The authors address the sizing of the components as well as the EMS. For the sizing they employ a MOO algorithm. The EMS on the other hand is designed to work online and uses a filtering-based approach. The power demand is split according to frequency and met by the individual sources. The FC provides the lowest frequency, the SC the highest and the LIB the frequency range between the two.

In [103], a fully connected HESS consisting of a FC and a SC is described. The DC/DC-converter is part of the EMS. The EMS is based on a radial basis function Neural Network (NN). A FLC is used as a point of reference. The EMS based on the NN outperforms the FLC. The system aims to minimize the hydrogen consumption and does not take the aging of the FC into account. The authors focus on the mathematically correct description of the optimization problem.

Secondly, EMSs based on FLCs have been developed. In [112], the combination of a filtering approach and a FLC is proposed. The system in this publication is a HESS consisting of a lead acid battery and a SC. The power demand is filtered by frequency. Consequently, high frequency power demands are met by the SC, while low frequency power demands are met by the battery. As this is not the only criterion that determines which power source is used, a FLC is implemented that combines the different criteria. It remains unclear which criteria are considered, but the authors state that the SoC of both power sources is included. The system can be used online, and it optimizes the battery lifetime as well as the energy efficiency. Due to the use of a lead acid battery the relevance of this publication is only limited.

Another instance for a FLC can be found in [118]. Like in [112] the combination of a SC and a lead acid battery is considered. The system is fully connected. The authors combine the FLC with a sliding mode controller to optimize the range. Additionally, battery aging is considered, but the focus remains on the range.

Thirdly, optimization-based strategies are used. In [108], a DP algorithm is used for the EMS of a HESS consisting of a SC and a LIB for a FC vehicle. The algorithm is implemented in Matlab and uses its vectorization of Matlab options efficiently. For the optimization, perfect foresight is assumed. The optimization is therefore global and cannot be used during the operation of the vehicle. The optimization goal is the reduction of the fuel consumption for the DC.

In [111], the authors propose a HESS consisting of a LIB and a SC. They implement the EMS using PMP. They consider the aging of the battery as well as the drive train efficiency. The emphasis of the paper lies finding a problem formulation that allows using PMP. The results are compared with those of a rule–based approach. They find that their approach yields better results in respect to energy consumption as well as battery aging. However, their approach requires perfect foresight and can therefore not be used online.

Styler et al [114] investigate a fully connected HESS consisting of a LIB and a SC. They utilize a database containing extensive data of real-world trips and avoid artificial DCs. Their aim is to minimize the RMS of the battery current. This includes the current flow between electric machine and LIB as well as between SC and battery. The RMS of the battery current serves as a measure for both the efficiency and the aging of the LIB. A higher battery current leads to decreased efficiency and accelerated aging. The authors compare three different EMSs: The first is a DP algorithm for offline use, which provides the optimal solution for the problem. The second is a simple rule-based algorithm, which uses the SC whenever possible and does not allow power flow within the HESS. The last algorithm is the novel approach proposed by the authors. This approach is based on a k-nearest neighbor search, which can be used offline. The authors find that the k-nearest neighbor search yields significantly better results than the rule-based approach.

Several extensive comparative studies of HESS exist. In [119] five different approaches are applied to an EMS for an urban street railway. The HESS integrated into the system consists of a FC, a LIB, and a SC. The individual storage types are not interconnected among each other. The authors compare a simple rule-based strategy, which is based on threshold values, with other approaches. These are a FLC, the Equivalent Consumption Minimization Strategy (ECMS) and a Model Predictive Control (MPC) approach. The optimization aim for all the strategies is the minimization of the hydrogen consumption. The aging of the FC and the LIB is only briefly mentioned. The authors conclude that the performance of the approaches is similar. However, the FLC and the MPC are computationally expensive, while the ECMS leads to the lowest fuel consumption. For these reasons, the authors recommend the ECMS.

Song et al ([106]) also compare different EMSs for a HESS consisting of a SC and a LIB in an electric city bus. They compare the overall life-cycle costs of five different strategies. To compute those costs, an aging model for the LIB is used. The sizing of the storage system is computed at the beginning and remains the same regardless of the EMS. The considered strategies are two rule-based strategies; one based on a flow chart, the other on frequency filtering. Moreover, they employ a FLC and MPC. These systems are all implemented to be used online. A DP approach is used as an offline strategy to compare with the others. Only the online strategies are considered as an option. For the comparison, a DC for buses in China is used. The authors conclude that the filtration-based approach is the least suitable and that the rule-based approach using a flow chart and the FLC are the most promising for an EMS.

Variable Intermediate Circuit Voltage

Another parameter that can be influenced by an EMS is the intermediate circuit voltage between the LIB and the electric machine. In the simplest and most common configuration, the battery voltage is automatically the input voltage of the inverter [74]. However, in different load conditions, different voltages are optimal for the machine. At full load, a high voltage leads to minimal losses [74]. Typically, these are the conditions for which the voltage is optimized [74]. Consequently, the losses in partial load conditions are higher than the minimal losses in full load conditions [74]. One option to solve the problem is to vary the voltage in the intermediate circuit depending on the load conditions. If the system is designed for voltage variation, an EMS is needed to find the voltage which leads to the highest efficiency of the overall system. To vary the intermediate circuit voltage two basic approaches can be found in literature: Firstly, active battery switching systems are implemented: The LIB consists of two blocks. These can according to the load conditions, either be connected in parallel or in series. This means the voltage can be switched between two values [74]. Secondly, an additional DC/DC-converter inserted between the LIB and the inverter. This allows the voltage to adapted to an arbitrary level [120–124].

The literature on EMSs for variable intermediate circuit voltage is far less extensive than on HESS. Most of the cited sources do not focus on the EMS but on the basic setup of the system.

The active battery switching system was developed by Wacker ([74]) and is only described in his publications. The EMS is described in [125]. The parameter that can be influenced in this system is whether the two blocks of the battery are connected in parallel or in series. The EMS is rule-based. The rules are determined using a model of the electric machine and the efficiency map for the machine including the converter.

More researchers investigate using an additional DC/DC-converter. The difference to the active battery switching system is that the voltage can be set continuously within predefined bounds. However, most authors focus on the overall setup of the system and not on the EMS. In [120–124] the EMS is based on a model of the electric machine but is not described in any detail. The reason for

Table 4 Overview of literature on variable gear ratios

	2-gear ratios	CVT
Rule-based	[127], [128]	[129], [130]
Optimization-based	[131], [132]	

this is that the optimal voltage can be calculated using the machine model. Therefore, the research focuses on these models.

Variable Gear Ratio

Most BEVs use a single gear ratio [78, 126]. This is feasible in BEVs because an electric machine, unlike a combustion engine, works for a wide range of rotational speeds. The single gear transmission can be realized with a higher efficiency and a lower weight for the gear box. Moreover, cutting out the shifting process reduces the complexity.

However, the use of a single gear transmission also has disadvantages. The most important one is that the electric machine cannot be operated in the operating range with the highest efficiency for all velocities. Studies show that this can counteract the higher transmission efficiency [126]. Another drawback of single gear transmission is the dynamic behavior of the vehicle. Employing multiple gear transmission allows a faster acceleration and higher maximum speed. For this thesis, variable transmission ratio is interesting, as it can be interpreted as a component-wise EMS and could be part of a holistic approach.

A variety of different configurations for the gear box exists. In the context of this thesis the exact mechanical setup is not relevant. Therefore, the gear box is interpreted as a black box that allows to choose between a predefined number of transmission ratios and is associated with an efficiency. Consequently, two main configurations are commonly found in electric vehicles: 2-speed transmission and Continuously Variable Transmission (CVT). The authors of [126] evaluated different gear boxes and found these two the most promising to replace single speed transmissions.

Regarding the gear ratio one type of optimization procedure is most relevant for the EMS: A so called shifting schedule can be optimized. This means that the conditions under which a transmission ratio is chosen are defined. Typically, they are specified using the required torque and the vehicle's speed. The optimization goals are usually the overall efficiency, the driving dynamic and the number of switching operations.

An overview of the literature can be found in Table 4.

Most literature focuses on rule-based approaches to the shifting schedule. These approaches are discussed first. In [129] the authors consider a gear box based on CVT in combination with Permanent Magnet Synchronous Machine (PSM). The CVT is additionally equipped with a gear reducer, to ensure fixed transmission ratios. For the publication a set-up with five gears is implemented. The goal is to maximize the drivetrain efficiency. To do that, they model the efficiency of the gear box and the motor efficiency. The shifting schedule is drawn up using an enumerative approach: For several combinations of speed and torque the optimal transmission ratio is computed. Based on these data, regions for every transmission ratio are defined. The resulting rules are used during the operation of the vehicle. Despite the lower efficiency of the gear box, the authors find that their approach improves the overall efficiency compared to a single speed transmission.

In [127] a shift schedule for a 2-gear BEV is developed. The authors use techniques developed for ICEV. They draw up two different shifting schedules: One optimizing the overall efficiency, the other the dynamic behavior of the vehicle. For both strategies a graphic approach is used. For the dynamic oriented strategy, the efficiency of the electric machine is considered with both transmission ratios at different speeds. The shifting point is set according to vehicle speed. For the efficiency-oriented strategy, the efficiency map of the machine is drawn up with each gear ratio. The shifting points are computed as a function of speed and acceleration. To avoid too frequent switching, a hysteresis is implemented in both strategies. The authors verify the results using a test bench.

The authors of [128] consider the shifting schedule as well as the optimization of the gear ratios and the switching process itself for a 2-speed transmission. The rule-based shifting schedule and the gear ratio are optimized together using DP. During vehicle operation, the shifting schedule is used. The goal of the authors is to maximize the efficiency and the dynamic performance of the vehicle. The maximum speed, the acceleration time, and the user experience of the shifting process are used to evaluate the dynamic performance. The concept is applied to a simulation model. For this model the efficiency of the gear box and the electric machine is modeled, as well as the internal resistance of the battery.

Further examples for a rule-based approach can be found in [78, 133, 134]. A few alternatives to rule-based strategies can be found: In [130], the author considers a CVT combined with a direct current machine. He develops a fuzzy-PI-strategy to maximize the efficiency of the electric machine. The efficiency of the gear box is not considered. The PI-controller influences the transmission ratio of the CVT at any given moment. The author compares the FLC with a traditional PI-controller using a simulation model. In his comparison the FLC outperforms the traditional approach.

The authors of [131] describe what they call an online shift schedule optimization for a 2-speed transmission. They use an analytical approach for the optimization of the gear ratios, not mixing it with the optimization of the gear shift schedule. They use the equivalent energy consumption as objective function. The equivalent energy consumption is computed using the energy consumption for the driven distance and the distance itself. The focus of this publication lies on the mathematically correct description of the optimization problem. They assume that during the trip, a prediction for the speed in the next segment exists. This prediction can be used to minimize the shifting operations and at the same time maximizing the efficiency. The optimization is done during the simulation of the DC utilizing PMP. This technique is efficient enough to be applied online. DP is implemented as a point of reference. The performance of the optimization based on PMP is satisfactory compared with the DP.

The authors of [132] also present an online optimization of the shifting schedule of a 2-speed transmission. However, their primary focus lies on the optimization of the gear ratio during the shifting process using Niche Multi-Objective PSO. During the trip the efficiency of the drive train for both transmission ratios is computed for every time step. If the other transmission ratio is more efficient, the gears are switched.

Multiple Electric Machines

Multiple electric machines can be installed in different configurations. An overview of these configurations can be found in [135]. In the following, three options are considered: Firstly, one machine can be built into each wheel as an in-wheel machine. Secondly, one machine can drive the front and one the back axle to form an all-wheel drive. Thirdly, the two machines can be connected by a gear box that drives only one axle thus replacing a single larger machine.

The first two configurations lead to an improved dynamic behavior of the vehicle especially during cornering [136]. In all configurations it is possible to use the multiple electric machines to improve the overall efficiency. Consequently, in literature one aim of a control strategy for multiple electric machines is typically to improve the dynamic performance for the vehicle. In the context of EMS, this is usually limited to the longitudinal performance, which can for example be quantified using the time needed to accelerate to a certain speed (e.g., 100 km/h) and the top speed. As stated above, it is also possible to improve the cornering response using a torque vectoring approach [136]. However, no source could be found in which this is integrated into the EMS. The second typical optimization goal is maximizing the overall efficiency. As far as the control variables are concerned, the literature can be divided into two categories. The first category only considers the torque distribution between the two or more machines. The second category additionally takes the gear ratio into account.

The authors of [137] describe a concept with only the torque distribution as control variable. The considered vehicle is equipped with in-wheel machines and the optimization searches for a compromise between driving dynamics and energy consumption. They use a single-track model for both the efficiency and the vehicle dynamic concentrating on the mathematically correct description. To quantify the dynamic performance, they evaluate the capability of the vehicle to track a given speed profile. They implement three different EMS. Two of the approaches are optimization-based. One focuses on only the efficiency and the other on the efficiency and the driving dynamic. Both determine the optimal torque distribution analytically and can only be employed offline. The third strategy is rule-based and can be employed online. The authors deduce this strategy from their results with the first two approaches. The rule-based strategy targets both the efficiency and the dynamic.

Another similar approach can be found in [138]. The authors also consider in-wheel machines for a BEV. The control for two machines is merged: The two rear machines and the two front machines cannot be actuated independently. The machines at the front are high-speed, low-torque machines. Those at the rear are high-torque, low-speed electric machines. In this study the sizing of the machines is done in the same optimization procedure in which the EMS is optimized. This means that for both types of machines the basic parameters are optimized and at the same time the torque distribution between front and rear axle is optimized for two selected DCs. The energy consumption for those cycles is chosen as the objective function. The authors compare the combination of EMS and design with the separate optimization of the two and find that their approach leads to better results. However, they do not present a solution to integrate the approach in a vehicle.

Most other sources concentrate on the combination of a variable gear ratio and multiple electric machines, for example [73]. The focus of this paper lies on the design of the electric machines. The vehicle is equipped with two electric machines. Each can propel the vehicle alone under partial load conditions. Both machines are connected to a gear box with two different gear ratios. The EMS can influence which gear ratio is chosen as well as the torque distribution between the electric machines. The paper differs from similar publications because the TMS of the machines is integrated into the optimization. Two EMSs are compared: Both are rule-based, one takes the TMS into account, the other does not. The objective function consists in both cases of the energy efficiency and vehicle dynamic. A comparison shows that the strategy encompassing the TMS of the machines does not lead to a higher energy efficiency, but it is able to avoid de-rating of the machines. This improves the vehicle dynamics.

The authors of [77] replace a single electric machine with two machines that are connected by a planetary gear set. Thus, a power split transmission is realized. The transmission ratio can be adapted to ensure maximum efficiency. The publication concentrates on the torque distribution between the two machines and on the machine speeds. As the total torque is defined by DC, the torque and speed of only one machine are optimized. For this optimization an enumerative method is used. The drive train efficiency is chosen as objective function and the dynamic of the vehicle is defined in the constraints. This method only determines the torque. The target velocity is found using a PI-controller. The authors find that their method can improve the overall efficiency compared to using a single machine.

In [139] the authors also replace a single electric machine with two machines connected with a planetary gear set. In this case the two machines have different characteristics. The system has the following options: Each machine can propel the vehicle alone; the machines can be torque coupled or speed coupled. The EMS works in two stages: First, an efficiency map is used to determine which of the four modes is used for maximum efficiency. If a mode is chosen in which both machines are active, the speed or torque distribution is determined in the next step. This is done using SQP. The authors find that they can improve the efficiency compared to a single electric machine with a 2-speed transmission.

In [140] the authors develop a comprehensive approach to the use of two electric machines and a multi-speed gear box. They see the advantages of two machines in both drivability and efficiency. They describe the design of this system. Moreover, they optimize the switching process itself using a rule-based strategy to avoid the so-called torque hole. The design variables of the EMS are the torque of one motor and the state of the 2-speed gear box. The objective function is the overall energy consumption. The parameters for the drivability are formulated as constraints. The authors argue that due to local minima traditional gradient based methods cannot be applied to the problem. Therefore, the authors discretize the torque and use an enumerative method. Thus, they can find the optimal combination of the two control variables for all states of the vehicle. This is done offline. For the online application it is used as a basis to draw up a rule-based strategy.

TMSs

Another aspect of the vehicle that can be viewed as a component-wise EMS is the TMS. The term TMS is used to describe two different aspects: The hardware that is used to keep the components of the vehicle within the predefined temperature limits and the strategy or software that is used to operate the hardware and the components themselves. Not all TMS hardware requires a strategy for its operation. For this thesis the focus lies on the strategy that is used to operate the hardware. The hardware of the TMS can be understood as one component of the BEV and the strategy for its operation as the EMS of this component. The EMS in this case focuses on the thermal energy, however, the strategy for TMS hardware can also influence the electrical energy consumption. TMS in BEVs typically have the following goals [141]: Firstly, they keep the drivetrain components within their safe operation range. Secondly, they keep the cabin within the temperature range comfortable for the passengers. Thirdly, a TMS can maximize the overall efficiency. Finally, it can aim at minimizing the component aging, in particular the aging of the LIB.

The components can either be considered separately, or in groups. The literature can be divided into TMS for the LIB (e.g. [73, 142–144]), for the LIB and HVAC combined (e.g. [145, 146]) and the entire drivetrain including the HVAC (e.g. [79, 147, 148]).

In [146] a TMS combining the LIB and HVAC is considered. The authors develop an EMS for this system. The aim is to minimize the battery aging, maximize the range of the BEV and keep up the comfort of the passengers. The battery aging is quantified by the average SoC and the deviation from it. The limitations of the systems are formulated as constraints. The state variables are the air flow rate, the damper ratio, the temperature of the outlet air and that of the supply air. All variables are directly linked to the HVAC system. The optimization is performed using MPC with SQP as optimization algorithm. Additionally, a Fuzzy Logic Controller (FLC) is used as point of reference. For most of the experiments perfect foresight is assumed, but the robustness towards prediction errors is also investigated.

Lahlou et al [149] present an EMS for the HVAC. They state that their aim is to maximize the range while maintaining the thermal comfort of the passengers. They investigate cold and warm weather conditions with varying temperatures during a trip. It is assumed that the route and traffic information as well as a forecast of the weather conditions is available at the beginning of the trip. This information is used for estimating the energy consumption. [149] describes a rule-based strategy that can be used online, and an offline strategy based on a DP. The focus of the description lies in the online strategy. The strategy is basic: The cabin temperature is adjusted to the target temperature at the beginning of the trip. This temperature is maintained if it is estimated that the available energy is sufficient to complete the trip. If that is not the case, the passenger comfort is restricted to reach the destination.

In [79] the fluid based TMS for the entire drivetrain including the cabin is considered. The optimization is based on a detailed vehicle model described in [150]. The goals of the TMS are the same as in [146]. However, an aging model of the battery is implemented, and the simulations are also conducted with the characteristics of an aged battery. The optimization is conducted with perfect foresight and with a more realistic limited foresight. The focus lies on utilizing the waste heat from the drivetrain for heating the cabin. Preconditioning the cabin is also considered as part of the strategy. The implemented TMS is optimization based, but no information on the utilized algorithm is given. Also, the control variables are not listed.

Table 5 Overview of literature on holistic EMS

Source	offline or online	Objectives	Considered Components
[155]	offline	minimize energy demand	Driving strategy and multiple electric machines
[156]	online	minimize energy demand	Driving strategy and multiple electric machines
[157]	online	minimize energy demand	Driving strategy and auxiliary consumers
[158]	online	maximize range and thermal comfort of driver	HVAC and driving strategy
[154]	online	maximize range, minimize battery aging, maximize driver comfort and vehicle dynamics	Driving strategy and auxiliary consumers
[82]	online	maximize range, vehicle dynamic and thermal comfort of driver	Auxiliary consumers, driving strategy and multiple electric machines

The author of [147] also describes a fluid based TMS for the entire drive train and the HVAC. The variables influenced by the system are compressor power, the cabin blower speed, the power of the Positive Temperature Coefficient (PTC) heater and the coolant flow into the battery. The aim is to maximize the range while maintaining the comfort of the passengers. The TMS is rule-based and combined with a thermostat control. The focus of this work lies on short distances as these are the typical commuter drives.

Some EMS focus exclusively on maximizing the range in cold weather conditions. These are for example [36],[151], [152] and [153]. The main objective of these works is to increase the efficiency of the BEV by using the energy recuperated while braking directly for heating, instead of storing it in the LIB. This is facilitated by a High Voltage Heater (HVH) which can react quickly. The focus of these studies lies on estimating the potential of this approach. In [36] the authors develop a rule-based strategy which reduces the energy consumption and the stress on the LIB while maintaining the cabin temperature. The effects on the range are mostly due to more energy being recuperated, if an intelligent heating strategy is applied.

3.3.2 Holistic EMSs in BEVs

This section introduces literature on holistic EMS. Only few authors explicitly concentrate on developing a holistic EMS. These are namely Basler [82] and Suchaneck [154] in their PhD theses. In the following, a holistic EMS is defined as an EMS that spans over two or more components. The components are those for which the EMS is discussed in the previous subsection.

All sources discussed in this section is summed up in Table 5. Most sources focus on the combination of a driving strategy and the EMS for one component. In all considered sources this is either the electric machine or the auxiliary consumers. These sources are discussed first. Subsequently, the two approaches [82, 154] aiming for a holistic EMS are investigated.

Several authors combine a driving strategy with the torque distribution between multiple electric machines. In [155] the velocity profile and torque distribution between in-wheel machines is optimized using DP. The authors aim to minimize the energy demand. The velocity is expressed as a function of the place. No predefined DC is used but the optimization chooses a velocity profile suitable for the driven route. The authors model the height profile of the route and employ a traffic model. This approach cannot be used online but can only serve as a reference.

[156] implements a similar EMS. They also consider a vehicle with in-wheel machines and optimize the torque distribution as well as the velocity profile. They also use traffic and terrain information in their model. They minimize the energy demand while maintaining a minimum distance to the preceding vehicle. The behavior of the preceding vehicle is predicted using Bayes Networks. The optimization itself is done using non-linear MPC. The optimization only chooses between discrete velocities. The authors use a vehicle to verify the results from their model.

In [157] the authors present a holistic EMS that computes the driving strategy as well as controlling the auxiliary consumers in the vehicle. For the driving strategy the system can choose a coefficient for the original velocity that is valid for a predefined number of time steps. For the control of the auxiliary consumers, the system can only decide whether they are switched on or off. The authors do not specify which auxiliary consumers are considered. The system receives the chosen route and the user preferences as input. It is configured offline with a complex model and then used online. In both cases the authors employ an enumerative method. The offline search is used to limit the number of combinations that must be explored during the operation of the vehicle.

Pan et al. [158] investigate an EMS that combines the HVAC with a driving strategy. Their approach is based on two FLCs and works online. The authors argue that little literature combining these two systems exists in the state of the art. They focus on categorizing and predicting driving situations using artificial DCs, Markov chains and machine learning approaches. This knowledge is aggregated into a driving condition that is used as part of the objective function. The SoC of the LIB is also used in the objective function. The first FLC controls the target torque of the electrical motor. It takes the driving condition, the SoC and the pedal opening as an input. The output of the second FLC is referred to as the power distribution coefficient. It defines how much power is used for the HVAC dependent on the power allocated to the machine and the total available power. This coefficient links the two controllers making the EMS holistic. The inputs for the second controller are the deviation from the target temperature as well as the pedal opening and the SoC. The FLCs are implemented in Matlab based on a triangular membership function. The authors test their concept using a Hardware in the Loop (HiL) test. The deviation from the original speed caused by the EMS is small. Altogether it can be deduced, that the authors aim to minimize the energy while the travel time and the cabin temperature remain mostly fixed. It should be noted that the authors do not consider the utilization of the recuperated energy.

Lahlou et al. developed an EMS the description of which spans over several publications: [149], [159], and [160]. Their focus lies clearly on the HVAC. In the following, only [160] is discussed. They base their optimization on DP, which makes their approach offline. The authors remain silent on the computation time. Due to the use of DP, it can be presumed that it is high. The model of the thermal comfort is elaborate, while the rest of the vehicle is modeled more simply. The optimization goals are to maximize the thermal comfort of the passengers while also maximizing the range of the vehicle. It should also be noted that [160] focuses on the cooling in hot ambient temperatures. The EMS itself only includes the HVAC and not the speed. However, the authors perform one set of experiments in which they vary the speed by a fixed factor and compare the energy consumption for different factors. Their focus for these experiments is whether the increase in the travel time has a positive or a negative effect on the energy consumption. They find that this depends on the original speed profile and the ambient temperature. The recuperated power is not included in these considerations. The main accomplishment of this work is the detailed representation of the thermal comfort of the passengers and the elaborate scenarios which are modeled. This source is not included in the overview table for this section, as the velocity is not included in the final EMS.

Suchaneck [154] develops an EMS that can be applied online. He does that by first implementing an optimization-based EMS for the offline use and then evaluating it for online use. He differs from the previously cited authors in the number of objectives he considers. Besides the range, these are the aging of the LIB, the comfort of the driver and the dynamic behavior of the BEV. For the battery aging he implements an aging model. The comfort of the driver and the dynamic behavior of the vehicle are expressed by simple indicators. These objectives are aggregated into one objective function. His optimization variables are the power consumed by HVAC and the velocity profile. For the optimization he uses Stochastic DP and PMP and compares the two approaches. He finds that Stochastic DP is too time consuming for online application. In contrast to that, PMP can be employed online. During most of his thesis Suchaneck assumes perfect foresight. However, a short section is devoted to the optimization with imperfect knowledge of the future. Here he finds that his approach still works under changing conditions. He does not explore the topic further. For the optimization he does not consider a height profile of the route and only optimizes predefined DCs, namely the Worldwide Harmonized Light Duty Vehicles Test Procedure (WLTP).

Basler [82] also develops a holistic EMS. His optimization aims are the range, the vehicle dynamic and the thermal comfort. The objective function he uses consists only of the range. The two other objectives are included into the optimization using constraints. For the optimization he uses black box models for the components of the drivetrain. These models are drawn up using NNs and are less computationally expensive than the original white box model. This facilitates the integration into the vehicle. Basler considers different operational strategies: The first strategy limits the torque of the electric machine. The second strategy limits the power used for the HVAC system. The third strategy reduces the battery losses by synchronizing the HVAC system and the power train. The fourth strategy minimizes the machine losses by distributing the torque in an all-wheel drive. Basler uses sensitivity analysis to explore the effects of these strategies on the objective function. He also models uncertainty to evaluate his approaches more realistically.

3.3.3 Criticism of the State of the Art

The analysis of the state of the art shows that some aspects of EMSs are not yet adequately explored. This subsection gives an overview of the neglected topics regarding EMSs. In the next chapter (Chapter 4) these findings are used to formulate the scientific objective of this thesis.

The following main shortcomings could be identified:

1. The focus of most literature lies on a single component and not on a holistic EMS. This means that the potential for an energy reduction that originates from a combination is neither evaluated nor utilized.

2. Most literature can be divided in optimization-based and rule-based approaches. Literature that explores hybrid methods exists but is rare. Moreover, the transition between a rule-based approach and an optimization-based approach is not sufficiently evaluated.

3. Little literature exists that illuminates how a HVH can be integrated into the overall EMS. As it could be illustrated that HVHs are becoming more important for BEVs, this is likely about to change.

4. A lot of the literature focuses on vehicles that are fundamentally different from standard BEVs. For example, the EMS uses a HESS to realize an energy reduction. This research is important, but the systems cannot be easily integrated into existing vehicles. Therefore, it will take more time until these systems will reach standard BEVs.

5. Most authors present one system and do little to analyze their approach. They often do not focus on how the energy reduction is effectuated.

4 Scientific Objective

The core objective of this thesis is to reduce the consumed energy of a BEV by using an EMS. For this objective the end of the previous chapter (Subsection 3.3.3) identifies several open research topics. The following research question for this thesis can be formulated:

1. Which optimization methods are suitable for an EMS?
2. How can an optimization-based approach be adapted to work with little forecast data and on-board computation capacity?
3. How can an optimization work on a partitioned trip and still lead to acceptable results?
4. Does optimizing two or more components simultaneously using a holistic EMS lead to better results than separate optimization?
5. How can the resulting EMS be integrated into a vehicle?

The aim of this thesis is to answer the above research questions. The answers that could be found are summarized in Section 7.2.

5 Approach

This chapter explains how the MORE is designed and how the results discussed in the next chapter (Chapter 6) are obtained.

5.1 Concept

This chapter is structured as follows: First, the vehicle model is introduced (Section 5.2). This is followed by the reference heating strategy in Section 5.3. These two sections provide the basis to enable the work of this thesis. Next, the optimization problem is described in detail (Section 5.4). The focus of this section lies on the offline optimization. In the following section (Section 5.5) the implementation of the two optimization methods used for this thesis is explained. Next (Section 5.6), the DCs used for the experiments are described. In Section 5.7 the approach to the online application is explained. The final section (Section 5.8) introduces the results obtained by preliminary research and explains how these impacted the approach used in this thesis.

The concept developed in this thesis serves three purposes: Firstly, it aims at reducing the energy consumption by simultaneously optimizing the velocity, the heater power, and the air mass flow. Secondly, offline optimization is used to analyze the effects that lead to the reduction in the energy consumption. Thirdly, it aims at showing that the concept can also be used online and draw up a concept to integrate it into a BEV.

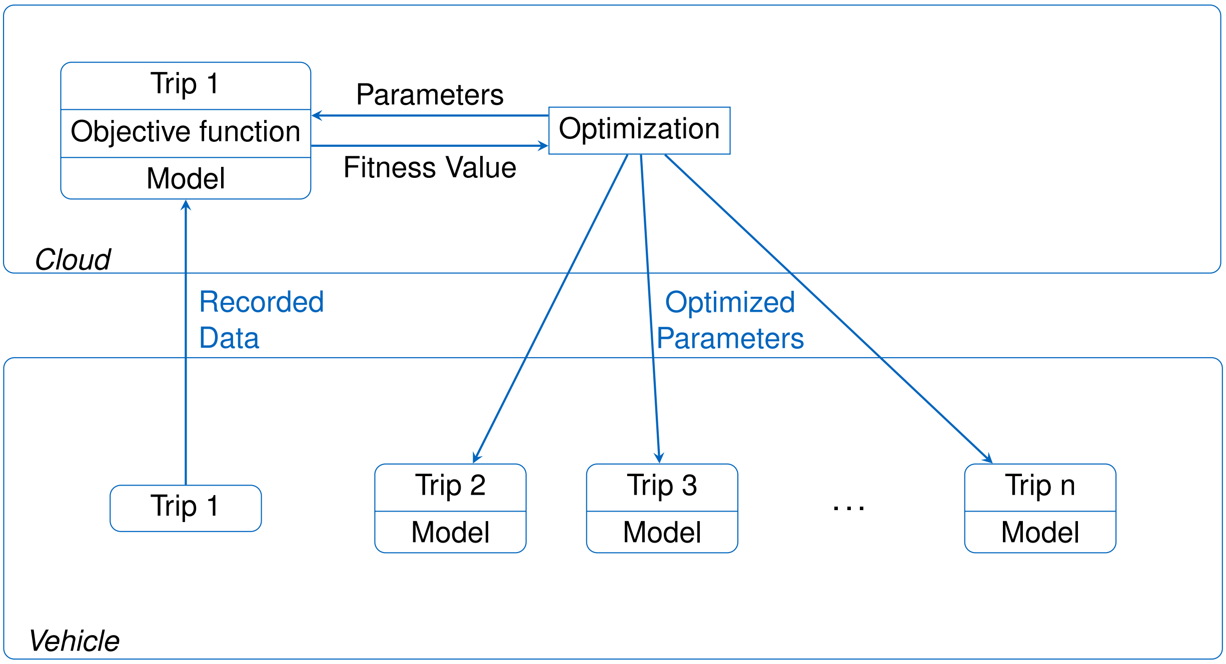


Figure 5.1 : Concept for integration into a vehicle

The concept of the MORE is based on the findings of Adermann et al. ([161, 162]). They explore what they refer to as Commuters' Cycle Monitoring (CCM). Their CCM is based on the idea that BEVs are predominately used for commuting or other recurrent routes. Moreover, they found that repeating the same route under different conditions still leads to a similar driving pattern. They use these findings to supply optimal SoC and SoH predictions for the LIB.

Figure 5.1 gives an overview of the concept of the MORE. It is assumed that the BEV is used for driving the same route repeatedly. This can for example be a commute. The idea of the CCM is applied to an EMS: The BEV is taken for the first trip (*Trip 1*) using a default EMS. This trip is recorded. When the vehicle is parked and has access to the internet it connects to a cloud and uploads *Trip 1*. The optimization strategy developed in this thesis is then applied to *Trip 1*. The result is a set of optimized parameters. It is important to note that all parameters are a function of the distance and not the time. Therefore, every location of the trip has a corresponding set of parameters. In the next step, these optimized parameters are downloaded to the BEV. When the same route is repeated (*Trip 2*) the parameters optimized for *Trip 1* are applied. All parameters for the heater can be used directly. How the optimized velocity can be applied, depends on the individual vehicle. Either the speed is adapted by a recommendation to the driver, or the vehicle is partly autonomous and can implement the driving strategy directly. This approach presumes no knowledge of *Trip 2*, other than that it is a repetition of the commute or other recurring drive. Additionally, no computation resources are required within the vehicle as all calculations are done offline.

5.2 Vehicle Model

The vehicle model is a key part of the development of an EMS. As explained in Section 2.3, the vehicle model is closely interlinked with the optimization procedure used for the EMS. In this section the vehicle model used for this thesis is introduced. The modeling is based on the work of Danquah et al. [163] and Koch [164]. First, the requirements for the model are collected in Section 5.2.1. In Section 5.2.2 the component library used for the model is introduced. Lastly, in Section 5.2.3 the model used for the EMS is described.

5.2.1 Requirements for Vehicle Model

The goal of this thesis is to use an EMS to reduce the energy consumption of a BEV. To do that and to test the concept of the MORE, the model must meet the below requirements. The list is split into mandatory requirements and additional requirements that are not mandatory but useful.

1. Mandatory requirements:

    - *Reproducible results:* The model must be fully deterministic and yield reproducible results. A stochastic model would require multiple runs and would therefore increase the computation time drastically. Moreover, changing results would complicate the evaluation and would make it harder for other researchers to reproduce the results of this thesis.

    - *Reasonably low computation time:* The model must have a reasonably low computation time, as it is run multiple times for the optimization.

    - *Reproduction of a prevalent BEV:* It must be possible to model a relevant type of BEV. This allows the results to be compared to the state of the art. Furthermore, it ensures that the findings are relevant for research and industry.

    - *Integration of user defined DCs possible:* The integration of arbitrary DCs must be possible with minimal effort. This ensures the comparability to the state of the art and facilitates the use of recorded real-world drives. To implement the concept of this thesis, it is necessary to integrate the recurring commuter trips into the model.

    - *Validated components and overall model:* The components and the overall BEV model must have undergone a validation process. This ensures that the findings of this thesis can be transferred to a real-world BEV.

    - *Restart from arbitrary starting point:* It must be possible to restart the model at an arbitrary starting point within the DC. For this, the current model parameters must be saved and reloaded into the model. This enables the optimization of segments of the DC.

2. Additional requirements:

- *Based on Matlab/Simulink:* The vehicle model must be based on Matlab/Simulink as it is the chosen programming environment for the optimization methods (refer to Section 5.2.4).
- *Comprehensible model structure:* The overall model structure must be comprehensible. This ensures that the working mechanisms of the optimization can be understood, and the optimization can be adapted. This requirement excludes black box models. However, it is possible to use black box models for individual components or to convert the model into a black box meta model to reduce computation time.
- *Detailed statistics available:* For the analysis of the optimization methods, it must be possible to access the signals passed within the model. This facilitates the detailed analysis needed for this thesis.
- *Representation of velocity as function of the distance:* For the optimization, the velocity v must be represented as a function of the distance x and not the time t. If this is not possible, the transformation must be done outside of the model as part of the optimization, which is more complex.
- *Implementation effort manageable:* As the BEV model is not the core element of this thesis, the implementation effort must be low. Moreover, the implementation must not require time and money consuming physical experiments.
- *Modular architecture:* The architecture must be modular to allow a variation of the scope of the EMS. Moreover, it should be possible to alter the accuracy with which the components are modeled.

The last two requirements indicate that the model should be based on an existing framework because otherwise the implementation effort would be too high. As no commercial tool can be used, the modeling is based on previous work at the Institute for Automotive Technology at the Technical University Munich (TUM).

5.2.2 Component Library for Modeling BEVs

The BEV model built from the component library developed at the Institute of Automotive Technology fulfills the requirements listed above. Hence, the optimization implemented for this thesis uses that model. The library is described in [163] and [164]. The authors partly reuse previous work done at the institute. For example, they use machine models developed by [53] and [165]. The overall structure of the library is based on a longitudinal dynamic model designed by Rohr [166] and Müller [167], which they use in their respective PhD theses. Their model is also described in [168].

The component library is designed to build a model which represents the powertrain and the longitudinal dynamics of a BEV. The resulting model is a mixed forward and backward simulation. The focus of the library is to provide a modular framework in which the components can be developed and reused by different developers [163]. Koch [164] gives a detailed description of the components that are initially implemented. The scope of each component is a trade-off between implementation effort and modularity [163]: A smaller scope increases the implementation effort, but also improves the modularity.

Another feature of the library that impacts the setup of the vehicle model is the implementation of the bus system used to transmit information within the model. The implementation of the bus is based on the work of Rohr and Müller described in [168] and also in [166, p. 37-42]. [163] explains, how it is integrated into the concept of the library.

In [164] the model is validated for the Ford Focus Electric [164, p. 41-52] and for the Volkswagen (VW) eGolf [164, p. 53-60]. In [163] the model is validated for an electric Smart Fortwo using data from [169] and [170]. The vehicle was converted from an ICEV to a BEV and is described in [125] and [161]. Both approaches have drawbacks. Koch [164, p. 51, 59–60] reveals a significant discrepancy between the modeled and measured energy consumption. This cannot be fully explained. The suggested reason is an imperfect knowledge of the vehicles and therefore problems with the correct parametrization. Danquah et al. [163] face this problem to a far lesser extent because they have a more extensive knowledge of their chosen vehicle. However, this particular Smart Fortwo is not a vehicle produced in series. This makes it hard to compare the results and for other researchers to comprehend them. Moreover, the power of the vehicle is not sufficient to follow the target speed of common DCs such as the New European Driving Cycle (NEDC) and the Worldwide Harmonized Light Duty Vehicles Test Procedure (WLTP). This further decreases the comparability of the results. The unavailability of a validated parameter set which can be used with the optimization is therefore the greatest weakness of the component library. To meet this challenge, this thesis uses the vehicle model based on the component library implemented by Steinstraeter et al. [36].

The component library is a good starting point to build a model that meets the criteria defined in Subsection 5.2.1. Additionally, it meets some of the desired features listed at the end of Subsection 5.2.1. Moreover, it is possible to adapt the model to fit the optimization procedure. The modular design makes it possible to exchange and update components.

5.2.3 Vehicle Model

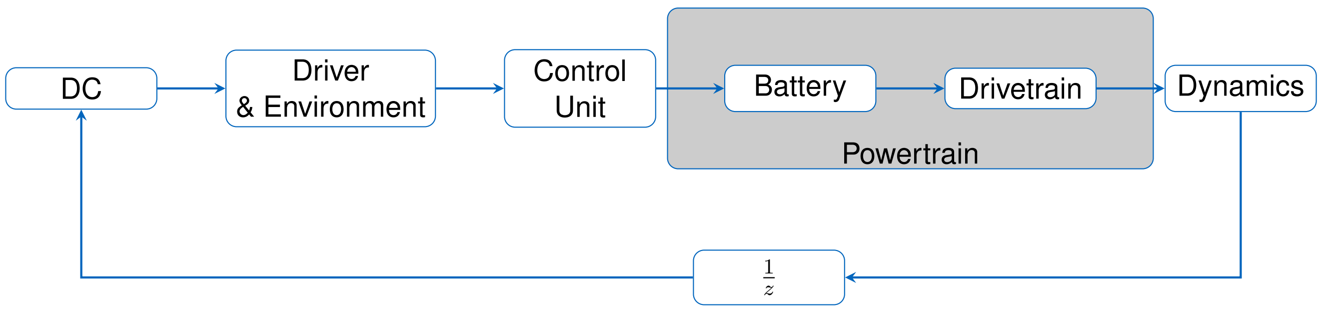


Figure 5.2 : Basic structure of model based on component library (refer to [163])

This subsection introduces the model that is used for the optimization. The aim is to provide the reader with enough information to comprehend and reproduce the results obtained in this thesis. Figure 5.2 shows the basic setup of the BEV model. It follows [164], [36] and [163]. The figure shows the information flow within the Simulink model. The arrows symbolize the bus used for the model. Each component can access all signals from the preceding components and from the previous time step. The time shift is symbolized by the $\frac{1}{z}$-block.

Not only the setup of the model but also the modeling of the components closely follows [163] and [164]. However, the components are altered for three reasons: Firstly, to form an interface for the optimization. Secondly, to model components needed for the optimization. Thirdly, to fulfill criteria needed for the optimization algorithms.

For this thesis the parametrizations of the Bayerische Motoren Werke (BMW) i3 $(60\ Ah)$ is used. The model was built up, parametrized, and validated by Steinstraeter et al. as described in [36]. The model is based on the component library, but differs in the battery, heater and cabin [36]. The model is validated with real-life test drives and tests on the roller dynamometer [36]. For the test drives the same route that is also described in Section 5.6 is used. The tests on the roller dynamometer copy the WLTP. The model only deviates in one aspect from the commercially available BMW i3 [36]: The heater itself is exchanged for a different model. Both heaters are HVHs. However, the original heater reacts more slowly to changes in the power demand. Moreover, it has a smaller overload capacity and a lower power rating. These features make it less interesting for taking in recuperated power. As this is the main objective of Steinstraeter et al. they exchanged the heater in the vehicle and in the model. A detailed description of the modeled heater can be found in [171, p. 61]. The brochure of the manufacturer also contains a detailed overview of the modeled HVH [172]. How the heater is modeled can be found in [173]. [36] gives a detailed overview of how the model was validated and how well it performs.

In the following paragraphs the parts of the model are introduced. The focus lies on the changes that were implemented for the MORE.

Driving Cycle (DC)

The block labeled DC is called 'Data' within the Simulink model. In this block the velocity profile for the simulation is inputted. In the original model this block simply contains a velocity profile in the form $v(t)$ [163]. However, to use the model with the optimization, two adaptions must be made. Firstly, the velocity must be expressed as $v(x)$. The DCs can be transformed from $v(t)$ to $v(x)$ using a pre-processing function in Matlab. This pre-processing must be done only once. The result is saved in a *.mat-file* and can be loaded to the model in every run of the experiment. The transformation and integration into the model can also be found in [179]. Secondly, the optimization procedure must be able to adapt the velocity. This is done by multiplying the velocity $v(x)$ defined by the DC with a vector supplied by the optimization procedure. If all entries of this vector are one, the velocity remains unchanged. The model uses the adapted velocity. The procedure is described in [178] and [179]. Any DC of the form $v(t)$ can be adapted to be used with the model. For this thesis the recorded drives described in Section 5.6 are used.

Driver and Environment

The driver translates the current speed and the target speed into an acceleration and a brake pedal position. This is done using a PID controller to model the human behavior. The block is described in [164, p. 29]. The environment block supplies a ground slope and a wind speed. In the original component library both values are set to constants. This simple implementation is retained for the optimization.

Control Unit

The implementation of the control unit is also not changed. The original implementation can be found in [164, p. 29]. The main task of this block is to translate the pedal positions into target torques and to compute the battery current limitations.

Battery

The LIB is part of the powertrain. In the library the powertrain is divided into one block for the LIB and one for the drivetrain. This can also be seen in Figure 5.2. As already mentioned above, [36] adapted the battery in comparison to the original library. Their model is more detailed and is based on the work of [174]. The battery is also validated for the BMW i3. [36] also developed an aging model. However, this is not used for this thesis. The battery block computes the voltage U available for the drivetrain. Moreover, the SoC and the battery temperature are updated.

Drivetrain

The drivetrain contains multiple library blocks and additions needed for the optimization.

It contains the electric machine. This block remains unchanged for this thesis. It is described in [164, p. 30-31]. It computes the analytic efficiency of the electric machine. The detailed implementation was originally done by Horlbeck and described in [165]. Here also the theory behind the implementation is explained.

The gear stage is also contained in the drivetrain block. For the gear stage, both the simple gear stage implemented by Koch [164] and a purpose-built component for the optimization are used. The original gear stage is a single gear as it is common for BEVs [164, p. 31]. The other block was built by Bollongino and described in [183]. This block allows to shift gears and it can be used to expand the scope of the EMS.

The blocks representing the brake fading and the wheel system are retained in their original form throughout the experiments. A description can be found in [164, p. 31].

Dynamics

Here the original block described in [164, p. 32-33] is used. The computation is done according to the elementary equation of longitudinal dynamics (Equation 2.23) described in Section 2.3.2.

Cabin and Heating System

The original component library does not contain a detailed model of the cabin and the heating system. Therefore, this block is not included in Figure 5.2. The block introduced in [36] is based on the work described in [152] and validated for the BMW i3. In the following, a short description of the block is given, more details can be found in the cited papers and in [173]. The block contains the cabin, the coolant circuit, and the heater itself. The heater heats up the coolant via a heat exchanger. In the original model the heating power is determined using different rule-based EMSs. For this thesis the model is expanded to allow integrating the heater power determined by the MORE. This is described in Section 5.4.5.

The coolant moves through a system with pipes. The heat exchange between coolant and cabin is done via another heat exchanger and a blower that creates an air mass flow into the cabin. The air mass flow is determined by a P-controller to maintain the target temperature for the cabin. The MORE can influence the air mass flow by adapting the target temperature. This again is described in Section 5.4.5.

The cabin is modeled to portray the influence of the air mass flow, the vehicle speed, and the ambient temperature on the cabin temperature. The cabin is not partitioned into zones, but a single cabin temperature is assumed. The solar irradiation is neglected.

5.2.4 Programming Environment

All computer experiments conducted for this thesis are implemented in Matlab/Simulink 2019 by Mathworks[1]. Matlab/Simulink is a standard tool used for prototyping software in automotive engineering and adjacent fields. In particular, it is used at the Institute of Automotive Technology of the TUM. The interaction between Matlab and the simulation environment Simulink allows the optimization of vehicle models.

One advantage of Matlab for this thesis is, that optimization methods can easily be implemented: Firstly, Matlab is a high-level language that can be programmed without much difficulty. Secondly, Matlab offers toolboxes in which several optimization methods used in this thesis are implemented. Using toolboxes rather than self-implemented code offers several advantages besides saving time: It avoids implementation mistakes which impede the comparison of the methods. Furthermore, it allows a fair comparison of the computation time. Additionally, it ensures the comparability to the state of the art. Another plus of Matlab is that figures showcasing the results and the working mechanisms of the algorithm can easily and quickly be drawn up.

However, using Matlab also has some disadvantages. The run-time for Matlab-code is typically longer than for code written in other programming environments. Additionally, not all parameters in the optimization algorithms can be adapted by the user. Lastly, no algorithm for DP is implemented in Matlab. This hinders the comparison of this method to SQP and GA. Nevertheless, Matlab is a fitting tool for prototyping the MORE because the advantages outweigh the drawbacks.

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[1] `https://de.mathworks.com/products/matlab.html`

Table 6 Overview of the optimization problem formulated for this thesis

Component	Chosen Option
Objectives	Energy consumption, cabin temperature, arrival time
Parameters	Velocity, Heater power, cabin target temperature
Approach to multi-objectivity	*a priori*, weighted sum method
Constraints	Maximum and minimum coolant temperature
Bounds	Maximum and minimum heater power, maximum and minimum velocity, maximum and minimum cabin target temperature

5.3 Reference Heating Strategy

For the velocity profile the originally not optimized trip is used as a reference. This is done because currently most commercially available BEVs do not employ a driving strategy to save energy. For the heating system a rule-based strategy is used as reference. It is one of a set of three rule-based strategies developed by Steinstraeter and presented in [151]. The three strategies are referred to as *standard strategy*, *charging-prioritized strategy*, and *heating-prioritized strategy*.

All three strategies can only influence the heater power. The air mass flow is governed by a P-controller, as described in the previous section. The standard strategy models the behavior of the vehicle in its original state without an EMS dedicated to the heating system. The charging-prioritized strategy uses the recuperated energy primarily to recharge the LIB. The energy that cannot be taken in by the LIB is used for heating. The heating-prioritized strategy takes the recuperated energy first for heating and stores the rest in the battery. The two latter strategies aim to increase the range and to alleviate the stress to the LIB. [151] shows that the charging-prioritized strategy leads to the highest increase in the range of the vehicle. Therefore, it is used as a reference strategy for this dissertation.

The reference strategy is chosen not to resemble the original state of the BMW i3. Instead, an advanced rule-based EMS is used. It seems likely, that with the use of flexible HVHs, advanced rule-based strategies will be used in commercially available BEVs and the MORE has to compete with such approaches.

5.4 Optimization Problem

This section describes the optimization problem that must be solved for the MORE. The optimization problem for this thesis is defined according to the basics discussed in Section 2.1 and the basic form shown in Equation 2.1. In the following, all parts of this equation are defined for the MORE. The important aspects are the parameters $\boldsymbol{y}$, the function $f(\boldsymbol{y})$ and the constraints $h(\boldsymbol{y})$ and $g(\boldsymbol{y})$. Table 6 gives an overview of the most important points.

5.4.1 Subdivision of the Optimization Problem into Windows

As discussed in [178] the optimization problem is partitioned into windows. The windows are not all the same length, but a window begins when the vehicle stops, and it ends at the next stopping point. In Figure 5.3 the windows are marked for the *DC12*. In this context two questions must be answered:

1. Why is the DC partitioned into windows?

2. Why do the windows start and stop when the vehicle is in standstill?

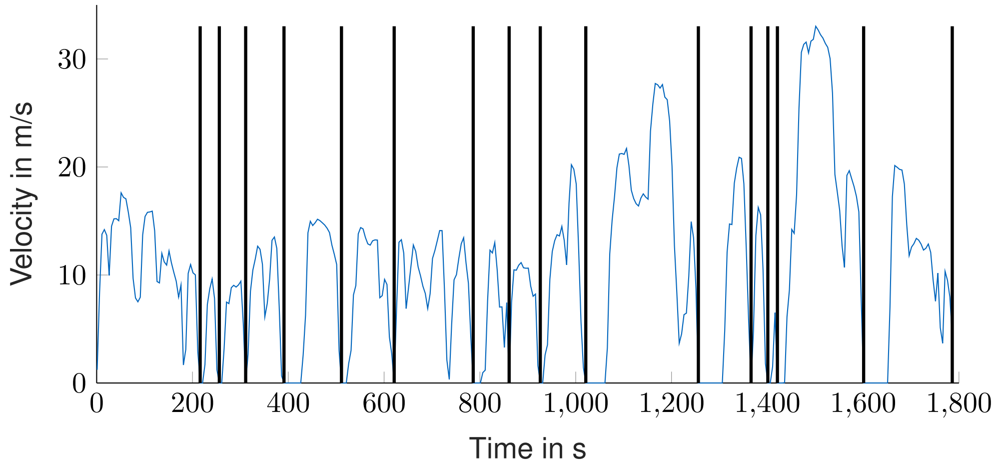

Figure 5.3 : Velocity profile for *RF12* with lines that mark the end of each window

The DC is not optimized as a whole for two reasons: Firstly, the length of the optimized time and distance respectively has a large impact on the computation time of the optimization. For the GA this correlation is hard to grasp, because the stopping criteria are often based on the experience of the user and heuristic criteria. However, for the SQP the correlation can be illustrated: In every step of the SQP the algorithm needs the gradient of $f(\boldsymbol{y})$. For every element of $\boldsymbol{y} = (y_1, y_2, \dots y_n)$ the function $f(\boldsymbol{y})$ must be evaluated once or twice to approximate the gradient using the difference quotient. The length n of the vector $\boldsymbol{x}$ is directly proportional to the length of the optimized window. Therefore, the number of function evaluations is directly proportional to the length of the window. It is safe to assume that each function evaluation takes the same time if the window is constant. However, the evaluation time is directly proportional to the window length. Therefore, the window length has a double impact on the computation time of the gradient: Firstly, via the number of function evaluations, secondly, via the time for one function evaluation. If the whole DC is optimized, its length has a quadratic impact on the optimization time. If the DC is cut up into windows its length only has a linear influence. Consequently, the optimization of a partitioned DC is considerably faster than that of the entire cycle.

Moreover, cutting up the DC into windows is closer to an online application of the MORE. It is unrealistic that the whole DC is known at the beginning of the trip. However, it is possible that a forecast exists for the next small section of the cycle. The division of the DC into windows introduces several challenges that must be addressed in the problem formulation. Therefore, it is important for a realistic EMS to consider this partition. The impact on the objective function is explained in detail in Section 5.4.3.

The second question is, why the next window begins when the vehicle is in standstill. The alternative would be to partition the DC into windows that either equal length regarding either time or distance. This would mean that at the end of one window and the beginning of the next window the speed of the vehicle is not zero. Consequently, the kinetic energy stored in the vehicle is also not zero. This transfer of energy from one window to the next must be considered in the objective function and complicates the optimization. For the thermal energy that is stored in the cabin and the coolant this problem cannot realistically be avoided. How this is treated is discussed in Section 5.4.3.

Another feature that is implemented for the windows is that they overlap by a predefined distance. This means that a window continues after the vehicle stops. However, as the next window begins at the stop point, the final values of the first window are discarded. In the following, the effects that make this procedure advantageous are explained. As the end of each window is not used, effects that occur because the window ends are neglected. At the end of the window the heating has no effect on the cabin or coolant temperature that can be discerned by the optimization. This could lead to two effects: Firstly, heating could be unappealing for the algorithm as energy is spent but no positive effects can be found. Secondly, if heating power is available through recuperation, the heater might overheat the coolant. Both effects are undesirable. Another effect is that the optimization can look ahead and adapt the parameters accordingly. This is particularly interesting for the recuperation utilization of the heater: At the end of the window the vehicle brakes. Due to the overlap the algorithm knows that the next stretch will be an acceleration phase during which no recuperated energy is available. The optimization can adapt accordingly. For these reasons the optimization profits from overlapping windows.

5.4.2 Composition of the Optimization Function

This section focuses on the optimization function $f(\boldsymbol{y})$. $f(\boldsymbol{y})$ is the central component of the optimization problem: It is the function for which the optimum must be found. In the case of this optimization problem $f(\boldsymbol{y})$ can be split into two functions:

$$\boldsymbol{f}(\boldsymbol{y}) = o(\boldsymbol{e}(\boldsymbol{y})) \tag{5.1}$$

The function $\boldsymbol{e}(\boldsymbol{y})$ represents the vehicle model implemented in Simulink and discussed in Section 2.3. The function o stands for the objective function. The objective function is drawn up to translate the output of the model into a fitness value which reflects the aims of the DM. The objective function is discussed in the next subsection (Subsection 5.4.3).

5.4.3 Objective Function

The objective function is the link between the vehicle model and the optimization method. To draw up an objective function, first the objectives of the EMS must be defined. These are:

- Energy consumption
- Cabin temperature
- Travel time

The energy consumption can be seen as the main objective. However, the cabin temperature and the travel time are also relevant for the driver and must therefore also be considered. As there are three objectives, the problem is a MOOP. The theory of MOO is explained in Section 2.1. For this thesis an *a priori* approach is chosen. This has two reasons: Firstly, *a priori* approaches tend to be computationally efficient. Secondly, the input of the DM is needed before the optimization. As the DM is the developer of the EMS, they are not available when the optimization is run in the field. For this thesis the weighted sum method is used to handle the multi-objectivity. For the basic principle refer to Equation 2.6.

The objective function can be written as:

$$min\,\boldsymbol{o}(\boldsymbol{y}) = min(\theta_{\text{energy}} \cdot \bar{f}_{\text{energy}} + \theta_{\text{temperature}} \cdot \bar{f}_{\text{temperature}} + \theta_{\text{time}} \cdot \bar{f}_{\text{time}}) \tag{5.2}$$

The vector $\boldsymbol{\theta} = (\theta_{\text{energy}}, \theta_{\text{temperature}}, \theta_{\text{time}})$ is called DM priority vector and reflects how the DM weights the individual objectives. The functions $f_{\text{energy}},\ f_{\text{temperature}}$ and f_{time} are the objective functions for the individual objectives. All the functions are normalized using the following equation:

$$\bar{f} = \frac{f - f_{\text{Utopia}}}{f_{\text{Nadir}} - f_{\text{Utopia}}}, \bar{f}\epsilon[0, 1] \tag{5.3}$$

The theory behind this normalization can be found in Equation 2.7. How the Nadir and Utopia values are computed is explained in the following paragraphs for the individual objective functions.

Before starting into the objectives, the conditions the objective functions must fulfill are discussed. The objective function is used in combination with both the GA and the SQP. The GA makes no demands in respect to the objective function. In contrast to that, the SQP requires the objective function to be twice differentiable. Another design target is that the objective function reflects what the DM expects the optimization to do. In the case of the EMS this implies that the objective function is adapted to the windows described in Section 5.4.1. The sequence in which the computations for

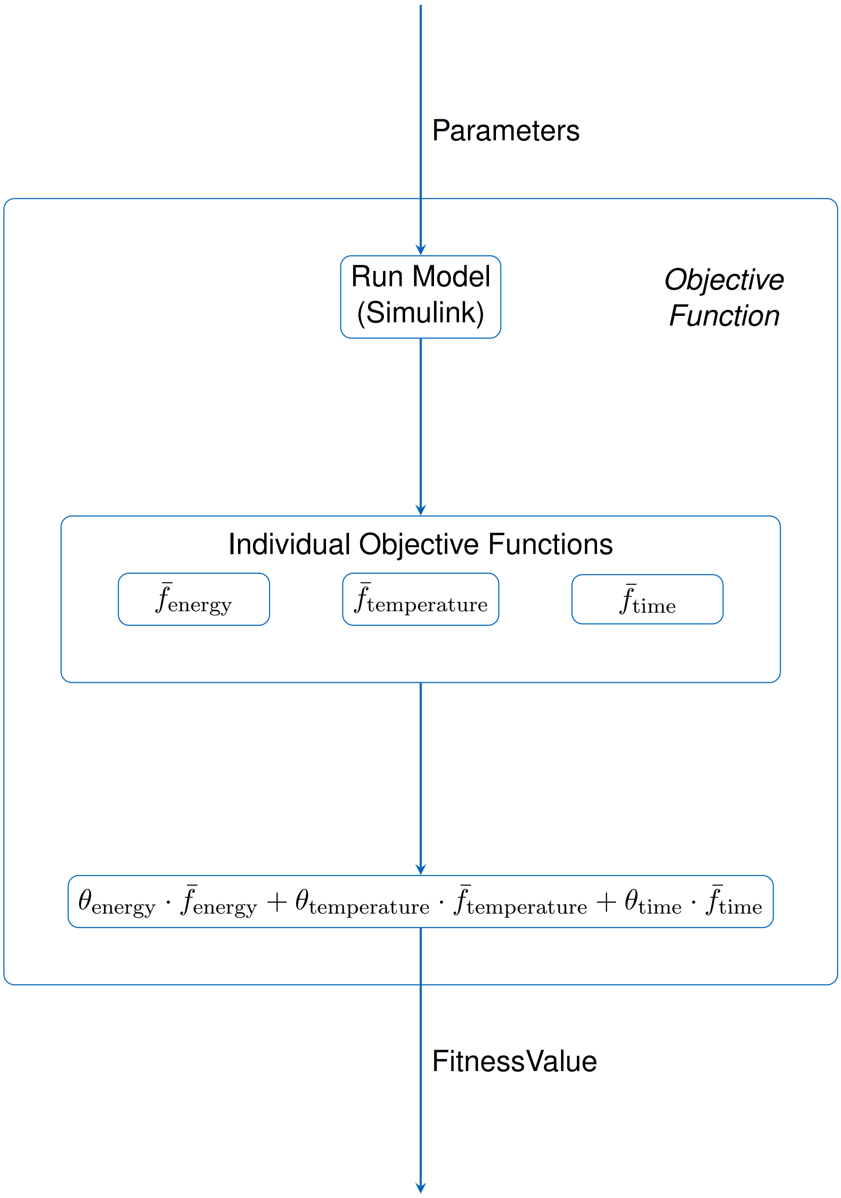

Figure 5.4 : Sequence for the computation of the objective function

the objective functions are performed is summarized in Figure 5.4. The input the objective function receives from the optimization are the parameters, the output is the scalar fitness value. First, the model is run in with the parameters. The output of the model is used to calculate and normalize the fitness values for individual objectives using Equations 5.5, 5.7 and 5.8. These values are aggregated using the DM priority vector to obtain a scalar fitness value.

In the next paragraphs the individual parts of the objective function are introduced.

Energy consumption For this objective function two variations are implemented: Firstly, a straight-forward approach based on the total amount of consumed energy is investigated. Secondly, an implementation based on the losses of thermal energy in the coolant and the cabin is introduced. In the following, it will be explained that the former is more suitable, if the entire cycle is optimized, while the latter yields better results for the window-wise optimization.

The objective function based on the total amount of consumed energy can be written as follows:

$$f_{\text{energy}} = E_{\text{bat}} + E_{\text{bat,loss}} \tag{5.4}$$

Here, E_{bat} is the complete energy taken from the battery. Consequently, it encompasses the energy for the powertrain as well as the energy for heating. The losses in the powertrain and in the energy transmission are part of E_{bat}. $E_{\text{bat,loss}}$ describes the losses that occur within the LIB during charging or discharging.

The objective function described in Equation 5.4 leads to the expected and desired results if the whole DC is optimized. If the DC is subdivided into windows, the optimum found with this objective function for the individual windows differs considerably from the optimum for the whole DC. This has two reasons: Firstly, the energy stored in the warmth of the coolant and the cabin is not considered. Consequently, only the heating power taken from the battery is minimized. This means that the optimum is to let the coolant and the cabin go as cold as possible. Due to the conflicting objective to keep the cabin temperature as close to the target temperature as possible, it is not viable to cease heating completely. However, letting the coolant go cold means that to maintain the cabin temperature in the next window, more energy from the battery must be used. Secondly, when the window ends, a small part of the energy in the heating system is neither still in the battery nor in the coolant or the cabin. This "ghost" energy is caused by the delays in the cabin and coolant model. The first problem can be solved by adding correction factors to the objective function. These factors emulate the thermal energy that is stored in the cabin and the coolant. To do that an approximation is made on how much energy is stored in the cabin and the coolant respectively per Kelvin temperature difference to the ambiance. This is done by determining the pulse response of each system to a heating pulse. This approach, rather than an analytical computation, ensures that the MORE can be transferred to other vehicles or used with other models. In the objective function itself the correction factor is multiplied with the temperature difference to have an approximation of the stored thermal energy. This approach has two drawbacks: Firstly, the thermal energies are only approximations. Secondly, the "ghost" energy cannot be integrated into the objective function.

Therefore, a second objective function is drawn up for the window-wise optimization. Figure 5.5 visualizes the second approach, which is based on the thermal energy losses. The main goal remains

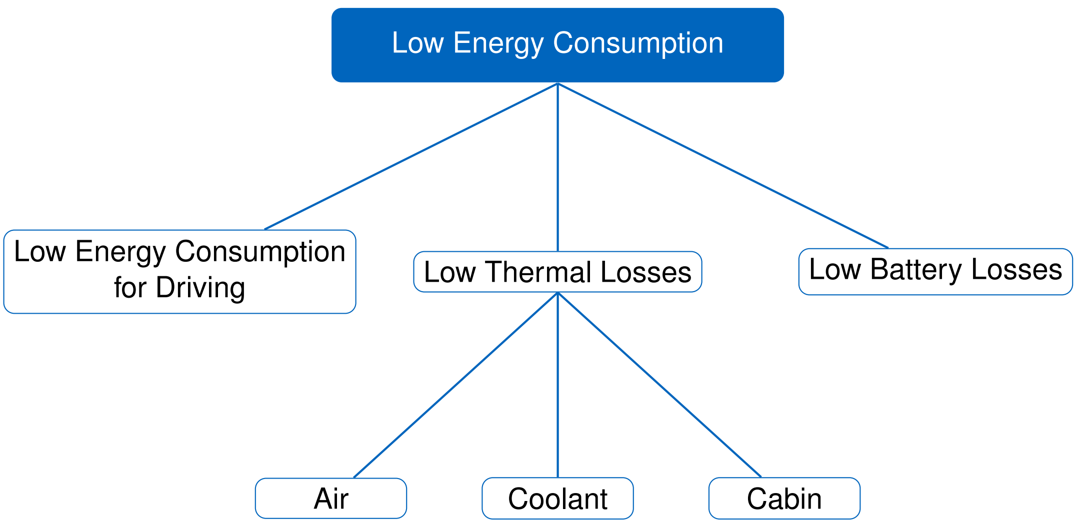

Figure 5.5 : Redrafting the energy objective function

a low energy consumption. This means that little energy is needed to overcome the driving resistance (refer to Equation 2.23) and little energy is lost within the battery. It also means that as little heat as possible is lost. The energy for the drivetrain is not problematic, because the velocity at the end of each window is zero. Therefore, no kinetic energy is transferred from one window to the next. The battery losses are also easy to extract from the model. The decisive part are the heat losses. These can be split into the energy lost via the cabin, the coolant, and via heated air streaming out of the cabin. The objective function can therefore be written as follows:

$$f_{\mathrm{energy}} = E_{\mathrm{bat}} - E_{\mathrm{heat}} + E_{\mathrm{bat,loss}} + E_{\mathrm{cabin,loss}} + E_{\mathrm{coolant,loss}} + E_{\mathrm{air,loss}} \tag{5.5}$$

The term $E_{\mathrm{bat}} - E_{\mathrm{heat}}$ describes the energy used in the drivetrain. The formulation is chosen because the energy used by the drivetrain is not directly available in the model. The terms $E_{\mathrm{cabin,loss}}$, $E_{\mathrm{coolant,loss}}$ and $E_{\mathrm{air,loss}}$ describe the thermal energy lost in the cabin, the coolant, and the air streaming out of the cabin, respectively. While the components E_{bat}, E_{heat} and $E_{\mathrm{bat,loss}}$ can be taken directly from the model, the thermal energy losses must be calculated separately using values from the model. This means that the objective function is closely linked to the model and should be adapted if the model is exchanged.

For the normalization of the fitness value, the Nadir and Utopia values are needed (refer to Equation 5.3). The Nadir value is the possibility in which most energy is consumed. Consequently, it is computed using a simulation with the maximum possible velocity and the reference strategy for heating. The Utopia value is linked to the lowest possible energy consumption. Therefore, it is extracted from a simulation with the lowest possible speed and deactivated heater.

The energy objective function also contains a penalty term for the coolant temperature. If the coolant temperature exceeds a lower limit or an upper limit a quadratic penalty term is added to f_{energy}.:

$$penalty = \beta \cdot \Delta T_{\mathrm{coolant}}^2 \tag{5.6}$$

$\Delta T_{\mathrm{coolant}}$ denotes the deviation from the upper or lower limit, respectively. β determines how heavy the deviation is penalized. The term is set so that small deviations are accepted. The upper limit is set to $353\ K$ and the lower limit to $310\ K$, the factor β is set to 0.01.

The upper and the lower coolant limits differ in their significance for the optimization: The upper limit serves to protect a physical limit of the system. In a real vehicle the coolant temperature must not exceed $373\ K$, as the coolant boils at this temperature. In practice, temperatures over $363\ K$ are avoided. This limit is not preserved by the model itself and must therefore be protected in the optimization. The lower limit on the other hand has no physical background. For the window-wise optimization it helps to avoid local minima due to low coolant temperature. Furthermore, it helps to limit the search space and therefore accelerates the convergence.

Travel time: The objective function for the travel time is simply the travel time:

$$f_{\mathrm{time}} = t_{\mathrm{travel}} \tag{5.7}$$

The Nadir value is the longest time it can take to drive the DC. Therefore, it is computed by running a simulation with the lowest possible velocity. In contrast to that, the Utopia value is extracted from an optimization with the highest possible velocity.

Cabin Temperature: The objective function for the cabin temperature is:

$$f_{\mathrm{temperature}} = norm((|\Delta T_{\mathrm{cab}}| - |\Delta T_{\mathrm{cab,Utopia}}|)^2) \tag{5.8}$$

ΔT_{cab} denotes the difference to the desired cabin temperature:

$$\Delta T_{\mathrm{cab}} = T_{\mathrm{cab}} - T_{\mathrm{cab,target}} \tag{5.9}$$

Equation 5.8 means that the objective function for the cabin temperature is the Mean Squared Error (MSE) of the cabin temperature deviation. $T_{\mathrm{cab,target}}$ can be varied.

The Nadir value is the highest possible deviation from the target temperature. It can be simulated by not heating the cabin. The Utopia value is computed using the reference strategy, because it is known, that this strategy prioritizes reaching the cabin temperature. It is important not to use zero deviation from the target temperature as Utopia value: When the cabin is heated up, it depends on the constraints of the heater and vehicle how quickly the target temperature is reached. However, it is never reached instantaneously.

An additional correction is added to the Nadir and Utopia values: Both values are limited to $4\ K$. This is done because the optimization works better if the values for $f_{\mathrm{temperature}}$ are close to zero and especially in the same range as the values of the other partial objective functions.

Constraints: The coolant temperature must be constrained: If the temperature is too high, it is implausible as the liquid would start to boil. The model itself does not prevent this from happening. Therefore, input that leads to an overly high coolant temperature must be avoided within the optimization. Moreover, experiments show that a too low coolant temperature leads to a local minimum and, therefore, suboptimal results. This can be avoided by adding a lower limit to the coolant temperature. Consequently, values above the highest desirable temperature and below the lowest desirable temperature are constrained with a quadratic penalty. The constraints are integrated into the energy objective function.

5.4.4 Parameters

This subsection discusses the final aspect of the optimization problem: the variables for the optimization. It fills the gap between the optimization and the vehicle model and describes how the variables are integrated into the model.

As the aim of the MORE is to work with a BEV that is close to a currently sold vehicle, the number of variables is limited. This thesis focuses on connecting a driving strategy with the HVAC. Therefore, the variables are the vehicle velocity, the heater power, and internal parameters of the heating system. For the internal parameters of the heating system only the air flow into the cabin is considered. In the following, the individual variables are described.

Velocity: To define how the variable is presented, it is helpful to determine how it can be integrated into a real-world BEV. For the integration of the velocity two options are viable: The first option is that the BEV is at least partly autonomous. The second option is that speed is chosen by a human driver who receives recommendations from the MORE.

For the autonomous vehicle the velocity calculated by the vehicle in accordance with parameters like the traffic situation can be adapted by the MORE. It is important that the velocity stays within the limits that the constraints allow.

In the second case the MORE can influence the velocity by recommendation to the driver. For example, the EMS can recommend decreasing the velocity. Currently commercially available models are already giving such recommendations for maximizing the fuel efficiency. In other locations the EMS could indicate that the driver should increase the velocity. The latter is not yet common in suggestions for a fuel-efficient driving style.

In both cases the MORE does not determine the velocity independently. Therefore, the influence the MORE can take on the velocity must be modeled. A reasonable assumption is that the MORE can trigger small deviations from the planned velocity. These deviations must stay within predefined limits. In this thesis the MORE influences the velocity via a factor that is multiplied with the original velocity. The range in which the factor can lie can be adjusted when starting the optimization. For the results discussed in the thesis it lies between 0.7 and 1.1. The range is not symmetric because it is typically more acceptable to drive slower than faster.

As already described in [178], the velocity is specified as a function of location, not time. The main reason is that the locations where the vehicle stops are fixed. However, the exact time when the vehicle stops is not relevant. The second reason is that for this thesis the optimization results from one trip are transferred to another. To facilitate this, the variables must also be a function of the location: The drives are the identical route but not the identical traffic situation. Consequently, the speed pattern differs but some regularities can be found in the velocity as a function of the location $v(x)$.

The velocity variable is presented as discussed in [178]: The optimization is provided with a time step size and with a translation velocity. These two parameters are multiplied to obtain the distance for which one velocity value is used.

Heater power: The heater power is easier to integrate into a real-life vehicle. Typically, the driver is not involved in the decision how the target temperature is reached by the HVAC. Moreover, the heater power is not influenced by external conditions like the traffic situation. Intuitively, the heater power is a variable that should be formulated as a function of time (refer to [178]). However, for two reasons it is also beneficial to translate the heater power into a function of location: Firstly, it accelerates the convergence of both GA and SQP, if the velocity is also optimized. This is because one of the main mechanisms of the optimization is using the recuperated energy for heating. The braking is often linked to a certain position of the route. If the optimization algorithm is in an iteration where the usage of the recuperation is optimal and in the next step the velocity is adjusted, for a time-based heating power, the heating power no longer aligns with the braking period. If the heating power is based on the place, this alignment is not lost by an adjustment of the speed.

Secondly, to transfer the results to another drive on the same route, the heater power also needs to be expressed as a function of the time.

The limits of the heater power originate in the physical limits of the heater. The maximum heating power is $20\,kW$. This power can only be sustained for $30\,s$, afterwards the power must be at least $30\,s$ $7\,kW$ or lower [151].

In the vehicle model, the heater power is a time-based variable. Hence, it needs to be translated into a representation as a function of the distance. This is done by partitioning the DC into sections that take equally long to drive. The time for one of these short distances is the time step size if it is driven with the original velocity for the DC. The distance for each segment remains fixed for the optimization. Consequently, if the velocity is adapted, the time it takes to drive one of the segment changes. This might change the overall effect a segment has on the coolant or the cabin temperature: For example, one segment increases the coolant temperature by $1\,K$, if it is driven with the original velocity. If the same segment is driven $10\,\%$ slower, it increases the coolant temperature by $1.1\,K$. How this challenge is met is discussed in Section 5.4.5.

Air Mass Flow: The air mass flow describes how much heated air streams into the cabin. While the heater power influences the cabin temperature only indirectly via the coolant, the air mass flow directly impacts the cabin temperature. The air mass flow is specified in $\frac{kg}{s}$. The value for the air mass must lie between $0.001\,\frac{kg}{s}$ and $0.0833\,\frac{kg}{s}$. The boundaries are defined by the physical limits of the blower.

In the reference strategy the air mass flow is determined by a controller that keeps the cabin temperature as close to the target temperature as possible. Consequently, the cabin temperature only differs from the target temperature, if the coolant is too cool to sustain target temperature. For the MORE two options for a variable connected to the air mass flow are implemented: The first possibility is to take the air mass flow itself as the variable. As the cabin temperature is part of the objective function (refer to Equation 5.2), the controller becomes unnecessary and the air mass can directly be used in the model. However, this approach leads to a problem: Regarding the air mass, the model contains a local minimum. The GA can handle this challenge, as it is a global optimization. The SQP gets stuck in the local minimum and yields results that are far from the optimum the DM expects. One possibility to meet this problem is implementing the air mass flow more indirectly. This is done by optimizing the target temperature instead of the air mass flow. The controller used by the reference strategy is retained and inputted with the variable target temperature. To maintain the comfort of the driver the deviation from the target temperature is limited to $0.5\ K$.

For both approaches the variables can either be expressed as a function of time or place. Only results for the optimization of the target temperature are presented in this thesis.

5.4.5 Integration of Parameters into the Model

This subsection explains how the integration of the parameters (described in Section 5.4.4) into the vehicle model (described in Section 5.2.3) works. The integration is discussed for every parameter separately.

Velocity: The velocity can directly be integrated into the model in the block DC. The only adaption that must be made is to map the variables from the optimization to the correct part of the route.

Heater Power: Integrating the heater power is more complex than the velocity. This thesis presents three options:

1. *Direct integration*: The heater power is directly integrated into the model.

2. *Basic controller*: A simple controller is used to integrate the optimized heater power into the model.

3. *Recuperation rule controller*: A more advanced controller which can independently increase the utilization of the recuperated power is used.

All options are independent of whether the heater power is presented as a function of time or place. Translating the location based representation is done via a look-up table before the controllers are used. The first option is the least complex: The heater power computed by the optimization is directly inputted into the model. This approach has three disadvantages: Firstly, if the heater power is represented based on the location and the velocity is varied, the duration for which a certain heater power is applied is also varied. This effect can lead to a suboptimal coolant temperature. As the heater power does not directly impact the cabin temperature, the problem is relatively small. Secondly, if the optimized variables are transferred to another trip, the time span for which each heater power is applied also varies compared to the original trip. This again means that the coolant temperature might be suboptimal. For the transfer, this effect is more pronounced than within one trip. Moreover, the location of the braking might be shifted compared with the original trip. Thirdly, if the heater power is directly integrated into the model, no pre-existing knowledge of the optimization problem and its solution is integrated. This means that a chance to accelerate the convergence is lost. For these reasons, two options for the integration of the heater power with an additional controller are investigated.

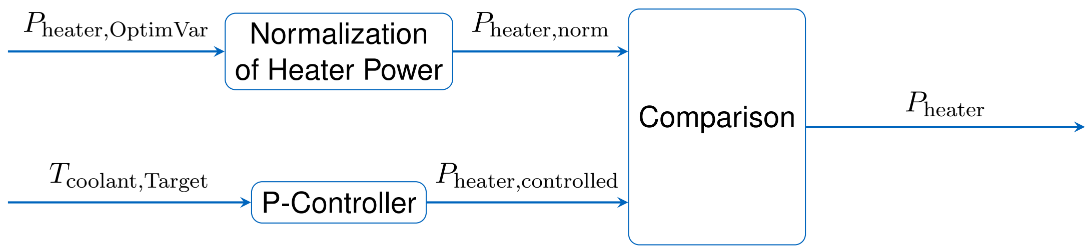

Figure 5.6 : Overview of the simple controller for the heater power

First, the simple controller is described. The basic signal flow is shown in Figure 5.6. The input of the controller is the heater power as it is used by the optimization. In the following, this parameter

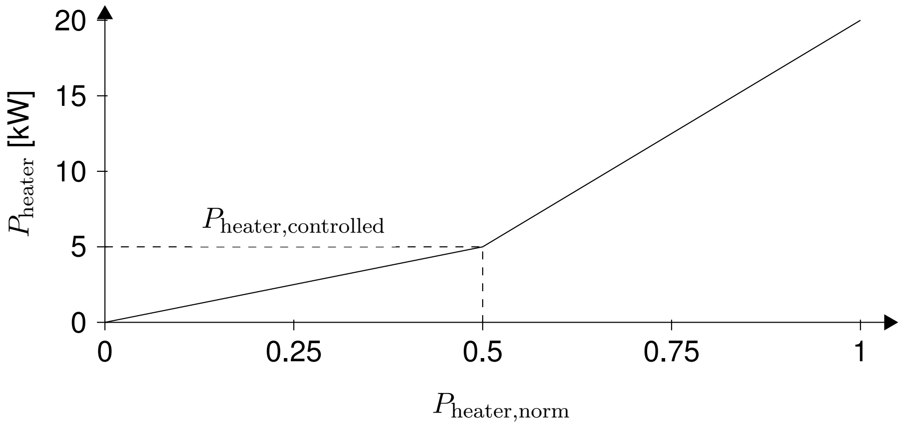

Figure 5.7 : Comparison function in the simple controller for the heater power

is referred to as $P_{\text{heater,OptimVar}}$. The output is the heater power P_{heater} as it is used by the model. In the upper branch shown in Figure 5.6, $P_{\text{heater,OptimVar}}$ is normalized using the maximum and the minimum values for the heater power. The resulting heater power is referred to as $P_{\text{heater,norm}}$. In the lower branch a P-controller is used to determine the heater power $P_{\text{heater,controlled}}$ to attain the optimum temperature for the coolant. In the final block these two values are compared to get the value for P_{heater}. How this comparison works is shown in Figure 5.7. $P_{\text{heater,norm}}$ is shown on the X-axis. The output of the block, P_{heater}, is depicted on the Y-axis. The graph that establishes a relationship between the two values is computed using $P_{\text{heater,controlled}}$. Figure 5.7 shows that the correlation between $P_{\text{heater,norm}}$ and P_{heater} is not linear: it increases between 0 and $P_{\text{heater,controlled}}$ for $P_{\text{heater,norm}}$ in $0 \ldots 0.5$ and between $P_{\text{heater,controlled}}$ and the upper limit for $P_{\text{heater,norm}}$ in $0.5 \ldots 1$. The target value for the coolant temperature is set in two different modes: Either the target temperature is fixed or the target temperature of the originally optimized trip is used is used. The first option is chosen for the optimization of the original trip. The target value for the coolant temperature is based on experience. The second option is used when the results are transferred to a different trip: The target value is set to the coolant temperature taken from the original optimization. This is discussed in more detail in Section 5.7.

The third method to set the heater power is the recuperation rule controller. It incorporates more previous knowledge than the simple controller. If the heater power is directly integrated into the model, or if the simple controller is used, it is important that the time step size is chosen to be small enough to mirror the shifts in the recuperation power. As already discussed in Section 5.4.1, reducing the time step size increases the computation time. To mitigate that problem, the recuperated power can be integrated into the controller. Figure 5.8 shows the principle of the proposed controller. The recuperation-based controller is an enhancement of the simple controller.

The first two blocks are identical to the simple controller: The heater power inputted from the objective function is normalized to attain a $P_{\text{heater,norm}}$ and a P-controller is used to compute a $P_{\text{heater,controlled}}$ that is dependent on the coolant temperature. Additionally, the recuperated power (P_{recu}) and a correction factor are entered into the comparison block. The correction factor is only used when the optimization is transferred to another trip. The correction factor is computed with a P-controller from the coolant temperature development from the original trip. This is discussed in more detail in Section 5.7. As for the simple controller, the core part of the controller is the comparison block. Its working principle is shown in Figure 5.9. The comparison block takes $P_{\text{heater,norm}}$ and computes P_{heater}. How this is done for two different amounts of available recuperated power, can be seen in the Figures 5.9a and 5.9b. In Figure 5.9a, a certain amount of recuperated power is available. The following sections based on the value for $P_{\text{heater,norm}}$ are defined:

- $P_{\text{heater,norm}} = 0$: The heater is switched off.

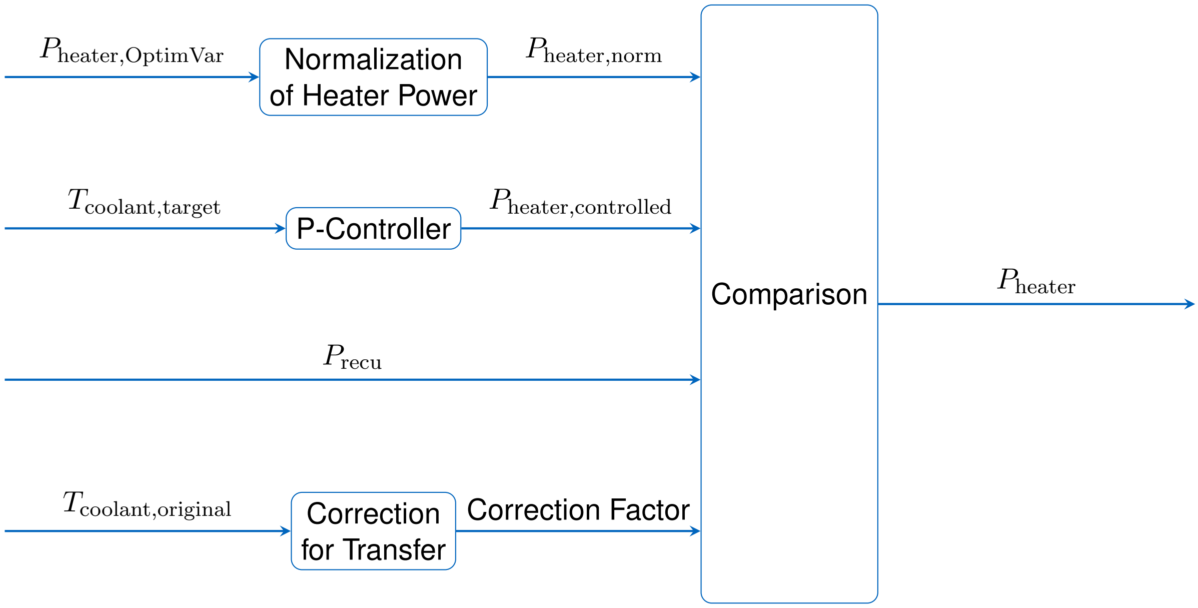

Figure 5.8 : Overview of the recuperation-based controller for the heater power

- $P_{\text{heater,norm}} = 0.25$: Only the recuperated power is used for heating.
- $P_{\text{heater,norm}} = 0.5$: The recuperated power plus $2\ kW$ is used for heating.
- $P_{\text{heater,norm}} = 0.75$: The recuperated power plus $7\ kW$ is used for heating.
- $P_{\text{heater,norm}} = 1$: The maximum heater power is used.

Between these values the heater power is linearly interpolated as can also be seen in Figure 5.9. This linear interpolation leads to problems with the SQP: As described in Section 2.2.3, the objective function for the SQP must be twice differentiable. The part where the different sections meet is not twice differentiable as can be seen in Figure 5.9. To solve this problem, the different sections of the function are blended: $5\ \%$ before and after each kink a quadratic function is applied, so that the gradient of the function changes slowly and does not have a discontinuity.

In Figure 5.9a the comparison block is shown when no recuperated power is available. This means for the same values of $P_{\text{heater,norm}}$ the output P_{heater} is different: For example, for $P_{\text{heater,norm}} = 0.25$ the heating is switched off. This means that if the recuperated power changes, the power used for heating changes even if the value for $P_{heater,OptimVar}$ does not change because it happens within one time step. This means that the recuperation rule controller opens up the possibility to use larger time steps.

Air Mass Flow: As described above the air mass flow is integrated via the target temperature. The controller used for the reference strategy is kept and inputted with the optimized target temperature instead of the original target temperature. The controller manages to keep the actual cabin temperature at the target temperature. To avoid sudden changes in the air mass flow, the rate at which the target temperature can change is limited.

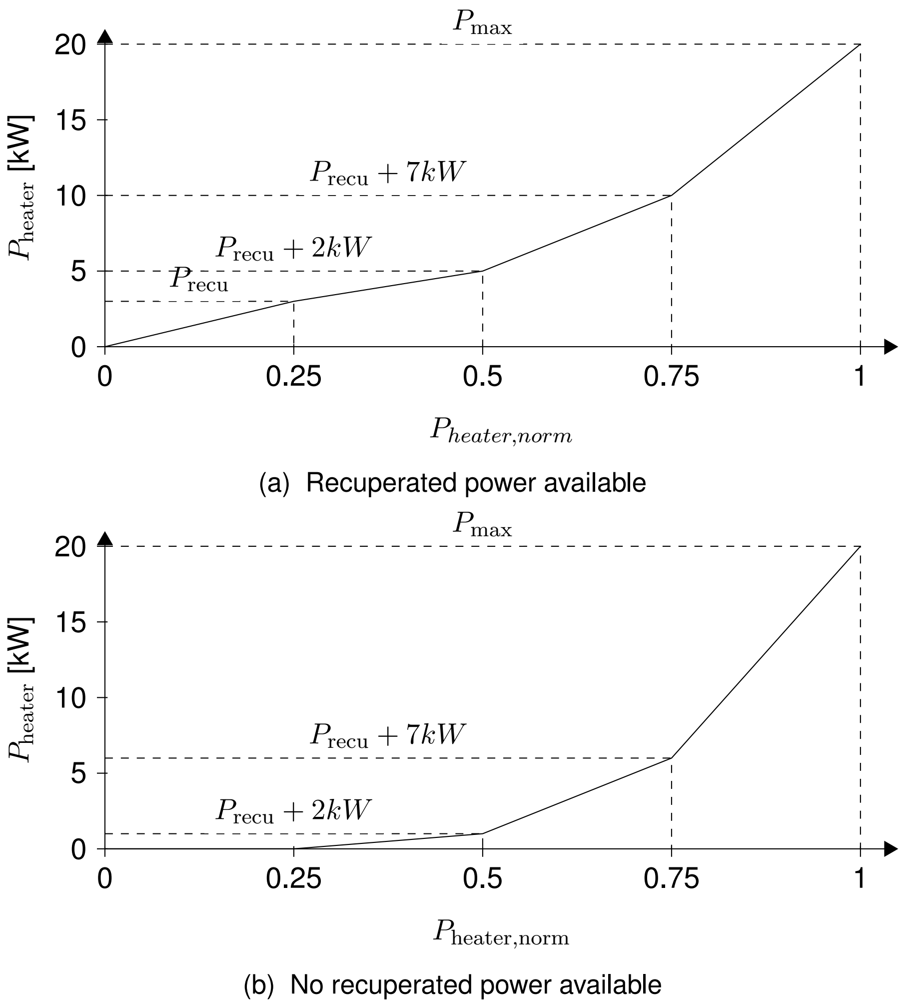

Figure 5.9 : Comparison function for the recuperation-based heater controller

5.5 Optimization Methods

In this section the optimization methods used for this thesis are introduced. The aim is to lay the foundation for comparing the methods in Chapter 6. This section provides the reader with implementation details and how the parameters of the algorithms are varied.

5.5.1 Genetic Algorithm

This subsection provides information on the specific implementation of the GA for this thesis. The working mechanisms of GAs are explained in Section 2.2.2.

For this thesis, a GA is applied because it is not specific to the optimization problem. This means that it can easily be adapted for different variations of the model. Furthermore, the GA works with a black-box model, because it only needs the results from evaluating the model and no further data. This allows the user to replace the Simulink model with a black box model which can be computed more efficiently. Another advantage is that the GA can be parallelized intuitively: The individuals of one generation can be evaluated on different cores. This significantly improves the run-time of the algorithm and allows the user to adapt it to the existing hardware.

How the GA is implemented in Matlab can be found in the documentation for the Global Optimization Toolbox [175]. In the following, only those options that are used for this thesis are explained. Therefore, this subsection reflects both how the algorithm is used for this thesis and how the GA is implemented in Matlab.

As explained in Section 5.4, the optimization problem is converted into a single objective problem using the weighting method. Therefore, a single fitness value can be assigned to every individual. In Section 2.2.2 the basic options for the different operators are introduced. The chosen implementation for the following operators is introduced: representation of individuals, initialization, mutation, crossover, selection, elitism, termination, constraint handling.

Representation of Individuals: For this thesis the individuals are real-valued. In Matlab this option is set under the keyword population type [175, p. 11.39]. Each individual consists of the parameters that are optimized for every time-step. In Figure 5.10 the individual for an optimization of the heater power and the velocity is shown.

v_1
v_2
v_3
$\cdots$
v_k
p_1
p_2
p_3
$\cdots$
p_n

Figure 5.10 : Example of an individual for an optimization with n time-steps and k spatial steps that takes the heater power $p(t)$ and velocity $v(x)$ as input

Initialization: The initialization of the population can be done by creating a uniformly random distributed population [175, p. 11.40]. Two subcategories relevant for this thesis exist [175, p. 11.40]: Either the population is randomly created within user defined boundaries, or it is created to meet the linear constraints. As the problem in this dissertation is constrained, the second option is chosen.

It is expressed as a function of the number of variables in each individual. This is necessary as the windows differ in length and therefore different numbers of variables need to be optimized. As the optimal population size depends on the number of variables an absolute number makes little sense. With k being the number of spatial steps and n being the number of time steps, the population size can be expressed as follows:

$$PopulationSize = \beta * (k + n) \tag{5.10}$$

The best value for β must be determined empirically through computer experiments. A larger population size might improve the result but can also increase the computation time. While Simon ([40, p. 50]) acknowledges that the population size is an important parameter, he gives no recommendation.

Mutation: For the mutation a user supplied function is integrated into the GA. It is a variation of the Gaussian mutation that is also integrated in Matlab [175, p. 11.46]: To each variable in the individual a random number with a Gaussian distribution around zero is added. The difference for the customized function is that the number of variables in one individual that are mutated changes over the iterations. This means that the mutation loses importance as the GA draws closer to the optimal solution.

Crossover: For crossover Matlab offers a variety of options. For the MORE the two-point crossover option implemented in Matlab is used [175, p. 11.50].

Table 7 Overview of the variations of the GA tested for this thesis

Option	Chosen Variation	Source
Population Size	1.5 times number of variables	[175, p. 11.39]
Crossover Type	*'crossovertwopoint'*	[175, p. 11.49-11.51]
Mutation Type	user supplied mutation function	[175, p. 11.46-11.48]
Constraint Handling	penalty integrated in objective function	
Crossover Fraction	0.8	[175, p. 11.46]
Elitism	0.05	[175, p. 11.46]
Parallel Execution	no	[175, p. 11.62]
Number of Generations	100	[175, p. 11.57]

Selection: For the selection the options implemented in Matlab are the standard options found in literature on GAs and, therefore, are the options described in the theoretical foundation. The default method, which is also used for this thesis, is the stochastic uniform selection [175, p. 11.44].

Elitism: Elite individuals can be used in Matlab [175, p. 11.46]. The number of such individuals is set as a fraction of the population via the elite count.

Termination: All termination criteria that are discussed in the theoretical foundation are implemented in Matlab [175, p. 11.57-11.58]. For this thesis the maximum number of generations is used as stopping criterion and is varied.

Constraint Handling: As explained in Section 5.4, the optimization problem discussed in this thesis is constrained. The constraints are only linear. Therefore, no techniques to handle non-linear constraints are discussed. On the one hand, constraint preserving operators in Matlab can be chosen. This ensures that all individuals satisfy the constraints. This option is mentioned for the respective operators. On the other hand, a penalty term can be added to the fitness function. This puts pressure on the population to develop individuals that satisfy the constraints. The advantage of the latter method is - besides the aspects highlighted in the theoretical foundation - that it can be applied in a similar way to the SQP. This ensures the comparability of the two methods.

5.5.2 Sequential Quadratic Programming

In this subsection the implementation of the SQP method is explained. The theory behind SQP methods is explained in the theoretical foundation (Section 2.2.3). Like for the GA, Matlab resources are used to implement a SQP method. The SQP algorithm can be found as part of the Optimization Toolbox. The SQP algorithm is implemented as part of the *fmincon* solver [176, p. 2.8].

The implemented SQP follows the description given in the theoretical foundation. In the following, a short overview of the implementation details is given. In [176, p. 6.31] four main steps for the SQP algorithm in Matlab are identified:

1. *Updating the Hessian matrix:* The Hessian matrix is updated using the Broyden–Fletcher-Goldfarb-Shanno (BFGS) method [176, p. 6.31]. The formula can be found in [176, p. 6.8].

2. *QP solution:* The QP subproblem is solved using an active set strategy [176, p. 6.34]. The exact algorithm can be found in [177] and in [176, p. 6.33-6.35].

3. *Initialization:* The algorithm for solving the QP subproblem requires a feasible starting point [176, p. 6.35]. If this is not given by the SQP algorithm, it can be found by solving an additional linear subproblem. For a detailed description of this process refer to [176, p. 6.35-6.36].

4. *Line search and merit function:* The exact implementation of the merit function is explained in [176, p. 6.36]. The description closely follows that given in the Theoretical Foundation.

For the optimization with *fmincon* the optimization problem is expressed in a similar way as with GA. The variables that are combined to an individual for the GA are interpreted as the decision variables and therefore the input for the objective function. In addition to the objective function, the *fmincon* solver can take the gradient of the objective function as input [176, p. 2.26]. If no gradient information is supplied, the solver calculates the gradient. For the considered optimization problem, the Matlab calculation of the gradient leads to numerical problems. Therefore, only the user supplied gradient is used. To speed up the calculation, the gradient is computed using the right-sided differential quotient. Comparisons showed that this leads to the same results as if the central differential quotient is used.

Using the *fmincon* solver for the SQP algorithm does not allow for many variations of the algorithm. Most variations that impact the quality of the solution can be made with the problem formulation as described in Section 5.4. However, a few choices pertaining to the stopping criteria of the algorithm must be made. The following stopping criteria exist [176, p.2.86-2.87, 2.89]:

- *StepTolerance:* Step tolerance is a relative lower bound that defines the minimal step length d_x [176, p. 2.86].

- *OptimalityTolerance:* Optimality tolerance is also a relative lower bound that defines how close the solution has to be to a first order optimality measure [176, p. 2.86].

- *ConstraintTolerance:* Constraint tolerance is a relative upper bound that defines how far the constraints may be violated [176, p. 2.86-2.87].

- *MaxIterations:* Maximal iterations limits the number of iterations k before the algorithm terminates [176, p. 2.87].

- *MaxFunctionEvaluations:* Maximal function evaluation works similar to maximal iterations but does not limit the number of iteration but the number of evaluations of the objective function [176, p. 2.87]. This has the advantage that the number of evaluations of the objective function is closely linked to the computation time, which might be a limiting resource.

As with the GA two or more stopping criteria are often combined.

For the MORE the SQP as it is implemented in Matlab is changed in two aspects due to small problems that occurred during preliminary computer experiments. Firstly, the last gradient computation is omitted. Secondly, the concept of super-iterations is introduced.

If the maximum number of iterations is used as a termination criterion, the SQP computes a gradient in the last step that is not used. As the gradient computation is time consuming, this unnecessary computation is prevented.

The super-iteration is in effect a restart of the optimization procedure with the last value of the first optimization as initial value for the next optimization. This feature is introduced for the following reason: As already mentioned above, Matlab computes the Hesse matrix numerically. In combination with the recuperation rule controller, the Hesse matrix is computed inaccurately. This leads to the SQP trying out values that lie in the wrong direction. Because of this, the optimization gets the

Table 8 Overview of the variations of the SQP tested for this thesis

Option	Chosen Variation	Source
User Supplied Gradient	yes	[176, p. 2.26]
Maximum Number of Iterations	variable	[176, p. 2.87]
Step Tolerance	10^{-16}	[176, p. 2.86]
Optimality Tolerance	10^{-6}	[176, p. 2.86]
Constraint Tolerance	10^{-6}	[176, p. 2.86]
Parallel Execution	no	[176, p. 1.2]

impression that the solution can no longer be improved and stops prematurely. This can be remedied by restarting the optimization procedure every three or four iterations. This is referred to as *super-iteration*. The Hesse matrix is built up step by step. Therefore, for the first iterations of each run, the Hesse matrix appears to be still correct. In effect the super-iterations wipe out the memory of the algorithm. Unfortunately, Matlab does not allow a user supplied Hesse matrix. Moreover, the exact working mechanism and, therefore, the exact problem also cannot be tracked in Matlab. Extensive experiments, however, showed that the proposed approach lead to satisfactory results.

5.6 Driving Cycles

For the computer experiments with the EMS a DC is necessary. This cycle must consist of the velocity as a function of the time: $v(t)$. For this thesis neither the slope nor the wind speed is considered. Therefore, $v(t)$ suffices to describe the DC completely. In [178] a standard DC, in this case the New European Driving Cycle (NEDC), and a recorded drive were used. For this thesis the focus lies on getting as close to a realistic situation as possible. Therefore, only recorded real world drives are considered. The structure of the used DC also allows to explore the online application as described in Section 5.7.

The same recorded drives as in [178] are employed. These drives were used by Adermann in his dissertation ([162]) and were published and described in [161]. Therefore, the reader is referred to these sources for a detailed description. In the following only the most important points are summarized. The aim of Adermann et al. [161] is to reproduce a typical commute. This aim is reflected in their choice of route: The distance is $18.79\,km$ and it consists of $67\,\%$ on urban streets, $22\,\%$ intercity roads and $11\,\%$ motorway. A map on which the route is shown can be found in [161]. The route was repeated 50 times in the winter of 2016/17. The difference in the driven distance is up to $13\,m$ or $0.07\,\%$. As the focus of Adermann's thesis lies on the battery, more drivetrain data is recorded. For this thesis only the velocity profile is used.

To work with the optimization, the recorded drives are transformed from $v(t)$ to $v(x)$. Moreover, the position and the time, at which the vehicle stops, are extracted to create the windows described in Section 5.4.1. The trips are automatically transformed into the necessary form and loaded into the model for the optimization.

5.7 Online Application

Section 5.1 describes the overall concept: The optimization is used to determine the optimal parameter set for an original trip. These parameters are transferred to a new driving scenario. This section explains the concept and the challenges for the transfer. In Figure 5.11 the workflow to simulate the online application is depicted. The optimization is done with one trip. The objective function and the model are used to compute the fitness value. The problem is formulated and optimization is done as described in the previous sections of this chapter. The optimized parameters are then transferred to other trips of the same route. The first part is computationally expensive and cannot be performed online. The transfer, however, needs hardly any computation time and it would be possible to perform it online.

The main challenge for the transfer to another trip is that the energy reduction can be maintained while keeping the cabin temperature in the acceptable zone. This can only work if two things are ensured: Firstly, the concept itself must be designed to enable the transfer. Secondly, the optimization procedure must be adapted to guarantee the possibility for the transfer. First, the requirements that must be met by the concept are highlighted: All trips cover the same route and the total distance differs only slightly (refer to Section 5.6). For an overview of the differences of the trips refer to the table displayed in [161]. The table shows that especially in regard to the stop times a considerable difference between the drives can be found. However, the velocities are similar. For the differences between the trips, solutions have to be found within the optimization.

These solutions within the optimization are discussed next. The first step to enable the transfer to another trip is that all parameters are expressed as a function of the location and not the time. As already mentioned in Section 5.6, the distance for the trips varies only slightly while the travel time fluctuates up to $5.7\,\%$ [161]. Moreover, the parameters are integrated into the model using controllers as described in Section 5.4.5. These controllers can compensate small changes in the DC and avoid distinctly suboptimal developments of the heater power and the air mass flow. Lastly, an additional correction mechanism is integrated into the model for the transfer to another trip. In Figure 5.8 the block *Correction for Transfer* is included. In this block a correction factor is computed using the coolant temperature at the current location of the optimization of the original trip. This correction factor means that the heater power is adapted, if the coolant temperature deviates from the original trip, i.e. the controller tries to reach the same coolant temperature as for the original trip. Hence, local deviations from the original trip have only limited influence at locations that are passed later. Three

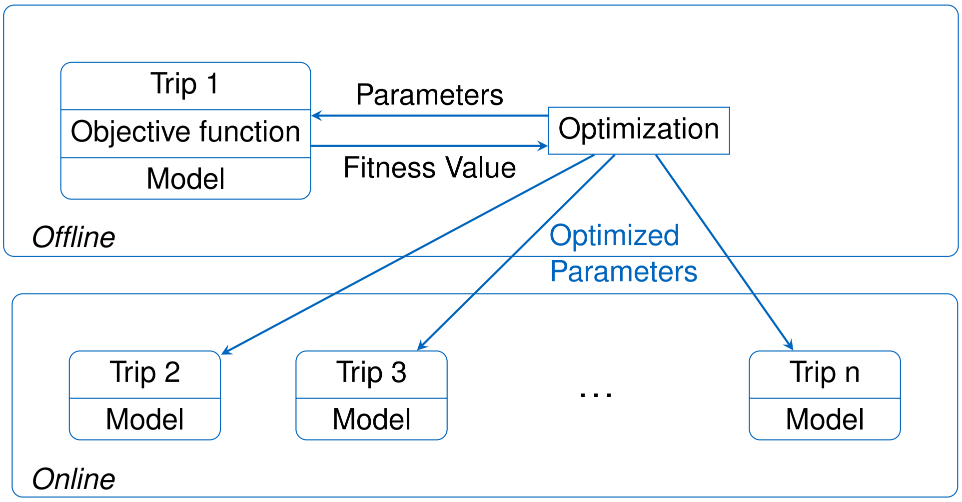

Figure 5.11 : Transfer to different trip

other deviations from the planned concept are conceivable and can be solved with minor adaptations of the concept:

1. *Small deviations from original route*: The driver varies their commute by adding a detour. For example, they go shopping on their way back from work. To tackle this scenario, Global Positioning System (GPS) coordinates can be used. During the detour the last valid set of param-

eters is used. The controller ensures that the deviation has only a local influence. Once the original route is picked up again, the variables are used as planned.

2. *Large differences of the velocity*: If for example an unusual traffic jam happens on the trip, the velocity might differ significantly from the originally optimized trip. In this case it is possible to update the optimization for the next segment of the trip using forecast data.

3. *The route is not the commute*: Firstly, this problem can be alleviated by having a good fall-back EMS that does not rely on optimization. Secondly, a data base can be built up and the parameters for a similar trip can be used.

5.8 Preliminary Results

In the following, the research that was conducted to develop the MORE is presented. All results introduced in this section are either part of master's theses or published in a peer reviewed journal or conference. Chapter 6 presents only original research that was not previously published. The preliminary results are only briefly discussed as they are not part of the final concept and can be looked up in their original sources.

5.8.1 Model Configuration for Preliminary Results

The model that was used for all the preliminary research is based on the component library described in Section 5.2. Compared to the model on which the final results are based, the model is reduced. It does not contain the cabin model and the heating system is modeled less sophisticated. The simpler model of the heating and the cabin has the following consequences: The heater power is the only parameter that can be optimized. The air mass flow is not modeled. The simpler model has the following features compared to the more complicated model: As the model is not originally designed to investigate the heating system, no elaborate rule-based strategies exist. Therefore, the reference strategy is simpler. This makes it easier for the optimization-based EMS to achieve a reduction of the energy consumption. In the simpler model the following reference strategy is employed: During the heat-up phase the heater uses its maximum power. When the target temperature of the cabin is reached, the power is reduced to a constant power that maintains the cabin temperature. This simple strategy is the best option to keep the cabin temperature close to the target temperature. However, the energy consumption of the heater is not considered. Consequently, the energy reductions attained with the reduced model are less meaningful than those for the full model. Moreover, the model takes less time for a single run. The cabin and heating system are one of the most time-consuming parts of the model. If they are only rudimentary represented, the overall computation time is significantly reduced. This allows for more experimentation with the reduced model. Lastly, the thermal energy stored in the vehicle is negligible. Therefore, the design of the energy fitness function is less challenging. However, the results differ more from the real vehicle and can therefore not be transferred seamlessly.

For the reduced model, only the direct input of the heater power is evaluated, and no additional controllers are used. Moreover, the reduced model does not model the BMW i3, but the Ford Focus Electric. Only the individual components are validated in the context of the library using existing literature. In summary, the reduced model focuses on low implementation effort and low computation times to quickly achieve results. A detailed description can be found in [178] and [184].

5.8.2 Comparison of Different Optimization Methods

Three theses focus on one optimization method each. For the preliminary results the GA was explored most in depth and the offline optimization-based EMS was also published based on a GA [178] and a hybrid GA respectively [179]. For the preliminary results the SQP and the GA as well as DP are investigated. In the following the results are briefly summarized.

The results using the GA can be found in [178, 179, 184]. It could be shown that the GA leads to significant energy reductions for both standard DCs and recorded real-world drives. The implementation of the GA is similar to the approach described in Chapter 5. The main difference is that only Matlab-implemented mutation functions are used, and not the adaptive mutation function designed for this thesis. Moreover, [184] and [179] evaluated a hybrid approach that combines the GA with a gradient-based approach.

The SQP is introduced in [185]. Both a window-wise and an optimization of the entire cycle are implemented using the NEDC as DC. The thesis also presents a comparison with the GA. It could be shown that the SQP outperforms the GA for the investigated set-up. The exact implementation of the SQP is based on the Matlab solver. It is not identical to the concept described in the approach. The main difference is that it uses no super-iterations. The reason for this is that with the reduced model no problems with the Hesse matrix were identified.

The last approach that was investigated is DP. It has the disadvantage that no existing Matlab implementation can be used. Therefore, the algorithm must be built up from scratch using the existing literature. This was done in [186]. The DP was compared to the implementations of the SQP, and the GA described above. The structure of the problem formulation is fundamentally different from the two other approaches. Particularly, the heater power cannot be directly used as a parameter because the system must have discrete states [186, p. 28]. Therefore, the target temperature for the cabin is implemented as parameter [186, p. 28]. This allows for discrete states. To determine the heater power a PID-controller is used [186, p. 26-28]. This thesis also contains the most extensive comparison of the three approaches implemented with the reduced model [186, p. 57-61]. For the DP different numbers of states for the variables speed and target temperature are evaluated [186, p. 60]. A higher number of states means a higher computation time (refer to Section 5.5). Therefore, a trade-off between computation time and quality of results must be found. A comparison shows that it yields the best results if the target temperature is more coarsely discretized, and the computation capacity is invested in the speed [186, p.49, 60]. However, even the best configuration for the DP is not significantly better than the SQP or the GA while taking about five times longer than the GA [186, p. 59].

For the more detailed model an analysis shows that the computation time for the DP would increase at least by the factor ten. This has the following reasons: Firstly, the model itself is slower. This also impacts the other methods, but the DP needs the largest number of model runs and is, therefore, most affected by the change. Secondly, the coolant temperature needs to be introduced as additional variable. This would lead to an increase in the number of states. The coolant temperature has a high variance. Consequently, it would add many additional states. The best implementation for the reduced model has two values for the cabin temperature and 30 for the velocity [186, p. 59]. This means that 60 states are modeled for each stage. If the coolant temperature is added and if to attain satisfactory results 10 discrete values for the coolant temperature are needed the number of states for each stage would increase to 600. This would also mean that the computation time would increase by the factor ten. This estimate is a best-case-scenario and contains the following uncertainties: To map the coolant temperature to ten discrete values might not be sufficient. It might be necessary to add even more states and therefore computation time to the optimization. Furthermore, the DP does not work with the proposed recuperation rule controller. Therefore, it could become necessary to add more stages to the optimization to obtain results that are better than those for the SQP. If the same number of stages as for the basic configuration of the SQP are necessary, the computation time would be increased by a factor of 15.

In summary, for the reduced model the DP does not lead to significantly improved results compared to the SQP and GA but has a higher computation time. For the more detailed model, it is reasonable to assume that the computation time would be so high that it makes DP infeasible. Therefore, it is not transferred to the detailed model and not part of the final concept for the MORE. Options how this can be done in the future are discussed in Section 7.5.

5.8.3 Integration of Additional Components into the MORE

The integration of two additional components was investigated. These are the gear box and a more elaborate coolant circuit for all components of the vehicle.

The integration of the gear box is described in [183]. The first step is to model the gear box and integrate it into the existing vehicle model. In the next step the shifting schedule is integrated into the existing EMS based on the GA. The combination of modeling and optimization revealed that the additional weight and lowered efficiency of the gear box cannot be outweighed by the energy reduction achieved by adding the shifting schedule to the EMS [183, p. 90]. Moreover, it is atypical for a BEV to have more than one gear stage. Therefore, adding the gear box removes the EMS further from a commercially available vehicle. For these reasons the gear box is not integrated in the approach introduced in this thesis.

For the elaborate cooling system, two approaches were implemented. The first can be found in [187]. Radinger implemented a cooling system that included the battery, the electrical machine and the converter using Simscape. While he found that the basic approach was feasible [188, p. 80], he also uncovered several problems: Firstly, the run time of the model is negatively influenced by the Simscape cooling system [188, p. 80]. Secondly, the validation of the cooling system is difficult as the publicly available data is not sufficient [188, p. 84-85]. Furthermore, even if a vehicle were available, it would be difficult to place the sensors for measuring all the necessary temperatures without access to the proprietary information of the OEM. Thirdly, for the commercially available vehicles that were investigated it is difficult to identify suitable parameters to integrate in an EMS.

For these reasons the thermal management of the individual power train components was not directly integrated into the system. However, a hybrid between a rule-based and an optimization-based approach was developed that focuses on the thermal management [189, 180]. This concept is not based on the simplified vehicle model as it is solely focused on the TMS. For this concept a more elaborate cooling system than typical for commercially available vehicles was developed. The basis of the system are detailed measurements of the energy losses conducted with a Renault Twizzy [180]. The approach can be described as an optimized rule-based approach [180]: Different states which the TMS can adopt are defined. The states are changed when the temperature of the individual components reaches a certain threshold. These threshold temperatures are optimized using a multi-criteria GA. Consequently, the EMS can be applied online. This approach showcases an example for a hybridization of optimization- and rule-based approaches. The approach was not included in the final implementation for this dissertation because the modeled system is much more elaborate than currently commercially available. Therefore, it was not in accordance with the mission statement for this thesis. Additionally, the simulation time for the model is also high [189, p. 64]. This makes a regular repetition of the optimization difficult. Lastly, while the state transition based EMS is a good fit for a TMS, integrating the cabin temperature and the velocity into the concept would be difficult. Therefore, the concept mainly serves as an alternative concept for fusion of rule-based and optimization-based approaches.

This section showcased the preliminary research that was done to develop the EMS that is introduced in the rest of the chapter. This research helped to sharpen the focus for the development of this concept. Especially, for the optimization method, the preliminary research explains the choice of methods. For the regarded sub-systems in the vehicle some background can also be supplied.

6 Results

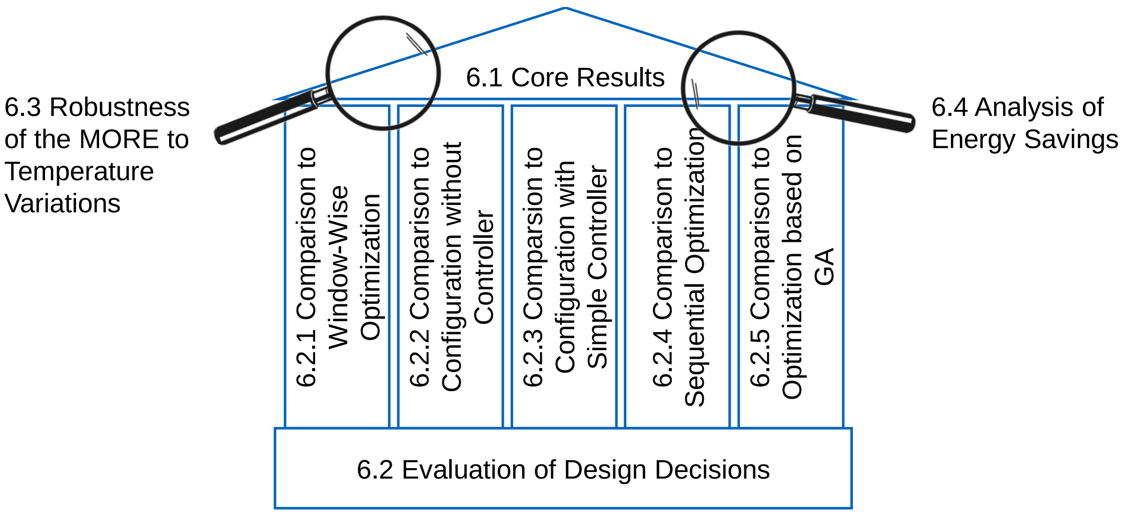

Figure 6.1 : Structure of Chapter 6

Figure 6.1 illustrates the structure of this chapter. It starts out with the core results in Section 6.1. The configuration for these core results is based on a detailed evaluation of the design decisions, which is presented in Section 6.2. The last two sections provide an analysis of two aspects of the MORE: Section 6.3 shows that the MORE is robust against temperature variations. Section 6.4 gives a in depth analysis of the energy savings, which can be obtained using the MORE.

6.1 Core Results

This section presents the core results of the MORE and demonstrates that the concept presented in Chapter 5 yields satisfactory results.

Figure 6.2 illustrates how the MORE reduces the total energy consumption for the trip. The upper bar shows the energy savings for the direct application of the MORE. This means that the parameters are applied to the same DC on which they are optimized. The middle bar depicts the energy savings, if the parameters are transferred to another DC. The lower bar corresponds to the reference strategy developed by Steinstraeter as described in Section 5.3. This reference strategy adds a HVH to a commercially available vehicle. Using this HVH, the strategy can reduce the power consumption by $6.28\,\%$ for the *DC12* and by $5.49\,\%$ on average for all DCs. The discrepancy between these values is a statistical effect. The MORE with perfect foresight, i.e. on the original DC, reduces the energy consumption by additional 2.65% using only an improved software application. Assuming imperfect foresight reflected in the transfer to other cycles, the MORE still leads to $1.45\,\%$. This highlights the advantages of the MORE over a rule-based strategy even if both strategies influence the same parameters. For a more detailed analysis of the reduced MORE see Appendix A.1.

If the velocity is integrated into the MORE the energy consumption can be reduced by additional 6.21% on the original DC and by additional 4.04% for the transfer. A detailed analysis of these results is presented in Section 6.4.

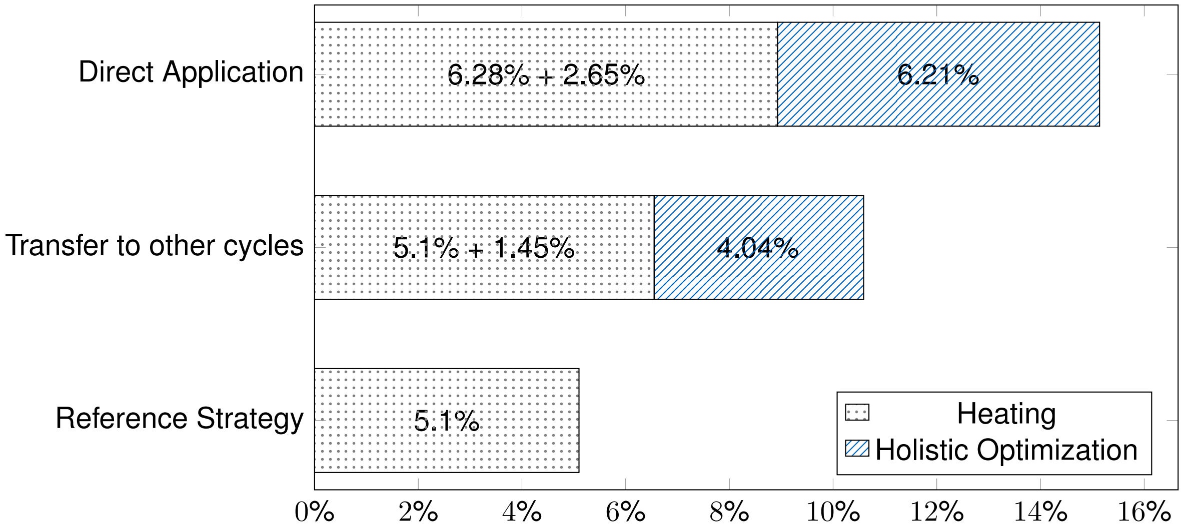

Figure 6.2 : Energy savings achieved with the reference strategy and with the MORE

6.2 Evaluation of Design Decisions

The MORE achieves this energy reduction based on several elements and design decisions developed in this thesis. This section evaluates these elements and shows that each of them contributes significantly to the performance of the MORE. As detailed previous chapter, the MORE can be configured in different ways. Table 9 summarizes the configuration used for the results presented in the previous section (Section 6.1). The table also comprises the configurations of the model. As detailed in Section 5.4.3 the DM priority vector is used to find a compromise between the different objectives of the MORE. The values are chosen such that the travel time remains fundamentally unchanged and that the deviation of the cabin temperature from the target temperature is similar to the reference strategy.

6.2.1 Comparison to Window-Wise Optimization

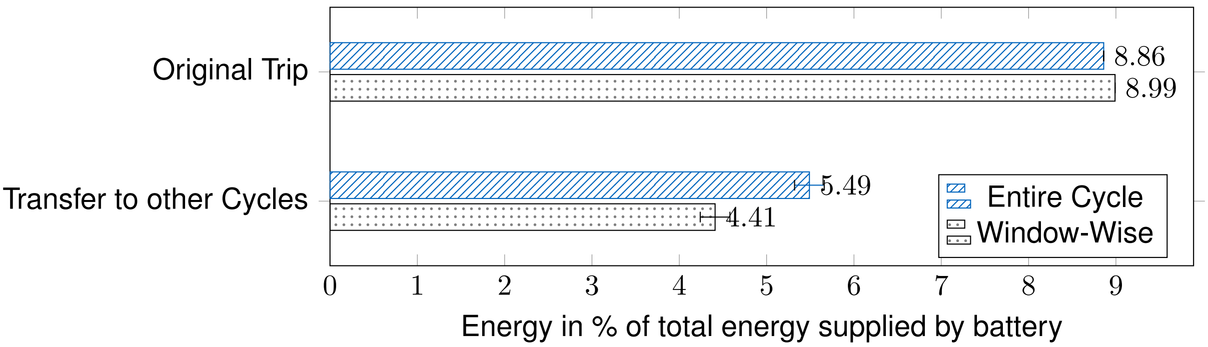

Figure 6.3 : Comparison of the energy consumption with the window-wise MORE and MORE based on the optimization of the entire cycle

As detailed in Section 5.4.1 an alternative to the optimization of the entire cycle is the window-wise optimization. The two approaches differ in how easily new information can be incorporated into the simulation. As the number of iterations needed for the SQP is strongly dependent on the starting point, parameters obtained from a previous trip can be used as a starting point and new information becoming available during the trip can be used to update the parameters. It is probable that the prediction is not sufficiently accurate to considerably improve the solution on the time scale of the

Table 9 Overview of configuration for the MORE and the simulation

	Parameter	Value
MORE	Optimization Algorithm	SQP
	Time Step Size	$30\ s$
	Division of Cycle	Entire Cycle
	Representation of Heater Power	Recuperation Rule Controller
Model	Ambient Temperature	$273.15\ K$
	Target Temperature	$293.15\ K$
	Original DC	*DC12*
	Transfer DC	*DC13*
DM priority	Travel Time	0.43
	Cabin Temperature	0.05
	Energy Consumption	0.52

entire cycle. However, this could work for the next optimization window. Therefore, the window-wise approach can more easily react to new information made available during the drive.

Another advantage of the window-wise approach is its lower computation time. For a detailed comparison of the computation time refer to the Appendix (Section A.2). Optimizing the entire cycle compared to the window-wise approach leads to an increase of the optimization time by $493.6\,\%$. The mechanism behind this is discussed in Section 5.4.1.

Table 10 gives an overview of the parametrization of the optimization and the DM priority vector. Figure 6.3 shows the energy savings for the window-wise approach and for the optimization of the entire cycle. The optimization of the entire cycle leads to similar energy savings for the original trip and to higher energy savings for the transfer to other trips.

Whether the window-wise approach or an optimization of the entire cycle is chosen, depends on the requirements of the particular application. If computation resources are limited, the window-wise approach should be chosen. The same is true in situations in which prediction data becomes available during the trip. If, however, the computation resources suffice and no additional prediction data is later integrated, the optimization of the entire cycle leads to better results. This could be for example the case in a set-up in which a daily commute is optimized once and than the optimized parameters are used every day.

6.2.2 Comparison to Configuration without Controller

This section highlights that for the transfer to other DCs the heater power must be integrated into the model using a controller. Section 5.4.4 describes the options for representing the heater power.

Figure 6.4 shows the cabin temperature for the transfer to another DC if direct integration of heater power is used. In the transfer the cabin cannot maintain the target temperature.

The behavior of the cabin temperature can be traced back to the coolant temperature displayed in Figure 6.5: The coolant is also initially heated up in a manner similar to the reference strategy. When it reaches a temperature within the acceptable range, the MORE does not maintain that temperature, but lets the coolant temperature drop again. The low coolant temperature means that irrespective of the air flow the cabin temperature cannot be maintained.

Table 10 Overview of configuration for the window-wise MORE

	Parameter	Value
MORE	Optimization Algorithm	SQP
	Time Step Size	$30\ s$
	Division of Cycle	Window-wise
	Representation of Heater Power	Recuperation Rule Controller
DM priority	Travel Time	0.35
	Cabin Temperature	0.08
	Energy Consumption	0.57

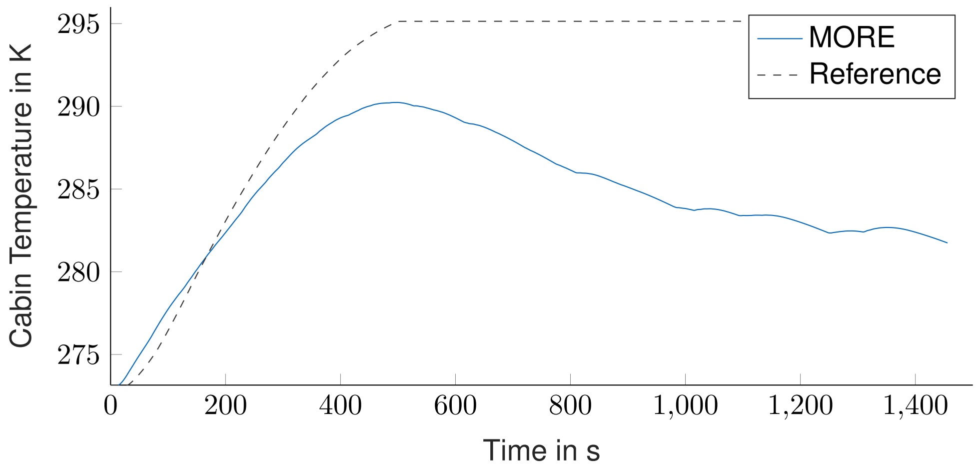

Figure 6.4 : Cabin temperature for the transfer to *DC13* for the MORE without controller

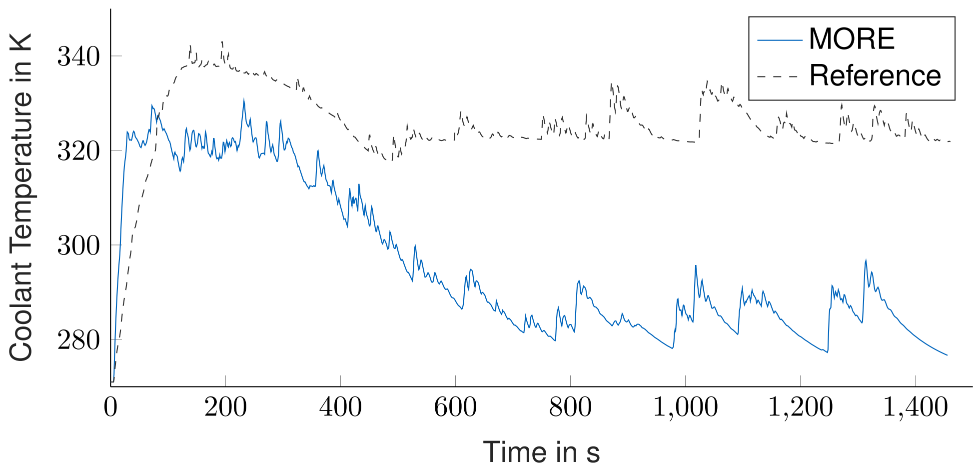

Figure 6.5 : Coolant temperature for the transfer to *DC13* for the MORE without controller

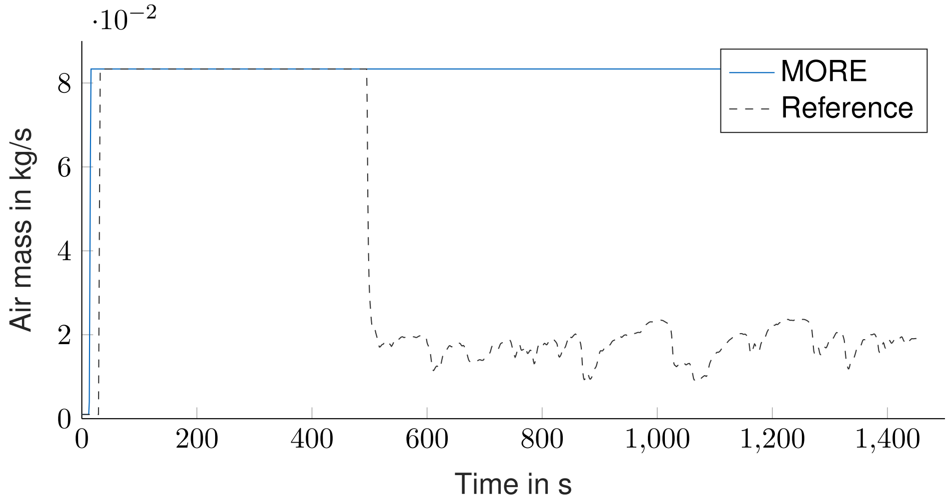

Figure 6.6 : Air mass flow for the transfer to *DC13* for the MORE without controller

Figure 6.6 displays the air mass flows for the reference and for the MORE. The air mass flow for the reference strategy starts at the maximum value for the time that the cabin needs for heating up. After this initial phase the air mass flow fluctuates at a lower level. In contrast to that the MORE maintains the highest value for the air mass flow for the entire trip. The reason for this is that the coolant temperature is too low. Therefore, the cabin does not reach its target temperature and the controller for the cabin temperature continually tries to heat up the cabin with the maximum air flow.

The coolant temperature is too low because the total energy used for heating is too low. The reason for this is that the same heater power for each location $P_{\text{heater}}(x)$ as for the original trip (*DC12*) is used for the *DC13*. The velocity profiles of the *DC12* and the *DC13* differ. Consequently, the same $P_{\text{heater}}(x)$ leads to a different heater power over time $P_{\text{heater}}(t)$.

6.2.3 Comparison to Configuration with Simple Controller

As described in Section 5.4.4 the MORE can also be implemented using no rule-based elements to integrate the heater power, but only a simple controller. For this option, the time step size must be small enough for the heater power to emulate the peaks of recuperated power. Preliminary experiments indicate that $2\ s$ is a suitable time step size. This smaller time step size means that only the window-wise approach is feasible, as the optimization of the entire cycle would take too much computation time. Table 11 provides an overview of the configuration of the MORE.

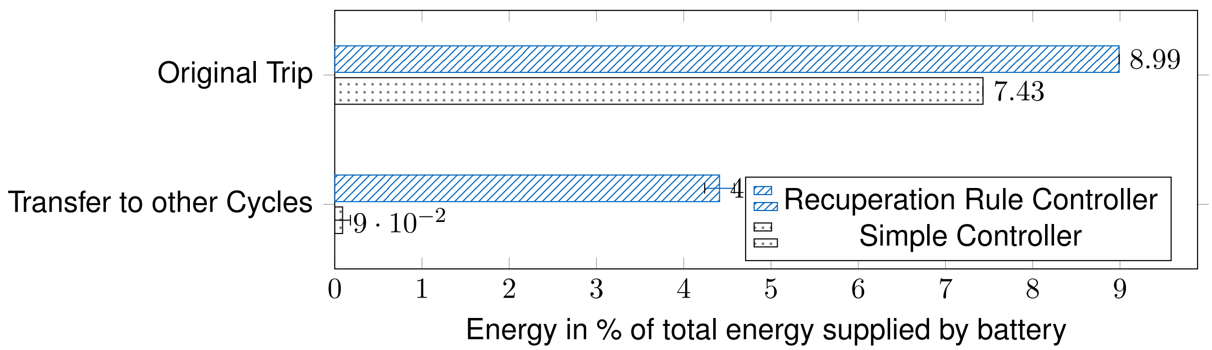

Figure 6.7 : Comparison of the MORE with a simple controller to the MORE using the recuperation rule controller

Figure 6.7 shows the energy savings on the original trip for the simple controller compared to the recuperation rule controller. Both are implemented using the window-wise approach. On the original trip, the MORE using the recuperation rule controller leads to higher energy savings than the MORE

Table 11 Overview of configuration for the MORE with a simple controller

	Parameter	Value
MORE	Optimization Algorithm	SQP
	Time Step Size	$2\ s$
	Division of Cycle	Window-wise
	Representation of Heater Power	Simple Controller
DM priority	Travel Time	0.35
	Cabin Temperature	0.08
	Energy Consumption	0.57

implemented with the simple controller. For the transfer to the other trips this difference becomes even more pronounced.

An additional drawback of the MORE based on the simple controller is the higher computation time due to the necessary smaller time steps. This increases the computation time by $406.4\ \%$. For a detailed comparison of the computation time refer to the Appendix (Section A.2).

6.2.4 Comparison to Sequential Optimization

The MORE is based on connecting the optimization of the driving strategy and the heating system. The idea is that this connection allows a higher energy reduction than the separate optimization.

Figure 6.8 contrasts the energy reduction of a sequential optimization with the holistic window-wise MORE based on the recuperation rule controller. The sequential experiment is undertaken as follows: First, the velocity is optimized. For this experiment the weight in the DM priority vector for the cabin temperature is set to zero. Therefore, the heater remains switched off. The velocity that is obtained by this experiment is used for a second optimization: This time the velocity remains constant and only the heater power and the target temperature is optimized. This setup corresponds to a separate optimization of the two systems.

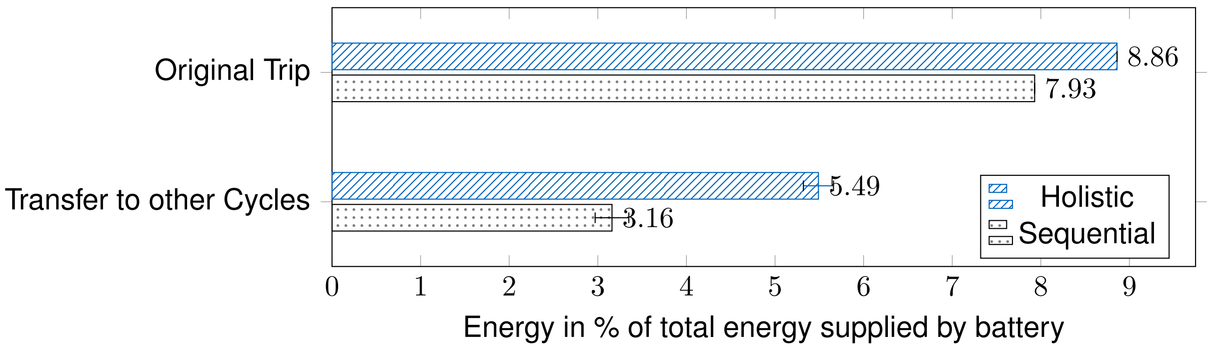

Figure 6.8 : Comparison of the energy consumption for the MORE based on a holistic approach to the MORE based on sequential optimization

The figure shows that on the original DC the energy reduction with the holistic approach is higher than with the sequential approach. The same applies for the transfer to other cycles. Consequently, the holistic approach outperforms the sequential optimization.

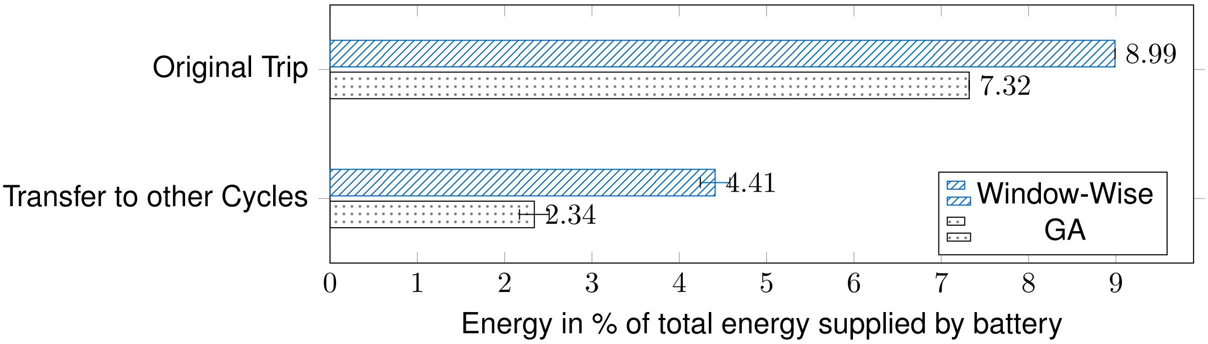

Figure 6.9 : Comparison of the energy consumption for the MORE based on a GA to the MORE based on SQP

Table 12 Overview of configuration for the MORE based on a GA

	Parameter	Value
MORE	Optimization Algorithm	GA
	Time Step Size	$30\ s$
	Division of Cycle	Window Wise
	Representation of Heater Power	Recuperation Rule Controller
DM priority	Travel Time	0.35
	Cabin Temperature	0.09
	Energy Consumption	0.56

6.2.5 Comparison to Optimization based on GA

The major drawback of the GA is the computation time. For a detailed analysis of the computation time and an explanation of how the computation time is determined refer to the Appendix (Section A.2). Because of this higher computation time the GA is only evaluated with a window-wise approach.

Table 12 shows the configuration of the MORE with the GA. Figure 6.9 shows a comparison of the energy consumption between the MORE based on SQP and on GA. The figure illustrates that the MORE based on the SQP leads to higher energy savings in particular for the transfer to other trips. Therefore, the SQP outperforms the GA regarding both energy savings and computation time. An additional drawback of the GA is that it is a stochastic optimization method (see Section 5.5). Thus, the quality of results obtained using the GA is likely to vary.

6.3 Robustness of the MORE to Temperature Variations

This section looks at two types of temperature variations: Firstly, different ambient temperatures are looked at. The experiments replicate the previously discussed experiments only with another ambient temperature. Secondly, the ambient temperature for which the optimization is done and the ambient temperature for the transfer differ. Both experiments are done with the MORE based on an optimization of the entire cycle and use the recuperation rule controller. As the MORE is based on an optimization of the heater power, only temperatures for which the heater is used are relevant for this thesis. The previous experiments are done for $0°C$. The additional temperatures that are

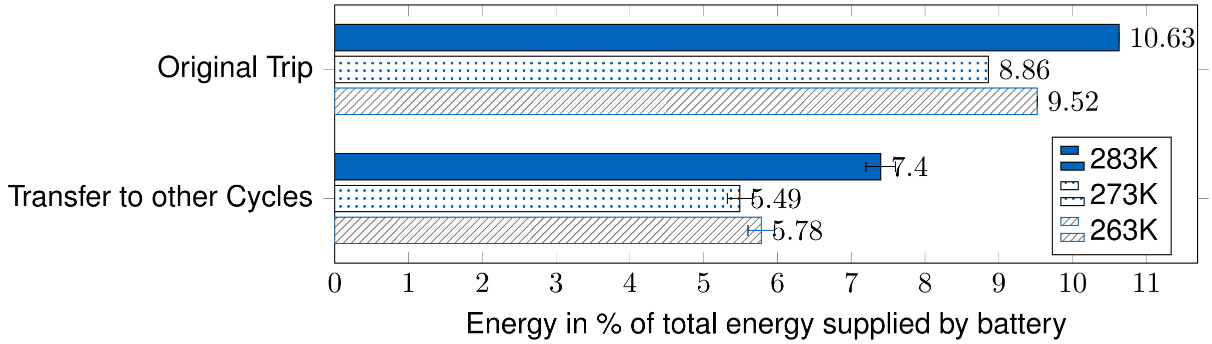

Figure 6.10 : Energy savings for the MORE at different ambient temperatures.

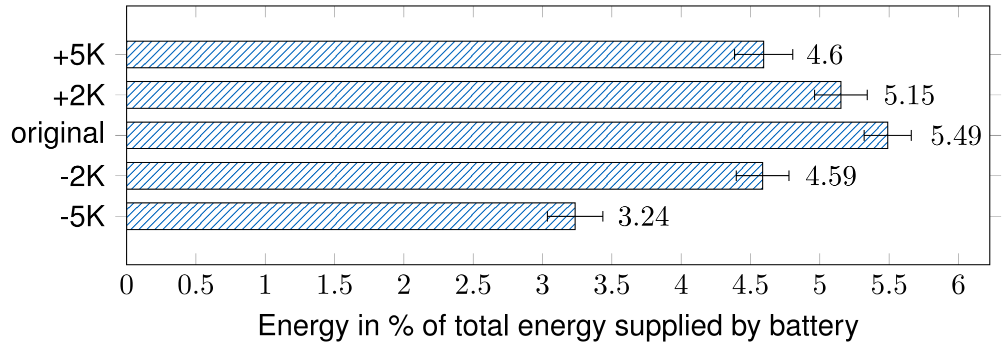

Figure 6.11 : Energy savings for the MORE transferred to ambient temperatures differing from the original ambient temperature

investigated are $-10°C$ $(263\ K)$ and $10°C$ $(283\ K)$. $-10°C$ is chosen, because at this temperature the heater power is high. Moreover, it is a temperature that occurs regularly in a central European winter. $10°C$ is of interest because it is a common temperature for which the heater is still needed, but the heater power is lower.

Figure 6.10 shows the energy savings for the three ambient temperatures. Firstly, the concept of the MORE works with all three ambient temperatures as the energy consumption can be reduced and this reduction can be largely maintained for the transfer to other cycles. Secondly, the energy reduction is highest at $10°C$ and lowest at $0°C$. The reason for this is that the reference strategy is adapted for $0°C$ and therefore it becomes harder for the MORE to reduce the energy consumption further. Since at the lower temperature the strategy that comprises using as much recuperated energy for heating as possible already leads to good results, at $10°C$ the energy savings are higher than at $-10°C$.

The transfer of the optimized parameters to other ambient temperatures corresponds to using the MORE with an inaccurate weather forecast. The concept can also be found in Section 5.7. For this consideration, only temperatures that are close to the original temperature of $0°C$ are considered, as it is assumed that the temperature forecast is close to the actual temperature during the drive. For this thesis "close" is defined as a deviation of $5\ K$. Figure 6.11 shows the results for a deviation of $-5\ K$, $-2\ K$, $+2\ K$ and $-5\ K$. The figure highlights that a higher deviation from the temperature for which the parameters were optimized leads to inferior results. However, all experiments still show a reduction in consumed energy compared with the reference strategy.

Therefore, it can be summarized that the transfer works for small changes in the ambient temperature. This finding increases the practical use of the MORE because no exact forecast of the ambient temperature is needed for the optimization.

6.4 Analysis of Energy Savings

The previous sections highlighted that the MORE can reduce the energy consumption compared to the reference strategy. This section illustrates what mechanisms lie behind this reduction in energy consumption. For this investigation the individual components that make up the total consumed energy are looked at. The same representation of the energy components is also described in [178]. The following components can be identified:

- E_{bat} is the total electric energy taken from the battery during the trip. E_{bat} can be expressed as: $E_{\mathrm{bat}} = E_{batt,eff} + E_{batt,loss}$.

- $E_{batt,eff}$ is the electric energy that is needed for the trip. It comprises the energy needed for heating and traction: $E_{batt,eff} = E_{\mathrm{tract}} + E_{\mathrm{motor,loss}} + E_{\mathrm{heat}}$.

- $E_{batLoss}$ represents the energy that is lost in the battery during charging and discharging. It is computed using the battery model.

- E_{heat} is the electrical energy used by the heater. It can be expressed as: $E_{\mathrm{heat}} = \int_0^{t_{max}} P_{\mathrm{heater}}(t)dt$. It depends on P_{heater} and is therefore directly impacted by the optimization.

- $E_{\mathrm{motor,loss}}$ are the losses that occur in the electric machine when the electrical power is transformed into mechanical energy or vice versa.

- E_{tract} is the total mechanical energy needed for traction. It is computed based on the elementary equation of longitudinal dynamics. Using Equation 2.23, E_{tract} can be written as: $E_{\mathrm{tract}} = E_{\mathrm{acc}} + E_{\mathrm{air}} + E_{\mathrm{roll}} + E_{\mathrm{sail}} + E_{\mathrm{recu}}$. The electrical energy needed for traction is computed as follows: $E_{\mathrm{tract}} + E_{\mathrm{motor,loss}}$.

- E_{acc} is the mechanical energy used for accelerating the vehicle. It is proportional to the acceleration ($E_{\mathrm{acc}} \sim a$). The total energy used for braking E_{brake} is equal to the negative acceleration energy: $E_{\mathrm{brake}} = -E_{\mathrm{acc}}$. This is true for the whole trip and for all windows because the vehicle is in standstill at the beginning and the end of the trip, as well as at the beginning and the end of each window.

- E_{recu} is the recuperated energy. It is a component of E_{brake}, as E_{brake} consists of the energy dissipated in the mechanical brake and the recuperated energy: $E_{\mathrm{brake}} = E_{brake,mechanical} + E_{\mathrm{recu}} + E_{\mathrm{sail}}$. Like E_{brake}, E_{recu} is negative. E_{recu} is limited by the maximum battery current. However, the recuperated energy can also be directly used for heating. By shifting the heating to time periods when recuperated energy is available, E_{recu} can therefore be influenced by the MORE.

- E_{roll} is the mechanical energy needed to overcome the roll resistance. The MORE can influence it because it is proportional to the speed: $E_{\mathrm{roll}} \sim v$.

- E_{air} is the mechanical energy needed to overcome the air resistance. It is influenced by the optimization because it is proportional to the square of the speed: $E_{\mathrm{air}} \sim v^2$.

- E_{sail} is the mechanical energy that is used during the deceleration of the vehicle to overcome the roll and the air resistance. Like E_{recu} and E_{brake}, it is negative.

All energy components are normalized using the total energy taken from the battery E_{bat} in the reference strategy. For the transfer to the other cycles the error bars represent the Standard Deviation (STD). Therefore, they illustrate the difference between the trips. Because the trips themselves differ and not primarily the MORE, the reference strategy is also supplied with error bars. Only E_{bat} of the reference has by definition no error bar, as all other values are given in relationship to this value.

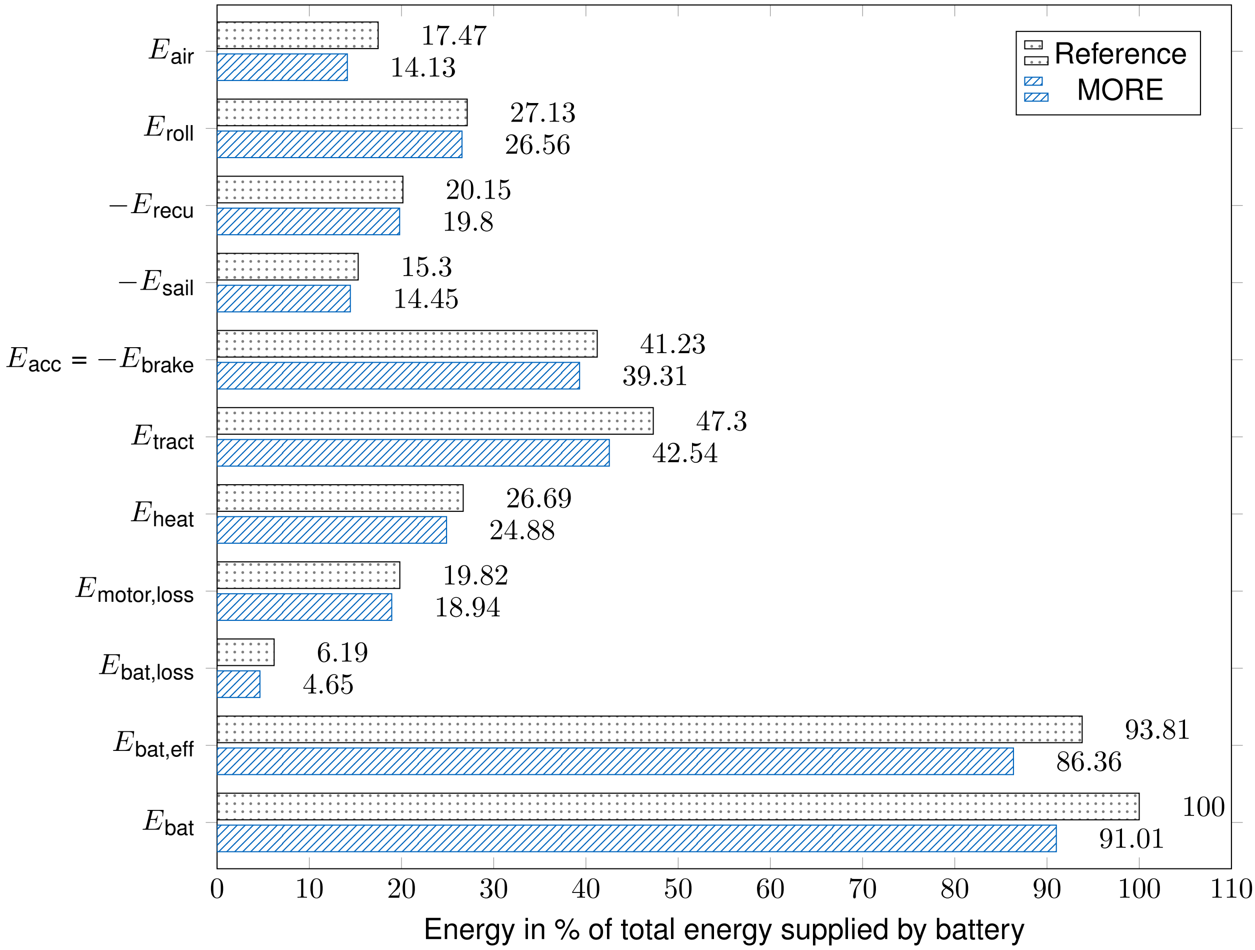

Figure 6.12 : Energy components for original trip of the MORE based on window-wise optimization

6.4.1 Window-wise Optimization

This experiment (energy components shown in Figure 6.12) uses the recuperation rule controller for the heater power as introduced in Section 5.4.5.

First, the results of the parameters used on the original trip are presented. Figure 6.12 shows the energy components bar graph. It can be seen that the energy consumption can be reduced by 8.99%. This energy reduction is due to reductions in all relevant components of the total energy: The battery losses $E_{\text{bat,loss}}$, the traction energy E_{tract} and the energy used for heating E_{heat}. In the following the mechanisms behind each of the energy reductions are discussed: E_{tract} is mostly reduced because E_{acc} and E_{air} are reduced. The travel time increases slightly by $0.05\ \%$. Figure 6.13 shows that the increase is not caused by an overall lower velocity but by a change in the velocity distribution. Figure 6.13 shows that the velocity peaks are mitigated. E_{heat} is the energy component that is most strongly influenced by the recuperation rule controller. Compared to the simple controller, it can be significantly reduced. The coolant temperature is displayed in Figure 6.14. As the objective function for the last window is different from that of the other windows, the optimal strategy for the last window is to let the coolant grow colder because a high coolant temperature is no longer needed (refer to Section 5.4.3). $E_{\text{bat,loss}}$ is reduced compared to the reference strategy and compared to the MORE with the basic controller.

Next, the transfer to other trips is explored. Figure 6.15 shows the energy components bar graph including the STD. The main finding of this figure is that the implementation with the recuperation rule controller can reduce the energy consumption for all cycles. The mean energy reduction is $4.41\ \%$. Even though the same effects as for the original trip apply it is worthwhile to take a look at the individual energy components: E_{tract} is also reduced for the transfer and again this effect is

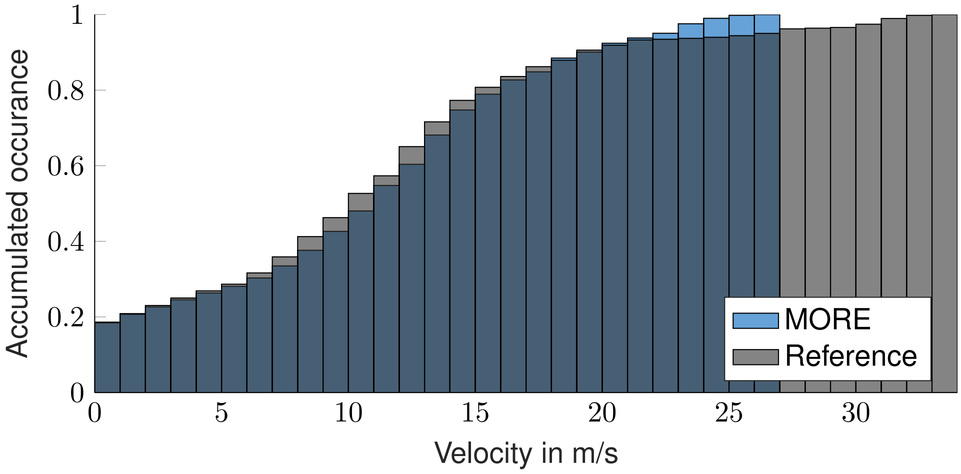

Figure 6.13 : Velocity histogram for the MORE and original cycle

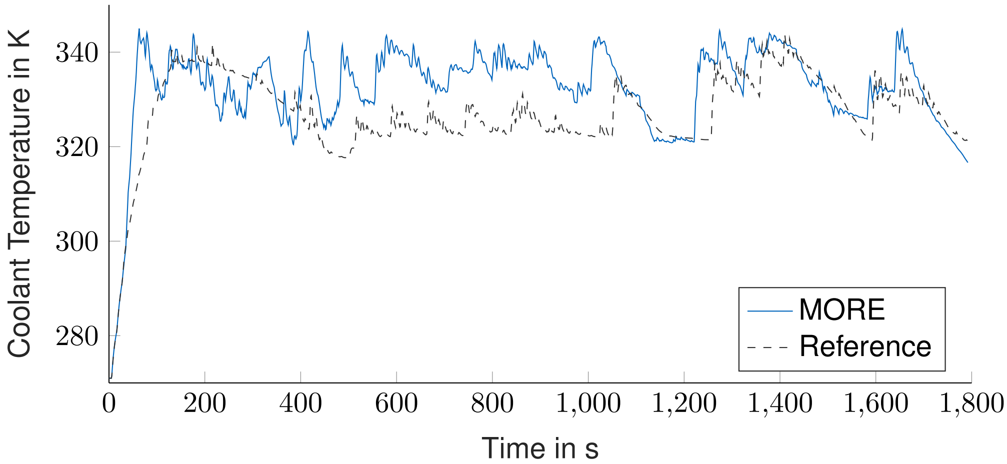

Figure 6.14 : Coolant Temperature for the MORE and reference strategy

mostly due to a reduction of E_{air}. Table 13 indicates that the maximal velocity has been reduced compared to the reference strategy. This effect can be preserved for all trips. The reduction of E_{heat} could also be sustained for the transfer. The reduction of $E_{\mathrm{bat,loss}}$ can be reproduced for the other trips. Again the reason is a reduction in $E_{batt,eff}$ and the increase in recuperated power that is used directly for heating. Table 13 shows that the other relevant parameters such as the travel time and the cabin temperature are also acceptable for all optimizations. The mean travel time is slightly increased when the MORE is used $(0.04\,\%)$. The STD for the reference strategy and for the MORE is close to equal. This suggest that the fluctuations of the travel time over the 49 trips are due to differences in the trips themselves not the MORE. The maximum of the coolant temperature is also higher for the MORE than for the reference. However, it is well below the temperature that is detrimental for the coolant, which is $373\,K$ (refer to Section 5.4.3). Moreover, the table shows that the STD is in a similar range compared to the reference strategy. This means it is significantly lower than for the MORE with the basic controller. This constitutes another advantage of the recuperation rule controller. The cabin temperature deviation is slightly increased (by $3.66\,\%$) and the STD is nearly the same for both approaches. The maximum velocity is reduced. This fits with the velocity histogram, which is reproduced for the original trip (Figure 6.13).

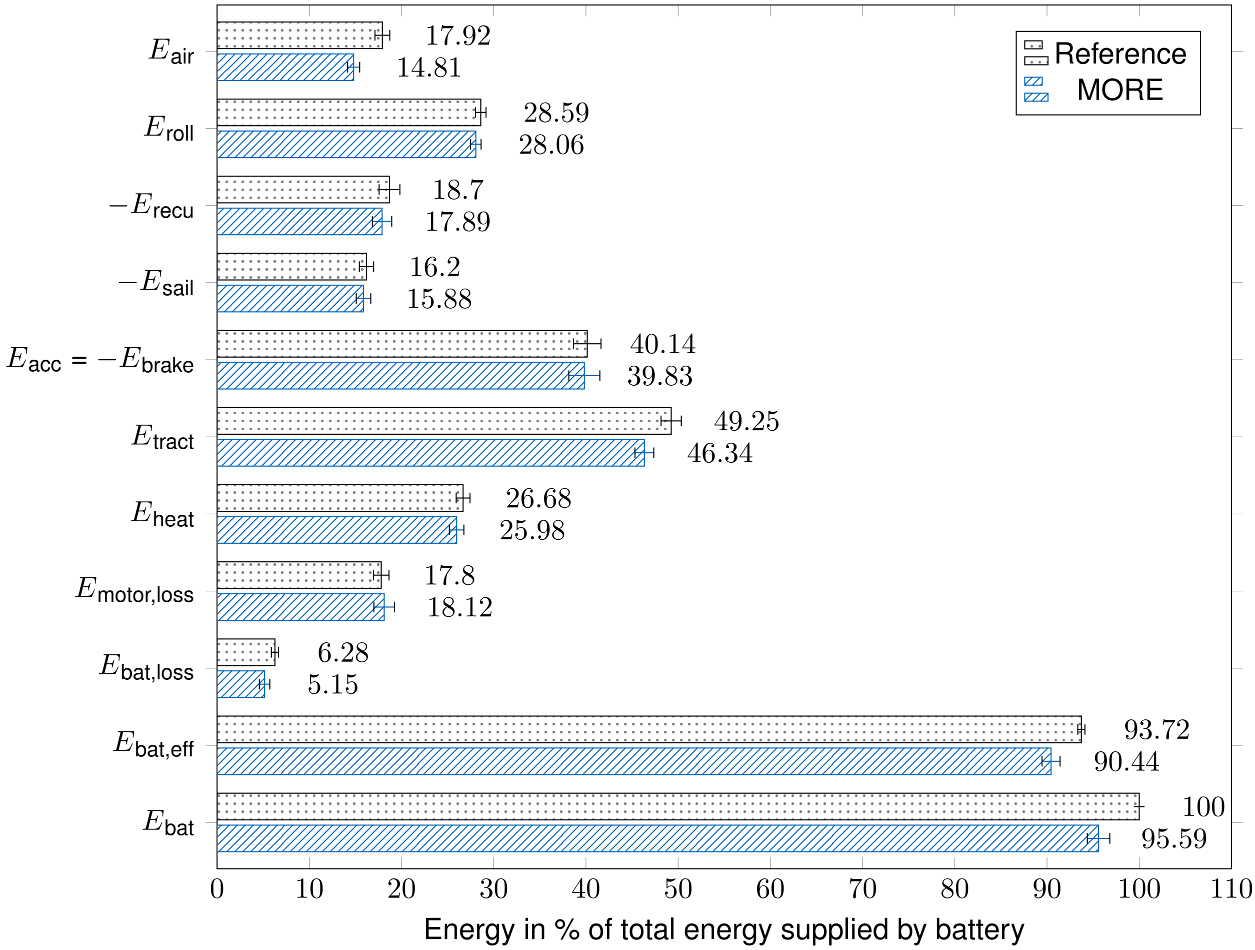

Figure 6.15 : Energy components for the transfer of the MORE based on window-wise optimization

6.4.2 Optimization of Entire Cycle

Figure 6.16 displays the energy components for the reference and for the optimization. The overall energy reduction is $8.86\,\%$ (compared to $8.99\,\%$ for the window wise optimization). Like in the previous sections, this figure is used as a starting point to understand the mechanisms behind this reduction. E_{tract} is reduced. This is due to a reduction of all its components. Figure 6.17 shows that the reduction is not due to a longer travel time. Like the previous experiments the high velocities are reduced, and the lower velocities are increased to adhere to the travel time. This means that especially the air resistance is significantly reduced as it is proportional to the velocity squared. Figure 6.18 shows the histogram of the original and of the optimized trip. The relative frequency of each velocity range is accumulated. E_{heat} is reduced by $15.30\,\%$. This reduction is significantly higher than for the window-wise approaches discussed in the previous sections. Figure 6.19 shows the cabin temperature. The optimization-based EMS heats up the cabin at the beginning of the cycle faster than the reference, but it lets the temperature drop at the end of the cycle. This behavior is also mirrored in the temperature of the coolant (Figure 6.20): The coolant is also quickly heated up to a level higher than the reference strategy. This high temperature is slightly reduced for the main part of the drive. At the end of the cycle the coolant temperature drops to nearly ambient temperature. Consequently, no or nearly no thermal energy is stored in the coolant at the end of the drive. As this energy can no longer be used when the drive is over this is the optimal strategy. That the cabin temperature also drops at the end of the cycle can be explained with the trade-off between energy consumption and passenger comfort. If the DM priority vectors are chosen differently, the drop in temperature can be prevented or intensified. For this thesis the trade-off is chosen as displayed for example in Figure 6.19. This strategy for heating can be chosen only because the optimization is applied to the whole cycle. $E_{\mathrm{bat,loss}}$ can also be

Table 13 Overview of key values for the transfer to all trips for the MORE based on window-wise optimization

Name	Reference	MORE
Energy consumption in $\mathrm{kW\,h}$	3.69 $\pm$ 0.08	3.52 $\pm$ 0.09
Travel time in s	1568 $\pm$ 84	1569 $\pm$ 84
Maximal velocity in $\frac{\mathrm{m}}{\mathrm{s}}$	32.65 $\pm$ 1.11	25.71 $\pm$ 1.23
Maximal coolant temperature in K	345 $\pm$ 1.02	354 $\pm$ 2.33
Mean cabin temperature deviation to target in K	3.28 $\pm$ 0.17	3.41 $\pm$ 0.17

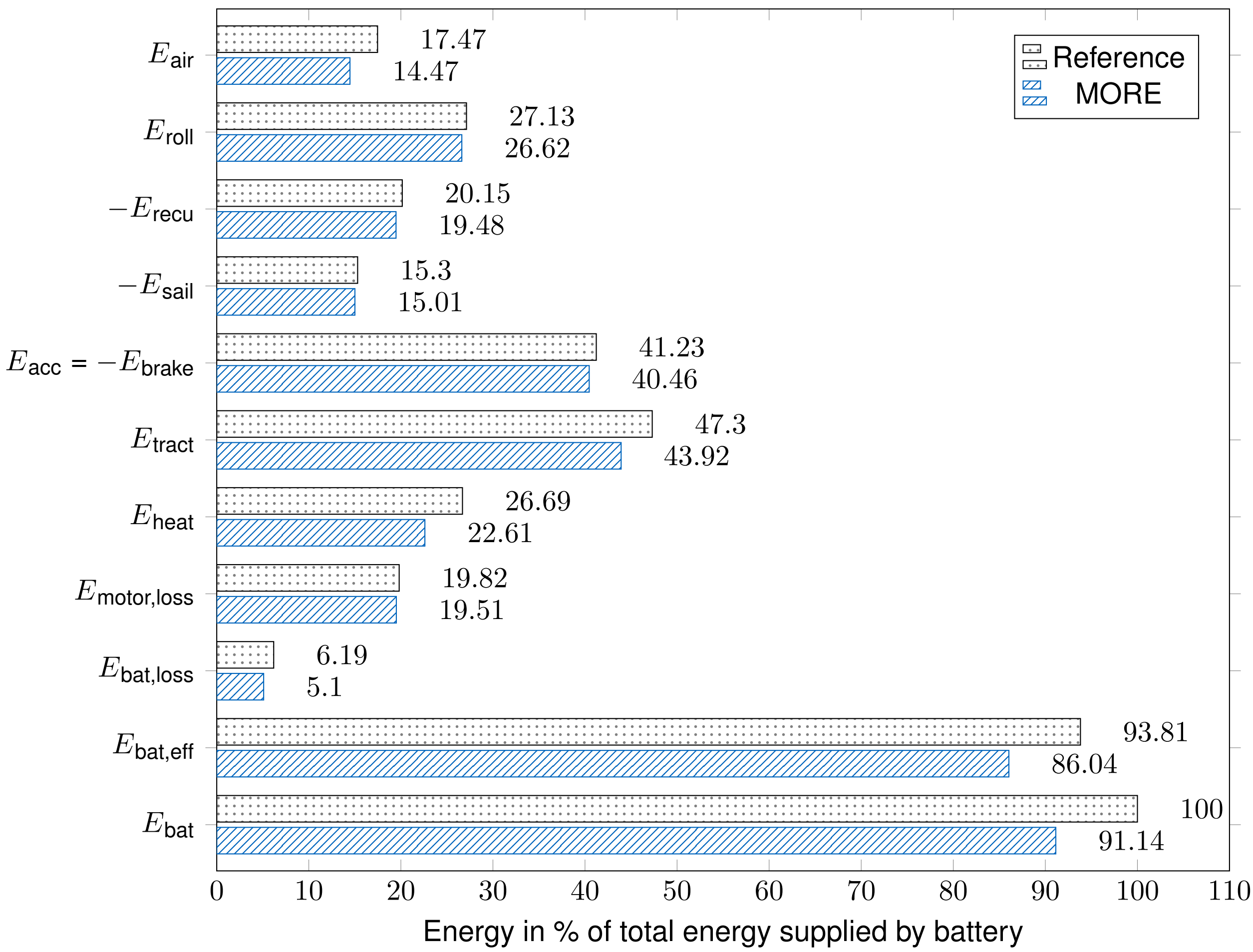

Figure 6.16 : Energy components for the original trip of the MORE based on optimization of the entire cycle

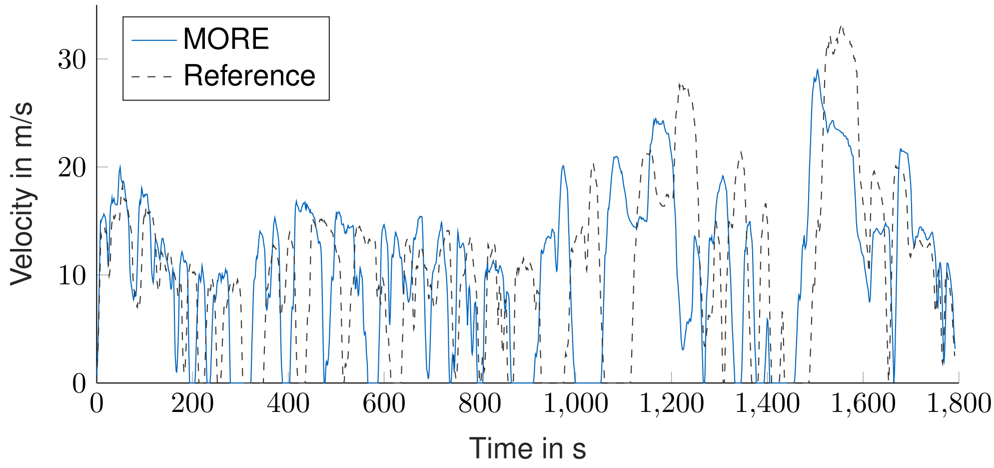

Figure 6.17 : Velocity plot for the MORE and reference strategy

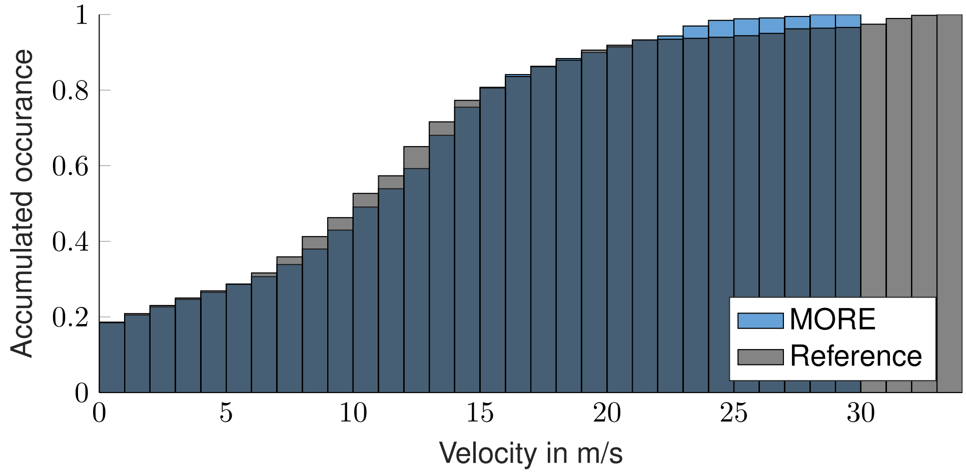

Figure 6.18 : Velocity Histogram for the MORE and the reference strategy

reduced by $17.65\ \%$. This has two reasons: Firstly, the total energy is lower and, consequently, the battery current that leads to the losses in the battery is also smaller. This effect is a by-product of the reductions in the other energy components. Secondly, the recuperated power is primarily used to heat the coolant and not fed back into the battery. This also reduces the battery current. This approach is also part of the reference strategy. The improvements can be achieved because the SQP can work with the entire cycle and with perfect foresight. Therefore, it can plan the optimal utilization of the recuperated power without overheating the coolant. Figure 6.21 shows the utilization of the recuperated energy. It is evident that most of the heating takes place when recuperated power is available. Phases with a high power demand for acceleration are counteracted by switching off the heater. Like for the window-wise approach the E_{recu} is reduced. Again, this has two reasons: Firstly, the available E_{brake} is lower, because E_{acc} is smaller due to the lower peak velocities. Secondly, Figure 6.21 shows that the recuperated energy can be efficiently used for heating. But at the end of the cycle the maximum heater power is not used to take in the recuperated power. On the surface this reduces E_{recu} but it poses no problem for the MORE. $E_{\mathrm{motor,loss}}$ is slightly reduced (by $1.56\ \%$). Similar to the reduction in $E_{\mathrm{bat,loss}}$ two reasons can be identified: Firstly, the overall energy that is transformed between mechanical and electrical energy by the machine is reduced. Consequently, the losses are reduced. Secondly, the adaption of the velocity leads to lower losses in the machine.

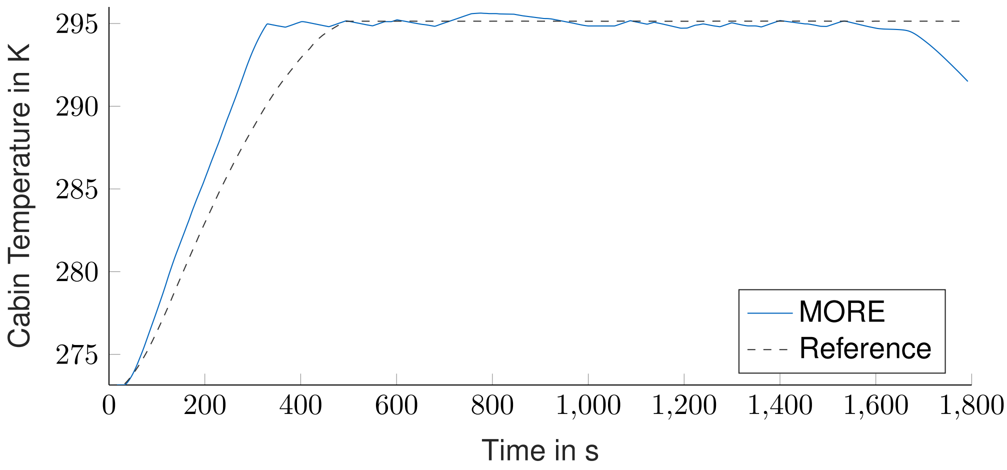

Figure 6.19 : Cabin temperature for the MORE and reference strategy

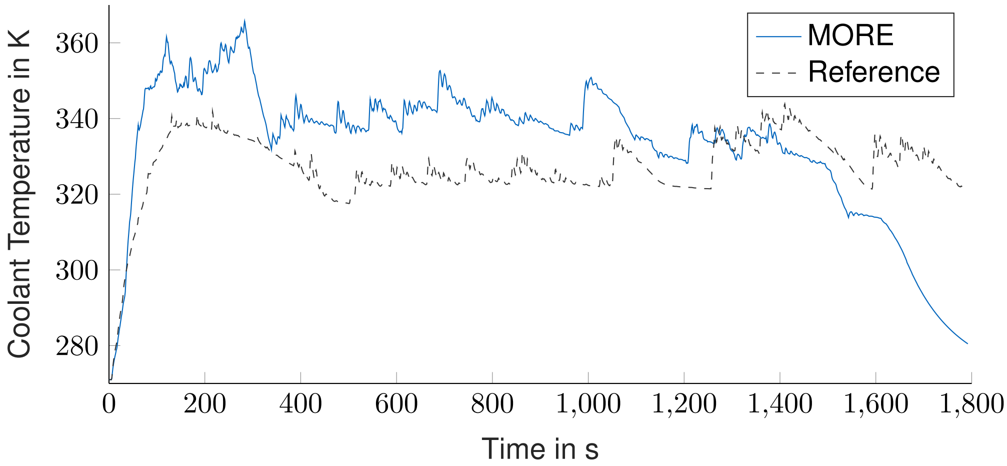

Figure 6.20 : Coolant temperature for the MORE and reference strategy

In the following, the parameters optimized for the *DC12* are transferred to all other 49 trips. First, the aggregated results for all of these trips are looked at. Next, the most important features are explained using a single exemplary trip.

Figure 6.22 shows the energy bar graph. The bars for each component represent the mean for this component over all trips. This applies to the reference strategy as well as to the MORE. Figure 6.22 shows that the energy consumption can on average be reduced by $5.49\,\%$ compared to $4.41\,\%$ for the window-wise approach. The error bar indicates that for every trip the MORE reduces the energy consumption compared to the reference. Moreover, a comparison with Figure 6.16 reveals that similar mechanisms are at work for the original optimization and for the transfer. In the following some findings are highlighted: E_{tract} remains lower than for the reference. This effect is mostly due to a reduction in E_{air}. This reduction varies little over the different trips. The reduction in E_{acc} decreases with the transfer and it experiences larger fluctuations over the different trips. This fluctuation is mostly due to fluctuations in the trips themselves and can also be found for the reference strategy. The reduction in E_{heat} remains stable for the different trips. The mean reduction is $12.03\,\%$ and with that in a similar range as for the original trip. The reason for this is that the main effect that is used to reduce E_{heat} (depleting the stored thermal energy) is independent of the velocity profile. The recuperation rule controller recreates that behavior for all trips. $E_{\mathrm{bat,loss}}$ also remains lower for the MORE than for the reference strategy. However, the reduction is smaller than for the original trip with an average of $8.77\,\%$. The mechanisms are again identical to the original optimization: The

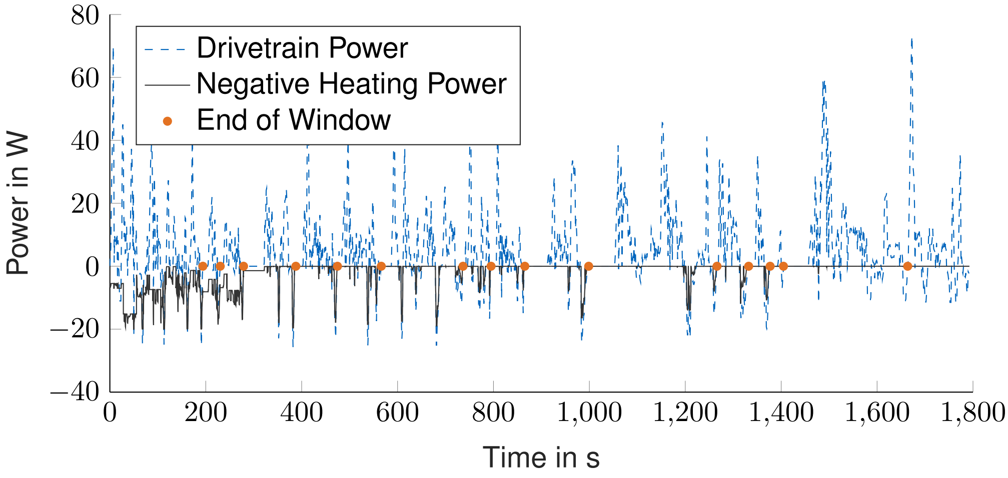

Figure 6.21 : Negative heating power and battery power for the MORE

recuperated energy can directly be used for heating. This reduces $E_{\mathrm{bat,loss}}$. The other mechanism is again the total energy reduction which has a positive effect on the battery losses. E_{recu} remains lower for the transferred MORE than for the reference strategy. The reason is the same as for the original trip. The reduction in $E_{\mathrm{motor,loss}}$ cannot be sustained for the transfer. Probably, the application of the velocity factor to another trip does not lead to velocities within the optimal efficiency range of the machine.

Table 14 summarizes the findings for the MORE on all trips. The mean travel time is on average

Table 14 Optimization of entire cycle: Overview of key values for the transfer to all trips (mean value ±STD)

Name	Reference	MORE
Energy consumption in $\mathrm{kW\,h}$	3.69 $\pm$ 0.08	3.48 $\pm$ 0.08
Travel time in s	1568 $\pm$ 84	1575 $\pm$ 84
Maximal velocity in $\frac{\mathrm{m}}{\mathrm{s}}$	32.65 $\pm$ 1.11	28.57 $\pm$ 1.42
Maximal coolant temperature in K	345 $\pm$ 1.02	363 $\pm$ 1.47
Mean cabin temperature deviation to target in K	3.28 $\pm$ 0.17	3.14 $\pm$ 0.16

slightly higher for the MORE. The maximal coolant temperature is considerably higher for the optimization, but in the acceptable range. The STD for the maximal coolant temperature is higher than for the reference, but considerably lower than for the approaches without the recuperation rule controller. The cabin temperature deviation is slightly smaller for the MORE than for the reference. This is because the MORE heats up the cabin more quickly than the reference. The maximal velocity is reduced. For all values except the coolant temperature the STD is similar for the reference and for the MORE. This indicates that the MORE performs similar on all trips and the difference is due to the trips themselves.

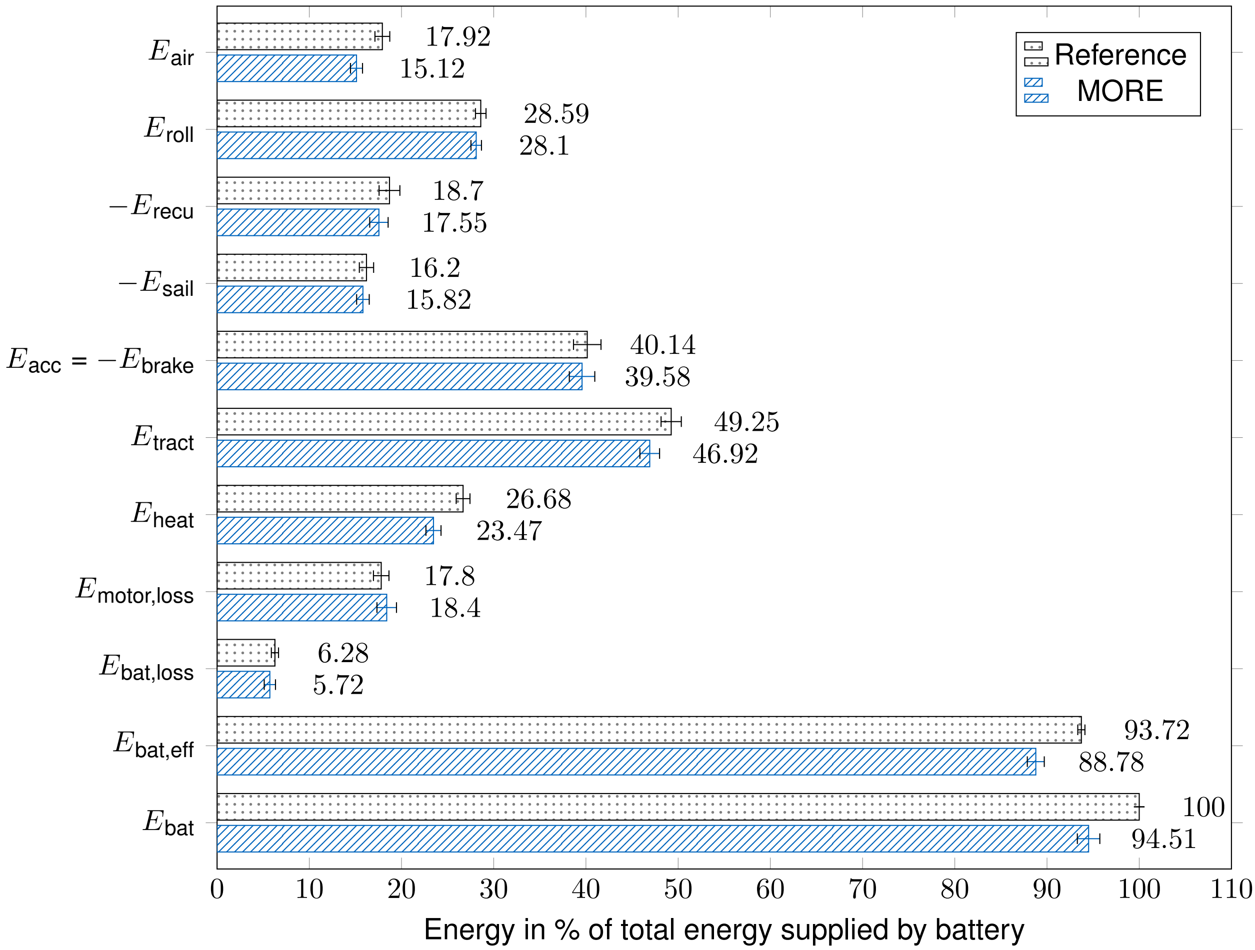

Figure 6.22 : Energy components for the transfer of the MORE based on optimization of the entire cycle

7 Discussion

In this chapter the results presented in the previous chapter (Chapter 6) are discussed. The aim of this chapter is to allow the reader to assess the results and understand how they are classified. For this purpose, Section 7.1 gives a short high-level summary of the results. Next, Section 7.2 provides answers to the research questions. The following section (Section 7.3) explains how the described EMS can be integrated into existing classifications of EMS. Subsequently, Section 7.4 qualitatively compares the presented EMS to selected other approaches. The final section (Section 7.5) provides an outlook on how the EMS could be improved.

7.1 Summary

Chapter 6 highlights that the concept of the MORE works. In particular, it shows that the MORE using the recuperation rule controller and based on the optimization of the entire cycle leads to a considerable reduction of the energy consumption (Section 6.1). A window-wise approach to the MORE also leads to satisfactory results and depending on the set-up this approach might be advantageous. A direct integration of the heater power does not facilitate the transfer to other cycles. Therefore, at least a simple controller is necessary for integrating the heater power. However, the simple controller is outperformed by the recuperation rule controller. A comparison between SQP and GA reveals that the SQP is better suited for use with the MORE.The chapter also indicates that the MORE is robust to variations in the ambient temperature.

7.2 Answering the Research Questions

This section presents answers to the initially formulated research questions in Chapter 4. These questions are discussed in the following. The aim is to answer the research questions with the findings presented in the results. When no definite answer can be given the findings are discussed.

Which optimization methods are suitable for an EMS? To design the MORE, three optimization methods were evaluated with a simple vehicle model. The results are presented in Section 5.8. The GA and the SQP perform well for an offline optimization, while DP is too computationally expensive. For the MORE both the GA and the SQP are implemented. Section 6.2.5 demonstrates that the SQP outperforms the GA for the offline optimization and for the integration into the MORE. Moreover, the section highlights that the GA is not deterministic. In summary, the SQP is the best option for an optimization procedure. The results illustrate that using a method that exploits the nature of the optimization problem is advantageous for an EMS.

How can an optimization-based approach be adapted to work with little forecast data and onboard computation capacity? This question can be answered by the concept of the MORE. The concept can be found in Section 5.1. The results presented in Section 6.1 show that the MORE works. The chapter also investigates how the MORE functions and illustrates its basic principles.

How can an optimization work on a partitioned trip and still lead to acceptable results? Subsection 5.4.1 explains how each trip can be split into smaller sections. Subsection 5.4.3 illustrates how the objective function must be adapted to work with the partitioned trip. Section 6.2.1 highlights that the results for the optimization of the entire cycle are still better than those for the partitioned trip. The knowledge of the entire trip allows the MORE to utilize effects that cannot be exploited if only the next window is known. In summary, the partitioning in windows could be realized as part of the concept of the MORE. However, the individual windows depend on each other so much that a global optimum is not possible for the window-wise approach. Therefore, whether the MORE is based on the entire cycle or on individual windows, should be determined by the concrete application.

Does optimizing two or more components simultaneously using a holistic EMS lead to better results than separate optimization? As the MORE combines a driving strategy with an EMS for the heating system, it is a holistic EMS. Additionally, the MORE is open for integrating additional components. Firstly, it can be shown that the energy reduction the MORE can achieve compared to the reference strategy is not only due to combining the two systems. Section A.1 illustrates that the MORE reduces the energy consumption if it has the same scope as the reference strategy. Contrasting the results obtained with the reduced MORE in Section A.1 with the full MORE in Section 6.1 reveals that some of the effects of the full MORE are due to the combination of the two components. In particular, two mechanisms can be identified: Firstly, the combination of heater power and traction power can be chosen so that it minimizes the battery losses. This is possible because the optimization aims can be weighed against each other. For example, at the beginning cycle it is the better strategy to reduce the traction power. The lost travel time can be made up later during the trip but reaching the cabin temperature fast is vital for the comfort of the passengers. This balancing of the sometimes contradictory objectives is not possible if the two are optimized separately.

Secondly, the speed influences the available recuperation power, while the heater helps to take in the recuperation power. If speed and heater power are optimized at the same time the two can be attuned to each other. This means that less energy is lost in the mechanical brake.

Consequently, it is plausible that the holistic optimization leads to better results than a separate optimization.

How can the resulting EMS be integrated into a vehicle? The MORE offers a concept that can be integrated into a vehicle with little additional effort (refer to 5.1). The results presented in Section 6.1 highlight that the concept of the MORE works. The SQP should be preferred regardless of the application as it fits better into the concept of the MORE. If additional data becomes available during the trip, the window-wise approach should be chosen. To enable an online update of the optimization, the run-time of the model needs to be reduced. For ideas how this can be accomplished refer to Section 7.5. If no additional forecast data becomes available during the trip, the MORE based on the entire cycle should be used. Section 6.3 illustrates that slight changes in the temperature do not make the transfer to other trips impossible. For integration this helps, as temperature forecast is not always accurate. The MORE in its original form influences the velocity. If this is not possible Section 6.1 illustrates that the application of the MORE is still worthwhile if only the heating system can be influenced in the available vehicle. The present MORE is limited to recurring drives. In summary, the thesis presents an EMS that can be integrated into a vehicle. A clear path how this can be accomplished is sketched.

7.3 Classification of the MORE

The MORE is a hybrid between a rule-based and an optimization-based approach. In this section it is put in this context. In Chapter 3 the main approaches to EMS are introduced. These are rule-based, optimization-based and Machine Learning (ML) approaches.

Figure 7.1 shows how the approaches can be categorized. The left part of the figure represents approaches, which need little data and are based on a well understood system. The far right stands for systems that either need much data or utilize more complex correlations. Points further up in the figure stand for more data, points lower down for more complex correlation. These systems are sometimes hard for a human to understand. Generalized ML approaches stand for an approach that needs a lot of data, but that are not based on an understanding of complex analytical relationships.

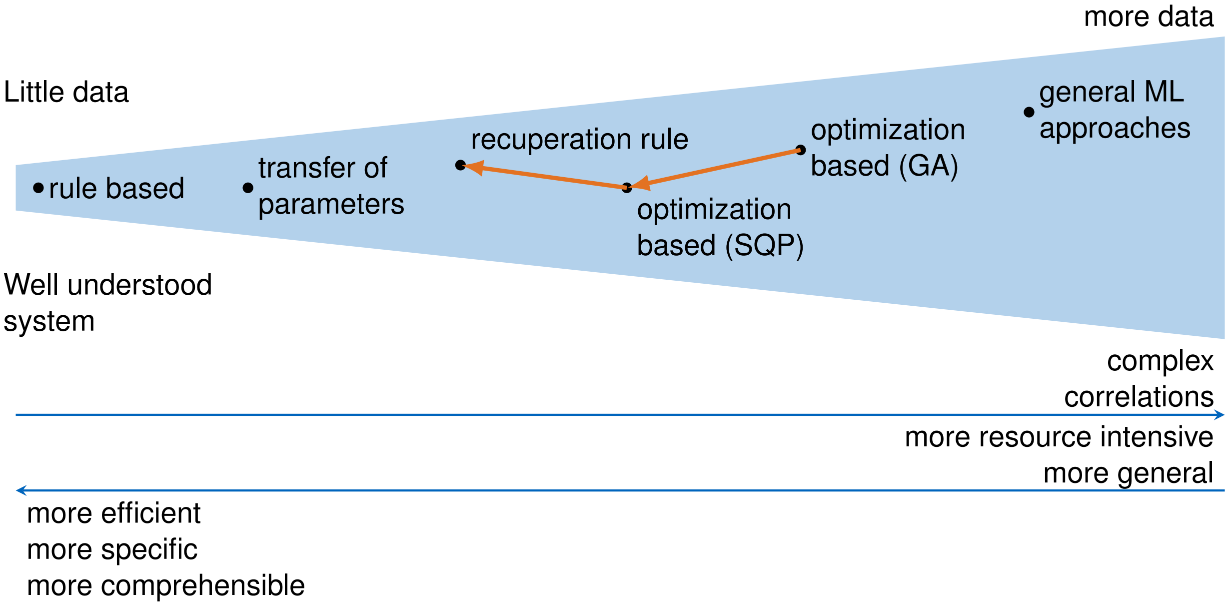

Figure 7.1 : Classification of EMS based on their rule-based and optimization-based elements

Optimization-based approaches occupy the middle ground. The GA also used in this thesis poses fewer requirement on the optimization problem than the SQP. The price paid for this is the higher computation time. On the opposite end of the spectrum lies the reference strategy, which is based on rules drawn up by an expert. This approach needs little data and is based on understanding the system well. The approach outlined in this thesis constitutes a journey through the landscape defined in Figure 7.1: The original starting point (mainly described in [178]) is an optimization-based EMS that utilizes the GA. In the first step the GA is exchanged for the gradient based SQP. In the next step the optimization is complemented with the recuperation rule controller. To do this the system needs to be better understood and the approach loses generality. Finally, the transfer to another trip is done. This causes the EMS to shift yet further toward a rule-based approach. In particular, it loses generality as it works best with recurring trips.

7.4 Qualitative Comparison with other Approaches

In Chapter 6 the hybrid approach is directly compared to an optimization based and to a rule-based approach. A summary is presented in Table 15. In this section the abstract idea behind the individual approaches is compared with the MORE. The following approaches are considered: rule-based, optimization-based and based on generalized ML method. All approaches are assumed to be capable of vehicle integration. Therefore, the optimization must be done online.

1. *Rule-based approach:* The rule-based approach needs little data because the rules are typically based on the experience and the expertise of the person drawing up the rules. This also means that the computing capacity is low offline as well as in the vehicle itself. However, it also means that the developer can overlook possibilities that an optimization procedure would have revealed. Moreover, the rules apply to all vehicles and the possibility to customize them is limited. Additionally, unlike for the MORE, forecast information cannot be integrated. Even though a rule-based approach is always sub-optimal, it is still the approach implemented in most series vehicles, because the results are only slightly inferior to more complex methods. This is for example demonstrated in Section A.1 of this thesis. Compared with the proposed approach it has the additional advantage that it works on all routes.

2. *Online optimization:* The online optimization needs more computing capacity onboard the vehicle than the proposed method. However, it needs no offline computing capacity. Because it needs to work in real-time it typically is complex to implement. Moreover, it relies on good forecast information for the current trip. If the quality of this data is not sufficient the solution suffers. Over the MORE it has the advantage that it optimizes the current trip. Consequently, if perfect foresight is assumed or very good forecast data is available, the optimal solution can be found. Additionally, it works on every route. In comparison to all other approaches, it performs well in uncommon but predicted driving situations. The reason for this is that the online optimization does not rely on information from previous drives. This also means that the solution is specific for each driver and each route.

3. *ML approach:* A general ML approach relies heavily on a large data base. Firstly, this means that this data needs to be made available. Secondly, it needs offline computing capacity to generate a solution using this data. The updating of the solution when additional data is made available is also time-consuming. This means that forecast information cannot be easily integrated during the drive. Lastly, the solution is not necessarily easy to comprehend for a human. Over the MORE it has the advantage that it works in more situations and with more routes, as a ML approach can further abstract the solution. Moreover, the larger data base means it still works even if one trip is not representative for the others.

In summary, it could be demonstrated that the MORE adds a relevant new option to the existing approaches for EMS. It offers advantages over the existing approaches, which make it worthwhile to further pursue this option. Like all other approaches it has also weaknesses. But it is assumed that these can be managed with the right implementation.

7.5 Outlook

This section gives an outlook to what future improvements to the system would be possible and worthwhile. For each improvement a rough outline on how it could be implemented is given.

7.5.1 Improvements to the Model

The model is not the main issue of this thesis. However, an improved model significantly impacts the quality of the optimization results. The overall concept of this thesis can be adapted to nearly every vehicle model. If the model is implemented in Matlab/Simulink, doing so is relatively easy. The model could be improved by making it more detailed. In particular, the following adaptions could be made:

- *Adding the slope*: Currently, the slope of the driven route is not implemented. Adding the slope makes the model more realistic and adds interesting aspects to the EMS as it influences the optimal velocity and the recuperated energy. The slope would not influence how the parameters can be transferred to another trip as it depends on the route and not on the particular situation on the day the trip is taken.

- *Adding the wind speed*: The wind speed is also not modeled. Like the slope it influences the optimal velocity and the recuperated energy. Unlike the slope, however, it differs between trips. Therefore, adding the wind speed could change the transfer behavior of the parameters. This would also depend on the individual weather conditions in the chosen area. It is possible that the wind speed does not vary much on different days and that it has no significant influence on the energy consumption.

- *Adding the solar radiation*: Currently, the model of the cabin temperature does not include the solar radiation. Consequently, the model is only accurate at night or during cloudy weather. In-

Table 15 Qualitative comparison of the implemented EMS with other approaches. All advantages and disadvantages are described in comparison to the implemented EMS.

Approach	Disadvantages	Advantages
Rule-based	• Prognosis data cannot be integrated • Needs to be tuned by developer; possibilities can be overlooked • No adjustment for the specific behavior of the driver possible • Can by definition not be optimal	• Low computing capacity needed both in the vehicle and offline • Most common approach for series vehicles • Yields only slightly inferior results to complex approaches • Works in all driving situations • Needs little data
Online Optimization	• High computing capacity inside the vehicle necessary • Dependent on a good forecast • Time-intensive implementation	• Can theoretically find the optimum for the available information • Good results in unusual but predicted situations • Specific for each driver • Needs no information about previous drives
Machine Learning	• Needs a large data base • Long training time for updating to a new driving situation • Not necessarily comprehensible for a human • Forecast information cannot be integrated • Large computing capacity offline needed	• Works for more situations and new routes • Does not rely on a single trip that might not be representative

cluding the radiation could reduce the overall demand for heating power. Moreover, it adds another potential difference between the trips that could make the transfer more difficult. However, as the transfer also works for different ambient temperatures it is likely that it would be salvaged by the recuperation rule controller.

- *Extending the model to include the thermal comfort of the passengers*: Currently, the thermal comfort of the passengers is only reflected by the deviation from the target cabin temperature. As Chapter 3 highlights, other researchers developed more elaborate models of the passenger comfort. Such a model could help to increase the energy reduction because the air mass flow and the heating power can be adapted closer to the requirements of the passengers. Moreover, the comfort of the passengers would probably be increased.

- *Expanding the system to also include air conditioning in hot weather*: Currently, only the high voltage heater for low temperatures is integrated into the model. It may be interesting to also add the air conditioning. This can enlarge the application area. However, the optimization would also have to be adapted to work with a full HVAC. Problems with the transfer are not to be expected.

- *Including a detailed aging model for the battery*: Battery aging is one of the most relevant challenges for current BEVs. Therefore, it may be interesting to add a detailed validated aging model. To make this worthwhile the battery aging must be integrated into the objective function. This could for example be done using stress factors or the predicted remaining useful lifetime if every trip was driven like the current trip.

- *Broaden the model to encompass a traffic model*: Currently it is assumed that the velocity can always be adapted within the predefined limits. It is unlikely that this is actually true in all traffic situation. The simplest way to encompass this in the simulation is to randomly determine whether the velocity for a certain segment can be adapted. A more elaborate traffic model is also possible.

- *Model more types of BEV*: For this thesis only a single vehicle is investigated. However, it may be interesting to test the approach on different vehicles. In particular different vehicle types would be relevant. For example, transporters, lorries or electric buses could be integrated. Especially electric buses used for public transport could profit from the approach as they repeatedly drive the same routes.

- *Add more components relevant for an EMS*: The current model closely resembles a series vehicle. The only marked differences are the high-voltage heater and the assumption that the velocity can be influenced. This means that few of the component-wise EMS discussed in Chapter 3 could be implemented. Consequently, it may be worthwhile to add more components to the model. For example, a second electric machine or a in particular a HESS.

7.5.2 Reduction of Computation Time

Even though the optimization of the parameters for the MORE is not done online, long computation times are detrimental to the real-life application of the system. Consequently, different options to lower the computation time could be implemented. To lower the computation time three main options exist: Firstly, the hardware on which the optimization is run can be changed. Secondly, the computation time for running the model can be lowered. Thirdly, the time that needs to be simulated can be reduced.

The first option is scientifically uninteresting. As the optimization is already moved to an arbitrary location outside the vehicle the user has the free choice of computer. The difference between the last two options is explained in Subsection A.2. The computation time of the model can for example be lowered by exchanging the model with a black-box model that only models the relevant effects for the EMS. Furthermore, the gradient for the SQP can be computed analytically instead of via the difference quotient. Both approaches could be combined with an implementation outside of Matlab/Simulink. Even if no other changes are performed an implementation in a different programming environment should lower the modeling time. The main advantage of Simulink is the user-friendly interface that allows to draw up complex yet comprehensible models quickly. This advantage is paid with a higher computation time.

The simulated time can be reduced via the optimization procedure. To this effect a better initial value can be used. For example, the results from the rule-based strategy can be used as initial value. Moreover, other gradient-based optimization procedures could be tested or a more efficient implementation of the SQP.

The last option to reduce the computation time fits in neither of the previous categories: Run as much of the optimization in parallel as possible. For the GA this would mean to evaluate the individuals of one generation in parallel. For the SQP the computation of the gradient could be parallelized.

7.5.3 Integrating Additional Components into the MORE

Currently, the MORE encompasses two parts of the BEV: The driving strategy and the heating system. To facilitate a truly holistic EMS more components need to be integrated. As a series BEV does not provide many opportunities for a holistic EMS it is necessary to expand the model. Options for this are already described in Subsection 7.5.1. For all options it is important to consider whether they lead to an overall energy reduction or whether the costs outweigh the benefits.

7.5.4 Facilitating Online Updates of the Parameters

Another interesting direction is to further hybridize the MORE. This means that the optimization of the parameters is done as described in this thesis. However, the model and the optimization are tuned to a faster computation time. Consequently, it is possible to run one or two iterations of the SQP online. This means that the parameters are updated during the trip with forecast data. This option favors a window-wise optimization. It can be assumed that for the next window some traffic and temperature information is available and can be used for updating the parameters. When no forecast data are available the MORE falls back to the parameters previously determined. Which of the two options is used, can be decided for each window of each trip separately.

In this context, it may also be worthwhile to change how the trip is partitioned into windows. For the current MORE this is done when the vehicle stops. Therefore, no kinetic energy is transferred from one window into the next. The time scale on which forecast data are available might not align with this division. If this is the case the fitness function needs to be changed to also encompass the kinetic energy stored in the movement of the vehicle. If that is done the windows can be chosen arbitrarily.

7.5.5 Integrating the MORE into a BEV

Of course, the biggest step for the concept is to integrate it into a real BEV. Thus, it could be determined how well the concept would work in a real-world application. The biggest challenges to do that are listed in the following:

- *Acquiring a suitable vehicle*: The first challenge is to acquire a BEV that allows to control the heater power and the velocity in the manner discussed in this thesis.
- *Adapt the model to the exact vehicle*: It is unlikely that the exact vehicle previously modeled could be acquired for the experiments. Consequently, the model must be adapted to match the vehicle.
- *Establish a procedure that transfers the parameters into the vehicle*: For the real-world drives the parameters need to be first computed offline and then transferred to a computing unit within the vehicle. This link must be established. Moreover, the computing unit must be put in a position to correctly set the parameters during the drives.

- *Acquire sufficient data*: To assess the EMS, sufficient drive data must be gathered. Probably, this data must be used to adapt the method.

To evaluate the MORE thoroughly, it would be particularly interesting to give a BEV equipped with the MORE to a typical user of a BEV. This would enable the researcher to find out the overall energy reduction of the MORE. If this is not possible the total energy reduction can be estimated using the recorded driving data of a typical BEV and use the MORE within a simulation.

7.5.6 Adapting DP to the MORE

For this thesis, DP is not implemented because the preliminary results indicated that the computation time is too high for the concept. However, this applies to an implementation of the original DP algorithm. Other publications mentioned in Chapter 3 use variations such as stochastic DP to reduce the computation time. Therefore, it is likely that DP could be adapted to facilitate the offline optimization needed for the MORE.

7.5.7 Integrating the Approach into a Larger Concept

The final future challenge is to integrate the approach into a larger concept. This would allow a vehicle manufacturer to create value from the concept. The most obvious is to sell the optimization of the parameters to premium customers. This can be targeted to costumers with a long and recurring commute. The costs for the service could be adapted so that they stay below the cost reduction due to the lower energy consumption. The EMS could also be linked to premium vehicles with advanced driver assistance functions. These would allow for the velocity to be adapted. Moreover, these vehicles also have forecast data for the next segment of the trip available, thus enabling the parameter updates described in Section 7.5.4.

Taking the concept one step further, it is possible to draw up a map that contains parameters for different segments. Consequently, a trip would constitute individual segments and each segment would be defined as a window. For each of these windows the BEV is supplied with a set of optimized parameters. The challenges for this approach are the different driving behavior of individual users and the different state that the vehicle is in at the beginning of the segment.

In summary, two options exist to generate revenues from the proposed concept. The first requires little adaption, while the second poses more new challenges. The current concept could only serve as a steppingstone to implement this larger vision.

8 Conclusion

This thesis introduces and analyzes an EMS for BEV that is based on a mixture of rule-based and optimization-based elements: the MORE. The MORE optimizes parameters for a reference trip and applies them to repetitions of the same route. It can be applied to repeating trips like commutes. Hence, it is useful for at least a quarter of the driven distance of a BEV. The MORE combines heating system and driving strategy into a holistic concept. The MORE uses rules to react to high frequency events like braking as well as to deviations from the original trip.

This thesis shows that the concept of the MORE works on a set of 50 repetitions of the same route. For this scenario it saves about $3\ \%$ energy compared with a recent rule-based approach, another $2\ \%$ compared to the industry standard and additional $5\ \%$ if the driving strategy is simultaneously optimized. The thesis also proves that the holistic approach of the MORE is superior to a sequential optimization. It gives an overview of different optimization algorithms and different options for integrating the optimization parameters into the system. It analyzes the various configurations of the MORE and compares them among each other and with the reference strategy. The results are discussed and compared qualitatively to other state of the art approaches.The thesis also gives an outlook to future research topics in the context of the MORE.

In summary the thesis shows that the concept of the MORE works. It also sketches a path how the concept can be integrated in BEVs and motivates why further research of the concept is worthwhile.

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A Appendix

A.1 Reduced MORE without Velocity Optimization

The last section of this chapter introduces a reduced EMS which does not encompass the driving strategy. Therefore, the velocity from the original trip is not included in the optimization. Only the target temperature for the cabin and the heater power are optimized. Even though the velocity is excluded, the parameters are optimized as a function of the position instead of the time. This is done to ensure that the parameters can be transferred to another trip. This experiment is motivated by the fact that the heater power and the target temperature are usually easier to influence in a vehicle than the velocity. Therefore, it is relevant to determine how high the energy reduction is, if only these two parameters can be influenced. Additionally, this experiment allows a fair comparison with the reference strategy for heating.

For this experiment, the whole cycle is optimized using the recuperation rule controller. This approach is chosen as it leads to the highest energy reduction in the previous experiments. The ambient temperature is set to $0°C$. Figure A.1 shows the energy components for the EMS without speed. For

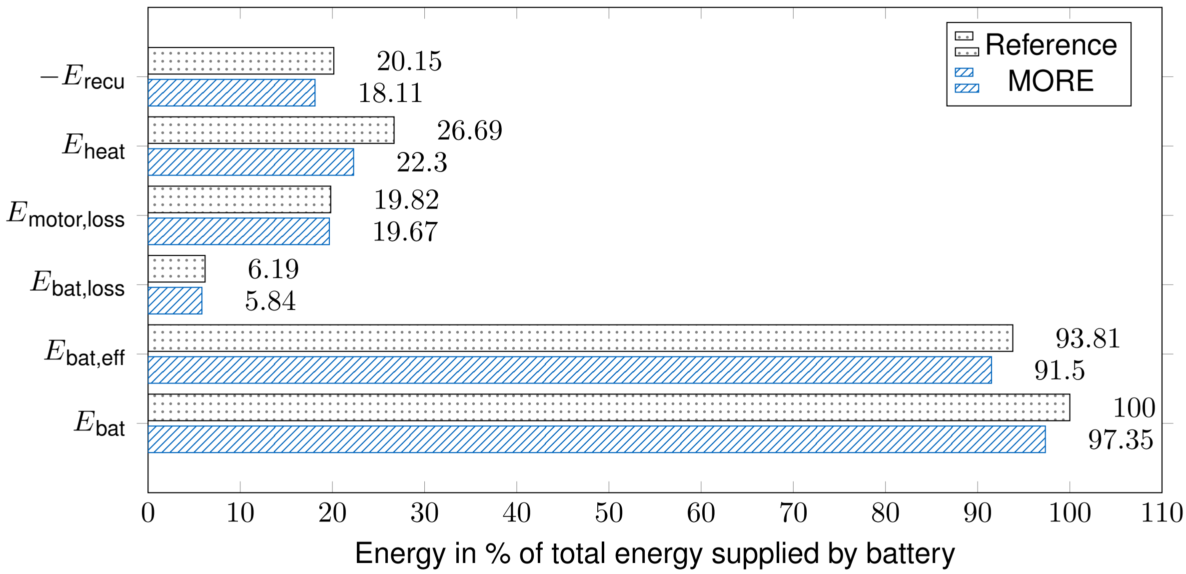

Figure A.1 : Reduced MORE: Energy components

this experiment the bar graphs are reduced to those energy components that are influenced by the heater power. The figure is similar to the results from the entire cycle including the speed displayed in Figure A.1. Of course, the overall energy reduction is considerably smaller ($2.65\,\%$ versus $8.86\,\%$) because the energy used for traction is the largest share of the total energy. The following components can be influenced by the heater power and target temperature: E_{heat} can be reduced by $16.46\,\%$. This is about the same as could be attained for the MORE based on the entire cycle that includes the velocity. $E_{\text{bat,loss}}$ is reduced by $5.56\,\%$. Here the reduction is considerably smaller than for the experiment that includes the velocity, which leads to a reduction of $17.65\,\%$. This has two reasons: Firstly, the losses also are linked to the total current which runs to the battery. Therefore, the higher energy reduction for the MORE with velocity also reduces the losses. Secondly, adapting the velocity allows the MORE to adapt the heater power and the power needed for accelerating such that the battery is in the optimal operating range. For the experiment without velocity the reduction in $E_{\text{bat,loss}}$ comes primarily from using more of the recuperated power directly for heating rather than storing it in the battery. E_{recu} is reduced as could be seen for the previously discussed configurations of the

MORE based on the SQP. Again, the reason for this is that the MORE does not store excess energy that yields no benefits in the coolant.

While the previous subsection showed that the optimization without the velocity leads to an improvement on the original trip, the more relevant question is, whether this can be sustained if the parameters are transferred to the other trips. Figure A.2 shows the energy component for the transfer of the parameters on all 49 trips in including the STD. E_{bat} is reduced for all trips. The effects behind

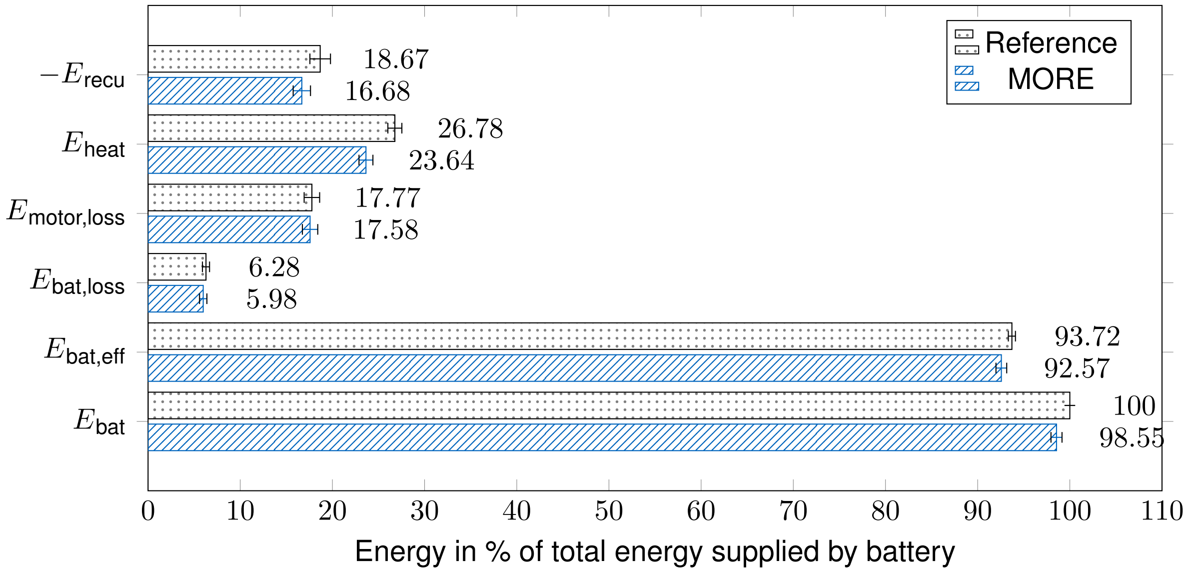

Figure A.2 : Reduced MORE: Energy components for the reference strategy and for the MORE transferred to all trips

this reduction are identical to those discussed in the previous section for the original trip. Table 16 summarizes the key values for the transfer. As the velocity is not changed the travel times remain

Table 16 Reduced MORE: Overview of key values for the transfer to all trips (mean value $\pm$STD)

Name	Reference	MORE
Energy consumption in $\mathrm{kW\,h}$	3.69 $\pm$ 0.08	3.64 $\pm$ 0.08
Maximal coolant temperature in K	345 $\pm$ 0.98	352 $\pm$ 1.24
Mean cabin temperature deviation to target in K	3.25 $\pm$ 0.16	4.10 $\pm$ 0.26

unchanged, too. The cabin temperature stays within the same region as for the optimization including the speed. The coolant temperature also does not exceed the acceptable range.

Figure A.2 shows that the MORE reduces the energy consumption by $1.45\ \%$ compared to the reference heating strategy. The STD indicates that a reduction can be attained for all trips. The energy reductions of all components remain for the transfer. This finding indicates that the MORE is as far as energy reduction is concerned superior to the reference strategy.

As the rule-based strategy is in particular adapted to cold climates, Figure A.3 presents the energy bar graph for the transfer for the $263\ K$ ambient temperature. This figure shows that for the colder temperature the energy reduction attained with the MORE can be increased. On average E_{bat} can be reduced by $4.31\,\%$. The reason for this is that the share E_{heat} and $E_{\mathrm{bat,loss}}$ have in E_{bat} is larger for the lower temperature. This gives the reduced MORE a larger leverage to lower the overall energy consumption.

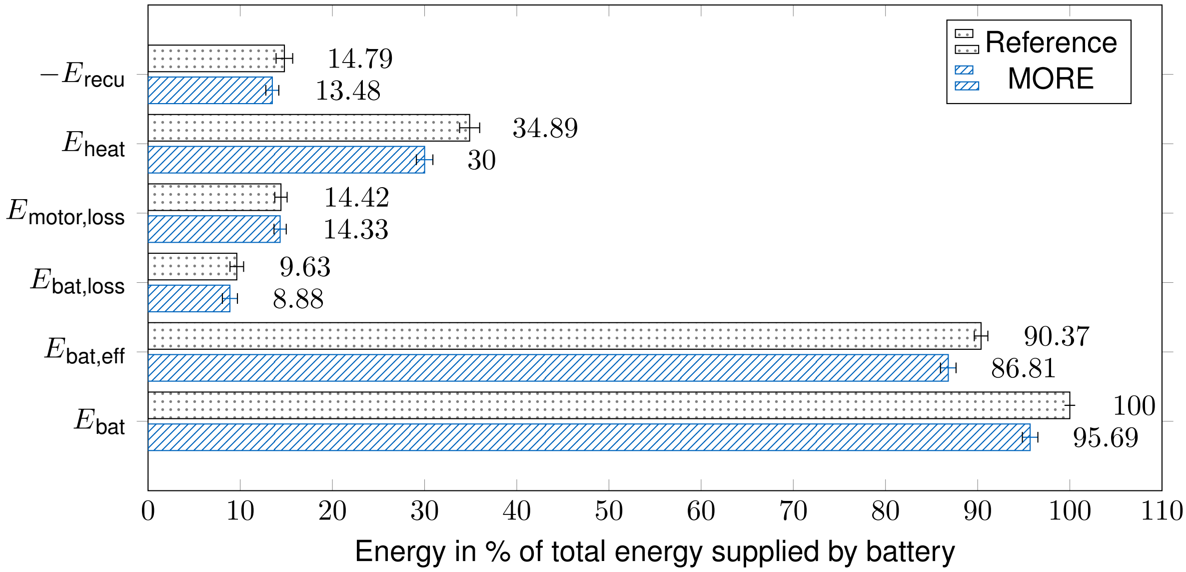

Figure A.3 : Reduced MORE $(263\ K)$: Energy components for the reference strategy and for the MORE transferred to all trips

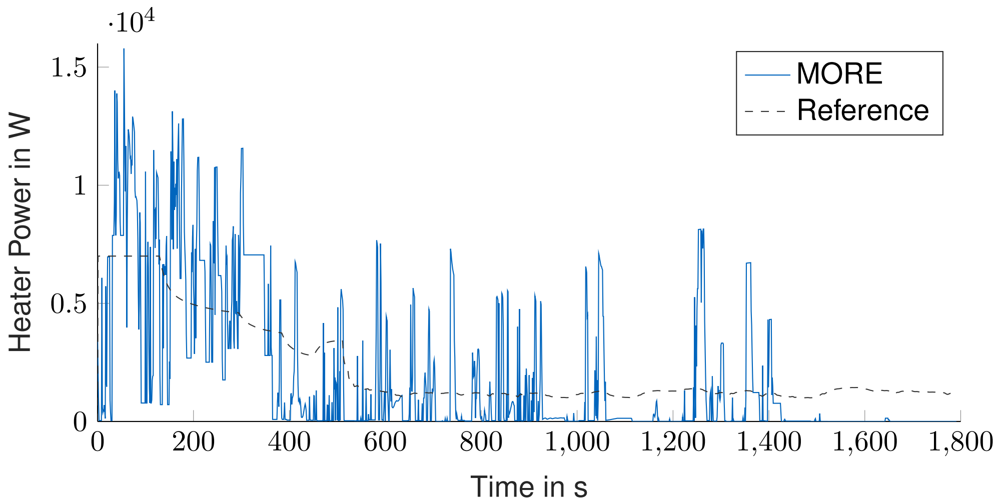

Figure A.4 : Reduced MORE and simple reference: Heater power comparison

A.1.1 Comparison to Simpler Reference Strategy

For all experiments the reference strategy that is used for the heating system, is the rule-based strategy developed by Steinstraeter as described in Section 5.3. This subsection also explains why it is a sensible option to apply that strategy as a reference. However, the energy reduction of the MORE is in reality higher because the reference is already better than the strategy currently implemented in commercially available vehicles. In [151] Steinstraeter et al also recreated the original heating strategy of the BMW i3. In this subsection the reduced MORE is compared to this original strategy. This strategy is not designed to optimize the recuperated energy that can be taken in by the HVH. Figure A.4 contrasts the heater power of this reference with that of the MORE.

Figure A.5 shows the bar graphs for the optimization and simple reference strategy. Compared to Figure A.1 only the reference strategy is changed. In comparison to the simpler reference the MORE can reduce the energy consumption by $8.93\,\%$.

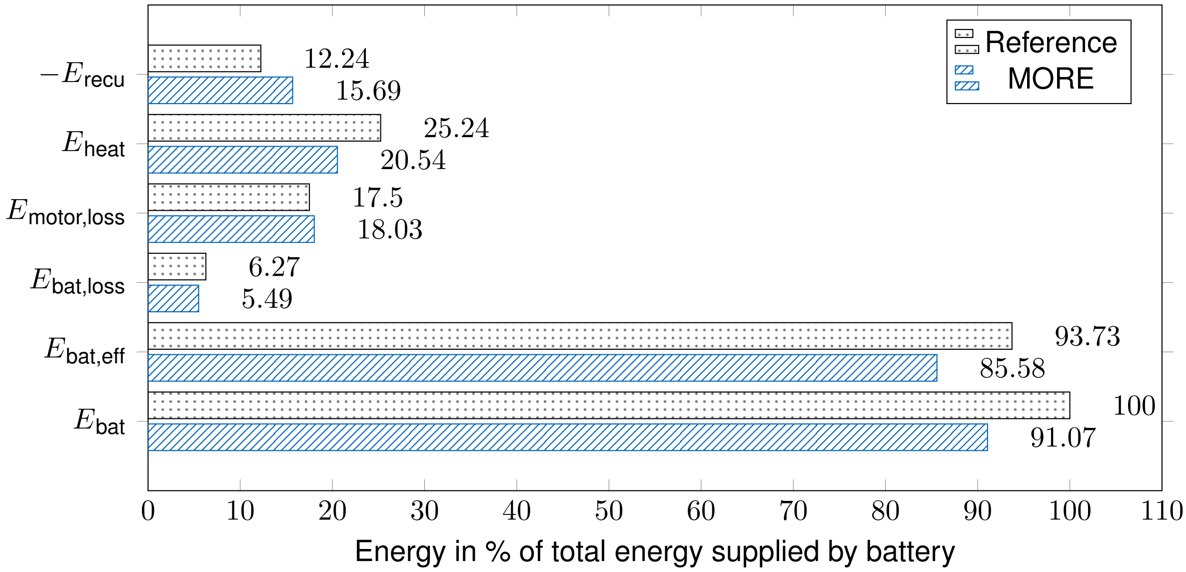

Figure A.5 : Reduced MORE and simple reference: Energy components

A.1.2 Conclusion

The reduced MORE leads to a reduction of the energy consumption. This reduction is considerably smaller than for the previous experiments which included the speed. However, the reduction can be maintained if the parameters are transferred for the other trips. The reduced MORE is tested for two ambient temperatures ($263\ K$ and $273\ K$). For both temperatures the energy consumption can be significantly decreased. The reduction is higher for the experiment with a lower temperature.

As the heater power can more easily be influenced, the reduced MORE is an option that can more easily be implemented into a current BEV. It requires nothing that is not available in currently commercially available vehicles.

A.2 Computation Time Comparison

In this section the optimization time for each approach is compared. It should be noted that only the time for the original optimization differs. The transfer of the parameters is equal for all implementations and is not time consuming. As all the EMS are based on the same model, the objective is to compare the computation time of the optimization approaches, not of the model itself. Moreover, the model is not the focus of this thesis, and many approaches exist that can lower the computation time for the model. Consequently, the measure that was chosen is the *simulated* time as opposed to the *simulation* time. The simulated time specifies how much time is simulated by the model for each optimization. It is irrelevant whether this simulation is done in one run or if the windows are simulated individually. This approach has several advantages: Firstly, it allows a comparison between the optimization of the entire cycle and that of each window separately. If the number of model runs was counted, the two approaches could not be compared meaningfully. For the optimization of the entire cycle a single model run takes more time than for the optimization of a single window. The simulated time is a measure that takes these differences into account. Secondly, the simulated time does not depend on the computer on which the optimization is run. Thirdly, it provides a measure that is centered on the optimization method and not on the modeling, as it is invariant regarding the model run time.

The computation time is relevant for this thesis because in a real-life scenario the optimization needs to be performed more than once. In particular, if it is run over night in a cloud service for multiple vehicles, it is important to use these resources efficiently.

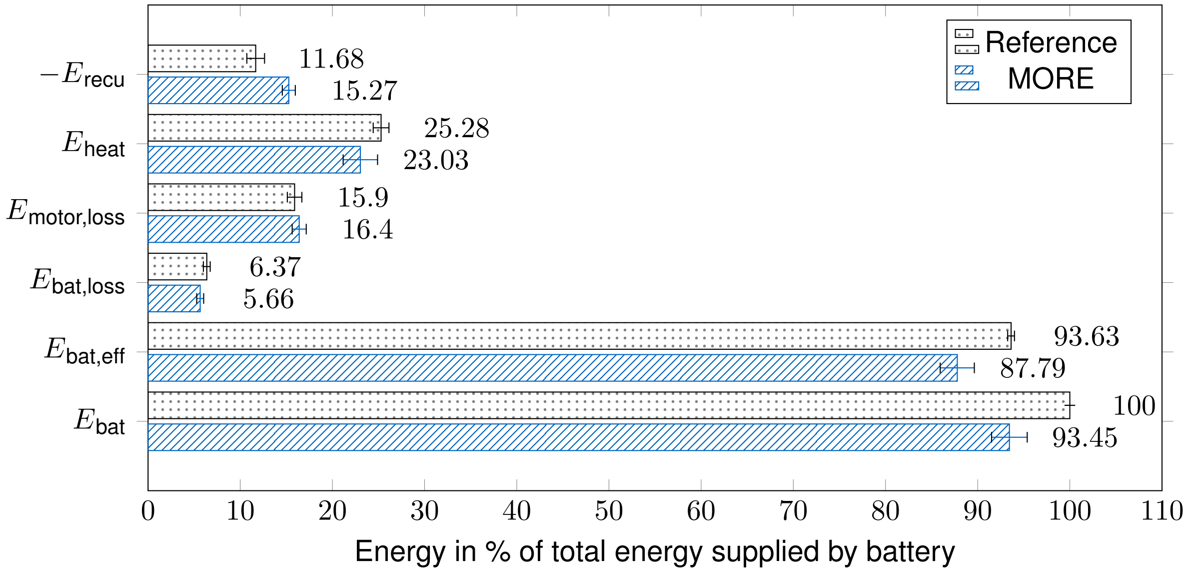

Figure A.6 : Reduced MORE and simple reference: Energy components including the STD

Table 17 Overview of the simulated time for the initial optimization

Section	Configuration	Simulated time in s
Section 6.2.3	Basic controller, SQP, windows	$10.28 \cdot 10^6$
Section 6.2.1	Recuperation rule controller, SQP, windows	$2.03 \cdot 10^6$
Section 6.1	Recuperation rule controller, SQP, cycle	$12.05 \cdot 10^6$
Section 6.2.5	Recuperation rule controller, GA, window	$8.64 \cdot 10^6$

Table 17 gives an overview of the simulated times of all experiments. The table verifies the expectations: The SQP in combination with the recuperation rule controller and the window-wise optimization needs the lowest simulated time and, therefore, also the lowest computation time. Using the basic controller leads to more simulated time, because more iterations are needed for convergence and the smaller time step size means more model runs for the gradient computation. The computation time is increased by $406.4\,\%$. Still the recuperation rule controller leads to a lower energy consumption.

The optimization of the entire cycle is in general computationally more expensive than the window-wise approach using the same controller. The mechanism behind this is discussed in Section 5.4.1. Optimizing the entire cycle leads to an increase of the optimization time by $493.6\,\%$. This increased computation time leads to better performance for the transfer to other trips.

The GA is also more computationally expensive than the SQP. This can be explained by the working mechanism behind each algorithm: The SQP uses the gradient to move systematically through the search space. In contrast to that, the GA uses no additional information beyond the fitness value and searches less systematically for the optimum. The price that is paid for this is the increase in simulated time by $325.6\,\%$ compared to the same configuration using the SQP. Additionally, the implementation with the SQP saves more energy for the original trip as well as for the transfer to other trips.