THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Optimizing Thermal Energy Management in BEVs via Distributed Optimization

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This thesis is dedicated to my family

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Abstract

The increasing global focus on energy conservation and environmental sustainability has highlighted the critical role of reducing greenhouse gas (GHG) emissions, particularly from the transportation sector. Battery Electric Vehicles (BEVs) have emerged as a key solution, driven by stringent regulatory targets and rising consumer demand for sustainable mobility. However, achieving widespread adoption of BEVs requires addressing challenges such as "range anxiety," which stems from the limited driving range due to high energy consumption, particularly for thermal management.

This thesis explores optimizing Thermal Energy Management (TEM) systems in BEVs to enhance energy efficiency and extend vehicle range. A novel control-oriented, system-level model is developed for a state-of-the-art Flexible Thermal Energy Management (FTEM) system, integrating HVAC and heat pump functionalities. The research focuses on applying distributed optimization techniques, leveraging Model Predictive Control (MPC) and the Alternating Direction Method of Multipliers (ADMM), to achieve real-time energy savings. The proposed methods target significant reductions in energy consumption, particularly under varying environmental conditions, making BEVs more competitive in the mass market.

This work contributes to the broader transition to zero-emission transportation by demonstrating advanced TEM strategies that improve both vehicle performance and sustainability.

Keywords: BEV, TEM, HVAC, Heat Pump, ADMM

List of Publications

This thesis is based on the following publications:

[A] **Prashant Lokur**, Nikolce Murgovski, Mikael Larssonn, "Control-oriented Model for Thermal Energy Management of Battery Electric Vehicles". Under review submitted to IEEE Transactions on Vehicular Technology Journal.

[B] **Prashant Lokur**, Nikolce Murgovski, Kristian Nicklasson, "Distributed Model Predictive Controller for Thermal Energy Management System of Battery Electric Vehicles". Published in 2023 62nd IEEE Conference on Decision and Control (CDC), Dec. 2023.

Other publications by the author, not included in this thesis, are:

[C] **Prashant Lokur**, Kristian Nicklasson, Leo Verde, Mikael Larsson, Nikolce Murgovski, "Modeling of the thermal energy management system for battery electric vehicles". *2022 IEEE Vehicle Power and Propulsion Conference (VPPC)*, Merced, CA, USA, 2022, pp. 1-7.

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Acronyms

ADMM Alternating Direction Method of Multipliers

BEV Battery Electric Vehicle

BTMS Battery Thermal Management Systems

CAN Controller Area Network

CO2 Carbon Dioxide

CEXV Chiller Electronic Expansion Valve

ECU Electronic Control Unit

ED Electric Drive

EEXV Evaporator Electronic Expansion Valve

EV Electric Vehicle

EXV Electronic Expansion Valve

FTEM Flexible Thermal Energy Management

GHG Greenhouse Gas

HEV Hybrid Electric Vehicle

HVAC Heating, Ventilation, and Air Conditioning

ICE Internal Combustion Engine

MPC Model Predictive Control

NEDC New European Driving Cycle

NLP Nonlinear Program

OCP Optimal Control Problem

RMSE Root Mean Square Error

TEM Thermal Energy Management

WCC Water-Cooled Condenser

WLTC Worldwide Harmonised Light Vehicles Test Cycle

ZEV Zero-Emission Vehicle

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Part I

Overview

CHAPTER 1

Background

1.1 Introduction

Global awareness and concern about energy conservation and environmental sustainability have grown significantly over the last decade. Human activities that produce Greenhouse Gas (GHG) emissions have severely impacted the environment [1]–[4]. In the European Union, more than 20 % of GHG emissions are attributed to transport activities, with passenger vehicles accounting for 50 % of those emissions [4], [5]. In the USA, transport activities contribute to over 28 % of GHG emissions, with passenger vehicles responsible for 56 % of those emissions [6], [7]. The carbon dioxide (CO_2) contributes the vast majority among these GHG gases [8].

To curb these emissions and promote sustainability, many governments have implemented measures to reduce emissions. The European Union has set stringent targets to achieve a 100 % reduction in CO_2 emissions from cars and vans by 2035. Both the US and the European Union have set net zero emissions by 2050. Zero-emission vehicles (ZEVs) would help to achieve these targets, as they produce no direct exhaust emissions of pollutants or greenhouse gases. This includes electric vehicles (EVs), hydrogen fuel cell vehicles, and any other vehicles that do not emit pollutants from their onboard power source. Among ZEVs, battery electric vehicles (BEVs) are considered the future of passenger vehicles. BEVs are projected to dominate the largest automotive markets by 2035 due to various government regulations and increasing customer demand for sustainable mobility [9]. It is estimated that by 2032, global sales of BEVs will account for around 34 % of overall passenger vehicle sales [10]. To be on track to reach CO_2 net neutrality by 2050, BEV sales must increase significantly [11].

To increase sales, BEVs must be competitive in the mass market, and consumers must perceive them as viable alternatives to combustion vehicles. One of the most desirable features consumers seek in BEVs is a longer driving range [12]. However, the challenge of reduced driving range, known as "range anxiety," represents a significant concern for potential BEV owners [13]. While equipping the vehicle with a bigger battery could increase the driving range, this solution would raise the vehicle's cost, diminishing its competitiveness with conventional vehicles. Therefore, improving system efficiency is a more cost-effective way to enhance the driving range of BEVs.

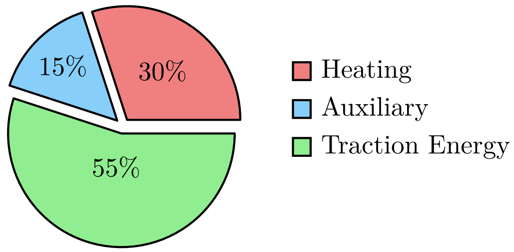


Figure 1.1: Energy consumption distribution in an electric vehicle.

The typical energy consumption of a BEV is shown in Fig. 1.1 [14]. Most energy consumption is due to traction demand, the energy required to move the vehicle. The second highest energy consumption is attributed to auxiliary loads, which include high voltage loads like heating, ventilation, and air conditioning (HVAC), battery cooling or heating, and electric drive cooling. The rest is low voltage loads such as horns, wipers, lamps, and infotainment systems. The energy consumption of high-voltage auxiliary loads is significantly higher than that of low-voltage auxiliary loads and highly depends on the climate. Extreme weather conditions lead to increased energy use to maintain

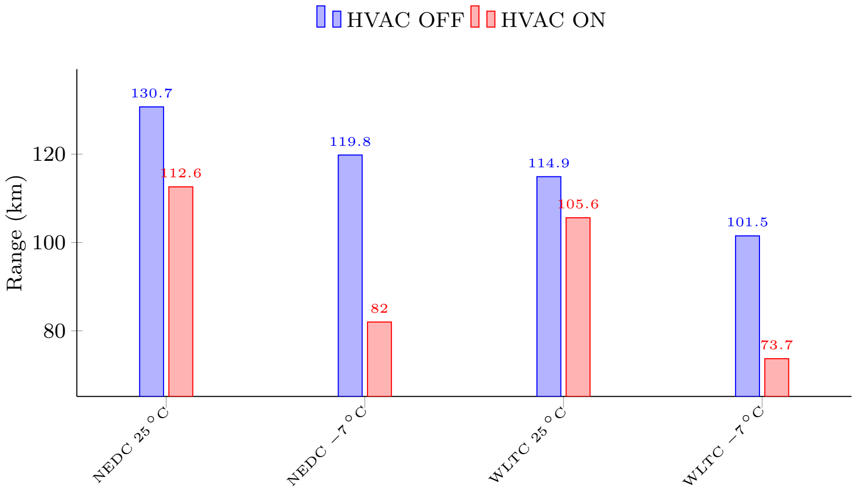


Figure 1.2: Impact of the thermal energy consumption on the range at different ambient temperatures. NEDC - New European Driving Cycle, WLTC - Worldwide Harmonised Light Vehicles Test Cycle.

cabin thermal comfort and required operating conditions.

In a test conducted on a small electric vehicle, the impact of the HVAC system on energy consumption was analyzed at different ambient temperatures [15]. The results showed that high-voltage auxiliary power demand varies significantly with temperature. When the HVAC system was on, the vehicle's range decreased significantly compared to when it was off during the same drive cycle as shown in Fig. 1.2. In particular, in harsh weather conditions, high-voltage auxiliary energy consumption can reduce the electric range by 30-35% [15]. This increased energy consumption is due to cabin and battery heating. Unlike internal combustion engine (ICE) vehicles, which use waste heat from the engine for cabin heating, BEVs lack this heat source. The battery pack in a BEV needs to be heated to maintain optimal performance, as lithium-ion batteries operate best within a specific temperature range. Cold temperatures can significantly reduce battery efficiency, power output, and charging capability, and may even cause permanent damage. Heating the battery ensures efficient energy absorption, faster charging rates, and overall safety, especially in cold weather conditions. The battery pack, weighing around 400 kg in mid-sized passenger vehicles, requires significant energy to heat, which is drawn from the battery itself, thus reducing the vehicle's range.

This challenge has driven innovation in thermal energy management (TEM) systems for BEVs, with the primary objective to meet the thermal demands of the vehicle's passenger cabin, battery, and electric drive (ED). The development of TEM systems has evolved over the years. In the early face of BEV adaptation, the focus was on developing separate component-level systems, such as battery thermal management systems (BTMS), HVAC systems, and motor cooling. However, recent advancements in TEM technology have led to integrated systems in modern vehicles. These systems encompass HVAC and heat pumps, efficiently transferring thermal energy among the passenger cabin, battery, and electric drivetrain. This innovative design utilizes waste heat from the electric drivetrain, achieving higher energy efficiency compared to traditional setups [16]–[19]. Notably, vehicles like the Tesla Model Y, Polestar 2, Volvo XC 40, and Zeekr incorporate TEM systems with HVAC coupled with heat pumps.

Recently a new system offering greater flexibility and potentially higher efficiency compared to existing TEM systems has been introduced, which is expected to be featured in future Zeekr vehicles. We will be referring to such a system as the Flexible Thermal Energy Management (FTEM) system. Unlike traditional HVAC systems with heat pumps, the FTEM system relocates the HVAC unit from the vehicle's interior to the front compartment, which enhances air disposal flexibility. Additionally, it incorporates an extra fan within the HVAC unit, streamlining the refrigerant loop and reducing the overall refrigerant usage. As a result, the FTEM system not only simplifies the refrigerant circuit but also holds the potential for superior energy efficiency. While the FTEM system's architectural design is inherently efficient, further optimization of its operation for specific scenarios could lead to even greater efficiency improvements.

1.2 Research scope

This research aims to study and enhance the efficiency of the FTEM system, focusing on optimizing its performance to reduce energy consumption while maintaining the necessary thermal conditions for the vehicle's components. The primary objectives are outlined as follows:

- Develop a control-oriented model for the FTEM system. This involves developing a simple mathematical model that accurately depicts the behavior of the physical system.

- Develop a real-time implementable controller for the FTEM system. This involves creating a control strategy that can dynamically adjust the system's operations based on real-time data inputs. The controller must be robust and computationally efficient to be feasible for vehicle implementation. By developing a model-based solution, we ensure that the developed methods apply to other BEV thermal systems.

- Achieve a significant reduction in energy consumption of the FTEM system. The target is to reduce energy consumption by 5-15 % through the optimization of critical components such as the compressor, coolant pump, and blower fans.

- Achieve an even greater reduction in energy consumption for autonomous vehicles, aiming for a 7-22 % decrease. This research will explore specific strategies to optimize the thermal management system for autonomous driving conditions, including the use of predictive algorithms that can anticipate and respond to changes in thermal loads and environmental conditions more effectively.

By achieving these objectives, the research aims to contribute significantly to the development of more efficient and sustainable thermal management systems for electric vehicles, supporting the broader transition to zero-emission transportation.

1.3 Literature Review

Extensive studies have focused on energy-saving strategies for HVAC systems in conventional vehicles [20]–[25] and fewer studies carried out specifically for BEV. Optimization methods have shown promising results in reducing energy consumption in BEVs. For instance, Pontryagin's maximum principle was investigated to optimize the BTMS in [26]. Additionally, Model Predictive Control (MPC) has emerged as a promising method for the energy-optimized control of automotive air conditioning systems [27]–[32]. These studies demonstrate that utilizing such optimal control methods can further reduce the energy consumption of TEM systems, enhancing the overall efficiency of BEVs.

In BEVs, the focus has primarily been on component-level energy consumption reduction, such as BTMS [26], [33], [34] and HVAC systems [27], [29], [32], [35]–[38]. This approach is insufficient for modern TEM systems, where BTMS and HVAC are integrated. Some studies have examined integrated systems in Hybrid Electric Vehicles (HEVs)[30], [31], but these do not fully reflect the modern BEV setup, making their approaches less applicable. For example, in [30], [31], the authors considered a simple setup to cool the battery by blowing cold air from the cabin.

Only a few studies have proposed energy reduction for modern TEM systems [39]–[41]. For instance, [39], [40] propose component-level energy reduction for HVAC with heat pumps, focusing on cabin cooling and heating, but lack comprehensive system-level thermal management. Developing a holistic system-level TEM increases control complexity, which can be mitigated by balancing computational simplicity with an accurate system-level depiction of HVAC and heat pump operations. In contrast, a recent study [41] considers the complete TEM system of BEVs, but its computational complexity hinders real-time application.

One approach to solving such complex problems is to implement a distributed method. Distributed solutions are useful in software optimization problems and are necessary in problems with physically distributed architecture. In modern automotive electrical architecture, various Electronic Control Units (ECUs) control different mechanical parts of the vehicle. These ECUs communicate via FlexRay or Controller Area Network (CAN), robust protocols designed for real-time data exchange in automotive environments. A distributed approach can spread the computational load across multiple ECUs, enhancing the system's efficiency and feasibility for real-time applications.

In a distributed approach, each ECU can manage a specific component or set of components, such as the BTMS, cabin HVAC, or power electronics cooling. This distributed method allows for parallel processing, significantly reducing the overall computational burden on any single ECU. Furthermore, advanced communication protocols like FlexRay or CAN ensure synchronized and reliable data exchange between ECUs, enabling coordinated control actions across the vehicle.

Implementing a distributed TEM also opens the possibility for modular upgrades and scalability. As new technologies and components are developed, they can be integrated into the existing system with minimal disruption, simply by adding or updating the relevant ECUs. This flexibility is particularly valuable in the fast-evolving landscape of electric vehicle technology.

In summary, while component-level energy reduction strategies offer some benefits, a holistic system-level approach is essential for maximizing the energy efficiency of BEVs. Addressing the computational challenges of such a system through distributed methods and advanced communication protocols can pave the way for effective real-time TEM implementations, ultimately enhancing vehicle efficiency and extending driving range.

1.4 Major Contributions

This thesis presents significant advancements in the field of TEM systems for BEVs. The following key contributions have been made:

- **A Control-Oriented, System-Level Model:** This thesis developed a comprehensive model for a novel TEM architecture. The same model could be reused for other TEM systems.
- **Distributed Optimal Control Framework:** Presented a distributed optimization framework utilizing MPC with the Alternating Direction Method of Multipliers (ADMM).
- **Energy-Saving Strategies:** Demonstrated the potential of the proposed control model to develop energy-saving strategies for TEM systems. We investigated the effects of uncertainty in predicted passenger data and formulated energy-efficient strategies to address these uncertainties.

1.5 Thesis outline

This thesis is structured as follows: Chapter 1 introduces the research, outlining its motivation and objectives. Chapter 2 provides an overview of the FTEM system and its key components. Chapter 3 focuses on the development and validation of the control-oriented model used in the research. Chapter 4 presents the distributed optimization approach, specifically utilizing the

ADMM. Chapter 5 discusses the implementation of the distributed MPC for the FTEM system. Chapter 6 showcases the simulation results and their analysis. Finally, Chapter 7 concludes the thesis by summarizing the findings and proposing potential directions for future research.

CHAPTER 2

System Overview

This chapter describes the thermal energy management system such as FTEM and its working principles. The FTEM system comprises three main circuits: the battery coolant circuit, the ED coolant circuit, and the refrigerant circuit. Each of these circuits plays a different role in managing the thermal energy within the system.

- The battery coolant circuit, represented by the blue line in Fig. 2.1, consists of a coolant pump, a cooling plate, and a chiller. This circuit primarily functions to regulate the battery's temperature.

- The ED coolant circuit, shown in yellow in Fig. 2.1, includes components such as the motor, a water-cooled condenser (WCC), an ED coolant pump, and a radiator. This circuit absorbs heat generated by the inverter, DC-to-DC converter, and motor. Additionally, it draws heat from the refrigerant within the WCC and dissipates it through the radiator with the aid of a fan.

- The refrigerant circuit, depicted in green in Fig. 2.1, comprises a compressor, a WCC, a condenser, a chiller, an evaporator electronic expansion valve (EEXV), a chiller electronic expansion valve (CEXV), and an evaporator.

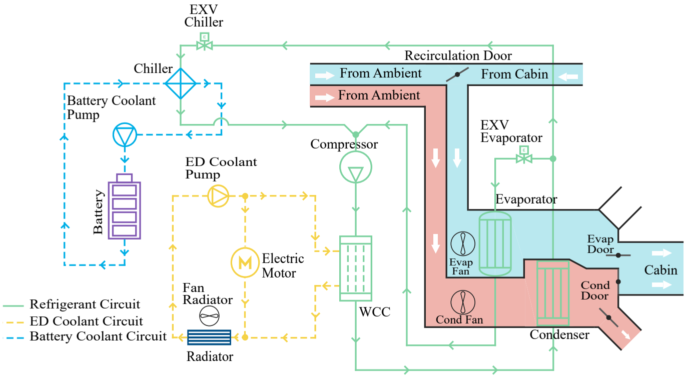


Figure 2.1: The thermal energy management system (FlexiEffi TEM) at Zeekr Technology Europe. The components are abbreviated as follows: EXV for Electronic expansion valve, WCC for Water cooled condenser, Evap for Evaporator, ED for electric drive, and Cond for Condenser.

The FTEM system uses two 4-way valves to exchange heat between the circuits, allowing it to operate in different modes. In the mode considered here, the battery is cooled via a chiller, transferring heat from the battery coolant to the refrigerant. The ED is cooled using a radiator fan, transferring heat from the ED coolant to the ambient air. Depending on the requirements, the system can switch to alternate modes where the battery coolant is cooled at the radiator and the ED coolant at the chiller.

This study focuses on the battery cooling and refrigeration circuits, particularly under hot climate conditions where both the cabin and battery need to be cooled.

2.1 Refrigeration circuit

The HVAC system within the FTEM encompasses three primary functions: heating, ventilation, and air conditioning. The ventilation function maintains a fresh interior atmosphere by expelling stale air and preventing carbon monoxide buildup from the exhaust. It achieves this by drawing in outside air through ducts and a cabin filter, purifying the air before it reaches the passenger compartment. Air conditioning in the FTEM system is accomplished through a vapor compression refrigeration system. This system integrates refrigeration with air distribution and temperature control to cool, heat, clean, and dehumidify the air inside the vehicle.

The principle of heat transfer within the HVAC system relies on moving heat from a low-temperature region to a high-temperature region due to pressure differences, a process known as refrigeration. The refrigerant fluid absorbs heat in its liquid state and becomes gaseous through evaporation. Its boiling point varies with pressure: increasing the pressure raises the boiling point while decreasing it lowers the boiling point. This pressure manipulation allows heat removal from low-temperature regions by adjusting the refrigerant's boiling point.

The refrigeration system operates on a vapor compression cycle, which includes four distinct processes: compression, condensation, expansion, and evaporation, as illustrated in Fig. 2.2. These processes are facilitated by seven major components in the FTEM system: the compressor, WCC, condenser, two expansion valves, evaporator, and chiller. These components are interconnected by tubes, forming a closed system.

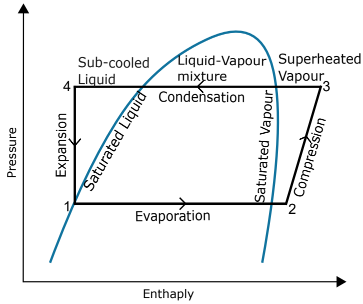
Compressor

The compressor is a mechanical device that circulates the refrigerant gas throughout the system. It compresses the refrigerant in its gaseous state, thereby increasing its temperature and pressure. In Fig. 2.2(a), the 2-3 segment represents the compression process where the refrigerant pressure rises. The TS diagram in Fig. 2.2(b) illustrates the corresponding refrigerant temperature increase during this process. The compressor power is nonlinear and dependent on the speed, compression ratio, and mass flow rate. The power consumed by the compressor can be estimated using the theory in [33], i.e.,

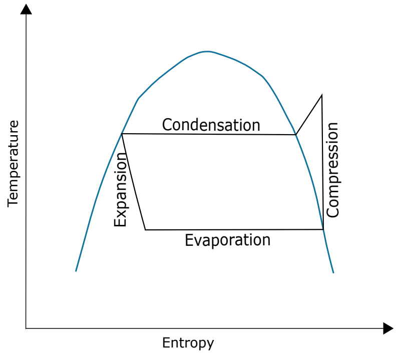
$$P_{\text{comp}} = \frac{\dot{m}_{\text{ref}} \cdot (h_3 - h_2)}{\eta_{\text{isen}}} \tag{2.1}$$

$$\dot{m}_{\text{ref}} = V_{\text{comp}} \cdot \eta_{\text{comp}} \cdot \omega_{\text{comp}} \cdot \rho_{\text{ref}} \cdot 2\pi/60 \tag{2.2}$$

where $\dot{m}_{\text{ref}}$ is refrigerant mass flowrate, V_{comp} is compressor cylinder volume, η_{comp} is the volumetric efficiency of the compressor, ω_{comp} is the compressor speed, ρ_{ref} is the density of the refrigerant, η_{isen} is the isentropic efficiency of



(a) The pressure enthalpy (PH) diagram.



(b) The temperature entropy (TS) diagram.

Figure 2.2: The Pressure-Enthalpy and Temperature-Entropy charts illustrate the thermodynamic properties of a refrigerant, depicting enthalpy and entropy changes throughout the various phases of the vapor compression cycle.

the compressor, h_3 is the refrigerant enthalpy at the exit of the compressor and h_1 is the refrigerant enthalpy at the inlet of the compressor.

To estimate power consumption, manufacturers often provide datasheets that include information on pressure rise, mass flow rate, and power consumption at different speeds based on physical tests. Power consumption can then be estimated by fitting a polynomial curve to the given data, as demonstrated in [30], [42].

In this study, we have considered the following state variables and control input for the compressor component:

$$x_{\text{compressor}} = \begin{bmatrix} \text{Refrigerant pressure at the inlet of the compressor} \\ \text{Refrigerant temperature at the inlet of the compressor} \end{bmatrix}$$

$$u_{\text{compressor}} = \begin{bmatrix} \text{Mass flow rate at the compressor} \end{bmatrix}.$$

Water-Cooled Condenser

The WCC is a heat exchanger where heat is transferred between the refrigerant and the electric drive coolant. During this heat exchange process, the refrigerant releases heat to the coolant. Depending on the amount of heat removed from the refrigerant, it may exit the WCC in either a two-phase state (a mixture of liquid and vapor) or in a vapor phase.

Condenser

The condenser is a heat exchanger where the refrigerant is cooled, causing it to transition from a gas or two-phase state to a liquid. In Fig. 2.2(a), the 3-4 segment represents the condensation process where the refrigerant loses enthalpy to change from vapor to liquid at constant pressure and temperature. This occurs when ambient air is blown across the condenser, filled with hot refrigerant.

Expansion Valve

The FTEM system uses two electronic expansion valves: one for the chiller and one for the evaporator. The function of the expansion valve is to reduce the pressure of the refrigerant, allowing it to evaporate easily in the evaporator and the chiller and reach a superheated state before entering the compressor. An adiabatic process occurs within the expansion valve, meaning the energy content of the refrigerant does not change as it passes through the valve, which is represented by segment 4-1 in Fig 2.2(a). In the model, we consider the mass flow rate through the expansion valves as the control input for this component

$$u_{\text{EXV}} = \begin{bmatrix} \text{Mass flow rate at the evaporator EXV} \\ \text{Mass flow rate at the chiller EXV} \end{bmatrix}.$$

Evaporator

The evaporator is a heat exchanger where heat from the cabin air or ambient air is absorbed into the refrigerant. As the refrigerant moves through the evaporator tube, it absorbs heat, which causes it to evaporate while simultaneously cooling the air. The cooled air is then vented back into the cabin, ensuring a comfortable interior temperature. This evaporation process is represented by the 1-2 segment in Fig. 2.2(a).

Chiller

The chiller operates similarly to the evaporator, where heat is absorbed from either the battery coolant or the ED coolant into the refrigerant, depending on the mode of operation.

Blower fan

The FTEM system features two blowers, one for the evaporator and one for the condenser. Air is blown over these heat exchangers using the blowers, facilitating convective heat transfer between the refrigerant and the air. The power consumption of the condenser blower $P_{\mathrm{cond}_{\mathrm{fan}}}$ and evaporator blower fan $P_{\mathrm{evap}_{\mathrm{fan}}}$, can be estimated similarly to the compressor. In the model, we consider the following control inputs for this component,

$$u_{\mathrm{blower}} = \begin{bmatrix} \text{Air mass flow rate at the condenser blower} \\ \text{Air mass flow rate at the evaporator blower} \end{bmatrix}.$$

2.2 Battery Coolant Circuit

In the mode of operation considered in this study, the battery is actively cooled using a chiller. However, depending on the cooling demand, the battery can also be cooled using a radiator in other operational modes. The battery pack is positioned on a cooling plate, and for this study, it is assumed that the opposite side of the cooling plate is perfectly insulated. The battery coolant pump is responsible for circulating the coolant throughout the circuit, and its power consumption P_{pump} can be estimated using similar methods as those used for the compressor and fan.

In recent years, various BTMS have been developed, including air-based, liquid-based, refrigerant-based, phase change materials, and heat pipes systems [43]. The FTEM system specifically employs a liquid-based BTMS, featuring a cooling plate located beneath the battery pack to facilitate efficient heat transfer. The primary sources of heat within the battery are Joule heating, which arises from internal resistance, and reversible heat effects [44]–[48]. Additionally, a secondary source of heat generation is attributed to the bus bar resistance, as the bus bar connects different cell modules within the battery pack.

Accurately modeling the rate of change in battery temperature involves calculating the heat retained in the battery pack after the coolant has absorbed the heat energy. This is determined by subtracting the heat removed by the coolant from the total heat generated within the battery. Dividing this retained heat by the mass and specific heat capacity of the battery pack provides an estimate of the rate of temperature change.

In the model, we have considered the following as the state and control variable for the battery circuit,

$$\begin{aligned} x_{\text{battery}} &= \begin{bmatrix} \text{State of charge} \\ \text{Battery temperature} \end{bmatrix} \\ u_{\text{battery}} &= \begin{bmatrix} \text{Coolant mass flow rate at the pump} \end{bmatrix} \\ d_{\text{battery}} &= \begin{bmatrix} \text{Traction power demand} \end{bmatrix}. \end{aligned}$$

Here d_{battery} captures the traction power demand over the complete drive cycle, allowing the model to account for real-world driving conditions that affect the battery's thermal behavior.

2.3 Cabin System

Passenger thermal comfort in a vehicle cabin is influenced by several factors, including clothing, journey duration, cabin air temperature, and external climate conditions. While some of these factors are difficult to control, cabin air temperature is crucial in determining comfort, as it directly impacts the heat exchange between the passenger and the surrounding environment [49]. For this analysis, we assume thermal comfort is achieved when the cabin air temperature stabilizes at a specified setpoint temperature.

The cabin air temperature is influenced by various factors, including the heat rejected by the passenger, the heat transferred from interior surfaces, and the heat transferred from interior parts, such as the steering wheel, seats, dashboard, and floor carpet, as depicted in Fig. 2.3. Different materials used for interior surfaces, such as window glass and door panels, can result in different temperatures due to their distinct thermal properties. Similarly, the steering wheel, dashboard, and seats may have different temperatures based on the materials used in their construction. To simplify the problem, a lumped thermal mass is assumed for all interior parts, resulting in all parts being at

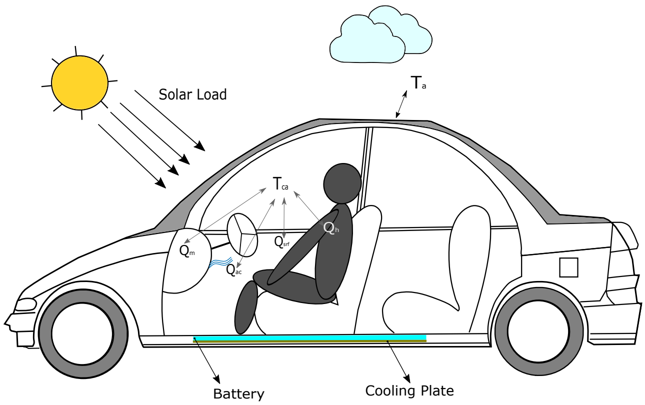


Figure 2.3: Cabin setup with a passenger where T_{ca} is cabin air temperature, T_{a} is the ambient air temperature, Q_{h} is the heat rate rejected by passenger due to metabolism, Q_{srf} is the heat transfer rate of the interior surface of the cabin, Q_{ac} is the air conditioning load and Q_{m} is the heat transfer rate of the interior mass like steering wheel, dashboard and seats.

the same temperature. Additionally, it is assumed that the interior surfaces have the same thermal properties, leading to the same temperature for the interior surface. The state and disturbance variables for the cabin are defined as follows,

$$x_{\text{cabin}} = \begin{bmatrix} \text{Cabin air temperature} \\ \text{Cabin interior surface temperature} \\ \text{Cabin interior mass temperature} \end{bmatrix}$$

$$d_{\text{cabin}} = \begin{bmatrix} \text{Ambient air temperature} \\ \text{Re-circulation door position} \end{bmatrix}.$$

Here, the ambient air temperature and re-circulation door position are considered disturbance variables as they introduce external and operational variability to the system.

2.4 Overview of Model Variables

This section provides a consolidated overview of the state, control, and disturbance variables used in the developed model, summarizing the key parameters that define the FTEM system's dynamics. Below is a detailed summary of these variables.

The state vector $x(t)$ includes the following variables:

$$x(t) = \begin{bmatrix} \text{Refrigerant pressure at the inlet of the compressor} \\ \text{Refrigerant temperature at the inlet of the compressor} \\ \text{Cabin air temperature} \\ \text{Cabin interior surface temperature} \\ \text{Cabin interior mass temperature} \\ \text{State of charge of the battery} \\ \text{Battery temperature} \end{bmatrix}$$

The control vector $u(t)$ consists of the following variables:

$$u(t) = \begin{bmatrix} \text{Mass flow rate at the compressor} \\ \text{Mass flow rate at the evaporator EXV} \\ \text{Mass flow rate at the chiller EXV} \\ \text{Air mass flow rate at the condenser blower} \\ \text{Air mass flow rate at the evaporator blower} \\ \text{Coolant mass flow rate at the pump} \end{bmatrix}$$

The disturbance vector $d(t)$ is defined as:

$$d(t) = \begin{bmatrix} \text{Ambient air temperature} \\ \text{Traction power demand} \\ \text{Occupant information} \end{bmatrix}$$

The nonlinear dynamics governing the system are expressed as:

$$\dot{x}(t) = f\left(x(t), u(t), d(t)\right)$$

A detailed description of the modeling approach, including the cooling systems and heat generation processes, is explained in paper A.

2.5 Model Validation

Model validation is a critical step in ensuring that the developed model can accurately predict system behavior under various operating conditions. This is particularly important for models intended for use in model-based controllers,

Table 2.1: Comparison of Model Results with GT-SUITE

	RMSE [%]
Cabin air temperature	1.54
Battery temperature	0.70
Compressor power	4.51
Coolant pump power	0.03
Evaporator fan power	0.48
Condenser fan power	0.05

where accuracy directly impacts performance and reliability. The validation process aims to establish confidence in the model's predictive capabilities by comparing its outputs with those from a high-fidelity simulation tool and experimental data.

In this study, the developed model is validated against results from GT-SUITE, a high-fidelity simulation tool widely used in automotive engineering. GT-SUITE offers a comprehensive set of features for modeling complex thermal and fluid systems, making it a suitable benchmark for validation. The GT-SUITE results have been previously validated against physical system data, ensuring their accuracy and reliability.

The validation process involves comparing key performance indicators such as temperature profiles, pressure drops, and energy consumption rates between the developed model and GT-SUITE. Statistical methods, including mean absolute error (MAE) and root mean square error (RMSE), are used to quantify the differences and assess the model's accuracy.

The results in Table 2.1 show that the developed model has high accuracy compared to the GT-SUITE results, demonstrating its reliability and robustness. These findings are further discussed and validated in the *Model Validation* section of Paper A.

2.6 Controller Objective and Purpose

The goal of this thesis is to develop an optimal controller designed to minimize the energy consumption of the FTEM system while ensuring that the thermal demands of the vehicle are met. Achieving this goal requires a systematic approach to control, where various energy-consuming components of the system are optimized simultaneously while adhering to essential constraints.

This objective can be formulated mathematically through an objective function. The objective function, denoted as $J(x(t), u(t))$, is a comprehensive expression that aggregates the energy consumption of key components along with penalties for deviating from desired thermal conditions. Specifically, the function is designed to minimize the total energy consumption while maintaining the required thermal comfort in the vehicle cabin and the optimal temperature range for the battery.

The objective function $J(x(t), u(t))$ is structured as follows:

$$\begin{aligned} J(x(t), u(t)) = {} & \text{Compressor Energy Consumption} \\ & + \text{Condenser Fan Energy Consumption} \\ & + \text{Evaporator Fan Energy Consumption} \\ & + \text{Coolant Pump Energy Consumption} \\ & + \text{Cabin Air Temperature Deviation Penalty} \\ & + \text{Battery Temperature Deviation Penalty}. \end{aligned}$$

The optimization process must satisfy several constraints to ensure practical and feasible control actions. These constraints include:

- State Constraints:

  $$x(t) \in [x_{\min}(t), x_{\max}(t)],\ \forall t \in [0, T]. \tag{2.3}$$

  The state constraints ensure that the system's state variables, such as temperatures and energy levels, remain within specified bounds throughout the operation. The time horizon $[0, T]$ represents the entire duration over which the system is constrained, beginning at the initial time $t = 0$ and concluding at the final time $t = T$.

- Control Constraints:

  $$u(t) \in [u_{\min}(t), u_{\max}(t)],\ \forall t \in [0, T]. \tag{2.4}$$

  Control constraints limit the range of control inputs, such as fan and compressor mass flow rate, ensuring that these actions remain within realistic and practical limits.

- General Inequality Constraints:

  $$g\big(x(t), u(t)\big) \leq 0,\ \forall t \in [0, T]. \tag{2.5}$$

These constraints represent additional operational and safety limitations that must be adhered to during the optimization process, such as ensuring the system does not exceed its thermal capacity.

The optimal control problem (OCP) integrates these elements into a cohesive framework that systematically minimizes the cost function, considering the dynamic behavior of the FTEM system and the impact of control decisions over time. The problem is formulated as a nonlinear optimization problem:

$$\min_{u} V(x(T)) + \int_0^T J\left(x(\tau), u(\tau)\right) \mathrm{d}\tau \tag{2.6a}$$

$$\text{s.t. } \dot{x}(t) = f\left(x(t), u(t), d(t)\right), \ \forall t \in [0, T) \tag{2.6b}$$

$$x(t) \in [x_{\min}(t), x_{\max}(t)], \ \forall t \in [0, T] \tag{2.6c}$$

$$u(t) \in [u_{\min}(t), u_{\max}(t)], \ \forall t \in [0, T) \tag{2.6d}$$

$$g(t)\big(x, u\big) \leq 0, \ \forall t \in [0, T) \tag{2.6e}$$

$$x(0) = x_0, \ x(T) \in \mathbb{X}_f. \tag{2.6f}$$

In this formulation, the objective function (2.6a) aims to minimize the total cost, which includes both the terminal cost $V(x(T))$ and the running cost $J(x(\tau), u(\tau))$ integrated over the time horizon $[0, T]$. The system dynamics (2.6b) describe the evolution of the state $x(t)$ over time, governed by the nonlinear function $f(x(t), u(t), d(t))$, with the initial state $x(0) = x_0$ and the final state $x(T) \in \mathbb{X}_f$, which has to reside withing the final set $\mathbb{X}_f$.

CHAPTER 3

Optimal Solution for Distributed System

This chapter provides a brief overview of the theory behind the optimization method used in this thesis.

The OCP presented in equation (2.6) is a centralized optimization problem where a single decision-making entity controls the entire system. This centralized entity optimizes a global objective function while considering all relevant constraints and variables. The OCP is initially formulated in continuous time, requiring the solution of continuous-time differential equations and integration over continuous time horizons. However, directly solving such continuous problems is mathematically challenging and computationally intensive. To address these challenges, the continuous problem is discretized, breaking it down into a finite number of steps. This process allows for the application of numerical optimization techniques, making the problem more manageable for digital computation and real-time control. The discretized problem for (2.6) is formulated as follows:

$$\min_{u_k} \tilde{V}(x_N) + \sum_{k=0}^{N-1} \tilde{J}\left(x_k, u_k\right) \tag{3.1a}$$

$$\text{s.t. } x_{k+1} = \tilde{f}\left(x_k, u_k, d_k\right), ; \forall k \in 0, \ldots, N-1 \tag{3.1b}$$

$$x_k \in [x_{\min}(k), x_{\max}(k)],\ \forall k \in 0, \ldots, N \tag{3.1c}$$

$$u_k \in [u_{\min}(k), u_{\max}(k)],\ \forall k \in 0, \ldots, N-1 \tag{3.1d}$$

$$g_k(x_k, u_k) \leq 0,\ \forall k \in 0, \ldots, N-1 \tag{3.1e}$$

$$x_0 = x(0),\ x_N \in \mathbb{X}_f. \tag{3.1f}$$

where the objective function (3.1a) consists of the terminal cost $\tilde{V}(x_N)$ and the running cost $\tilde{J}\left(x_k, u_k\right)$, The system dynamics are discretized using methods such as the Euler method or the Runge-Kutta method.

The discretized nonlinear optimal control problem described in equation (3.1) can be effectively solved using MPC. MPC is widely used in real-time control applications due to its ability to explicitly handle system constraints, and optimize performance over a receding time horizon. MPC operates by solving an optimization problem at each discrete time step, using the current state of the system as the initial condition.

The primary advantage of a centralized approach is its capacity to optimize the entire system holistically, leading to solutions that are optimal and consistent. However, centralized optimization presents significant challenges, particularly in terms of the complexity of real-time implementation and the substantial computational burden. To overcome these issues, a distributed optimization approach can be adopted, which reduces the computational load and complexity. When implemented correctly, distributed optimization can achieve results comparable to those of centralized optimization.

The distributed optimization approach involves breaking down the large, complex problem into smaller optimization tasks, which are then executed by different ECUs or computational units operating in coordination. Distributed optimization offers several key advantages. First, it enhances scalability; as the system grows in complexity or incorporates new components, the optimization tasks can be further subdivided and distributed across additional ECUs, ensuring that no single processing unit is overburdened. Second, it increases flexibility and modularity, allowing new technologies and components to seamlessly integrate into the existing system with minimal disruption—achieved by simply updating or adding the relevant ECUs. This modularity is particularly valuable in the rapidly evolving field of electric vehicle technology. Additionally, distributed optimization supports parallel processing, where multiple ECUs can perform computations simultaneously, potentially addressing some of the slower convergence issues often associated with distributed methods.

In light of these advantages, this thesis delves into distributed optimization employing the ADMM approach, aiming to develop a controller that could be implemented in real-time.

3.1 Distributed Optimization

Distributed optimization refers to a class of optimization methods where a large problem is divided into smaller subproblems that are solved independently. One effective method within distributed optimization is the ADMM.

ADMM is an optimization algorithm that decomposes a large optimization problem into smaller subproblems, which can be solved independently, either in parallel or sequentially. The algorithm works by iteratively updating the solutions to these subproblems while coordinating them through a combination of local updates and global information sharing. Each iteration involves solving subproblems for each distributed component and then updating dual variables to enforce consensus among the subproblems. This process continues until convergence criteria are met, resulting in an optimized solution that satisfies the constraints and objectives of the original centralized problem [50]. The ADMM algorithm solves problems in the form:

$$\begin{aligned} &\text{minimize } M(p) + N(q) \\ &\text{subject to } Ap + Bq = c \end{aligned} \tag{3.2}$$

with variables $p \in \mathbb{R}^n$ and $q \in \mathbb{R}^m$, where $A \in \mathbb{R}^{p\times n}$, $B \in \mathbb{R}^{p\times m}$, and $c \in \mathbb{R}^p$. The augmented Lagrangian for the problem (3.2) can be written as [50]

$$L_\rho(p, q, \lambda) = M(p) + N(q) + \lambda^\top (Ap + Bq - c) + \frac{\rho}{2}\|Ap + Bq - c\|_2^2. \tag{3.3}$$

where λ represents the dual variable, and $\rho > 0$ is a penalty parameter. The

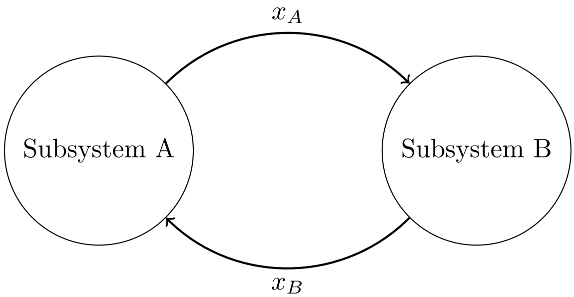


Figure 3.1: Coupled dynamical system with subsystems A and B, each requiring information from the other.

ADMM algorithm consists of the following iterations:

$$p^{k+1} := \arg\min_{p} \; L_\rho(p, q^k, \lambda^k) \tag{3.4}$$

$$q^{k+1} := \arg\min_{q} \; L_\rho(p^{k+1}, q, \lambda^k) \tag{3.5}$$

$$\lambda^{k+1} := \lambda^k + \rho(Ap^{k+1} + Bq^{k+1} - c). \tag{3.6}$$

The algorithm consists of three main steps in each iteration: the p-minimization step (3.4), the q-minimization step (3.5), and the dual variable update (3.6). For each iteration, the primal and dual variables are updated and shared between the steps. The iterations continue until the exit criterion $\|Ap^{k+1} + Bq^{k+1} - c\| <=$ tolerance is satisfied.

Let us now explore how we can utilize the ADMM method for a system where the dynamics are coupled. A distributed, dynamical, coupled, nonlinear system is shown in Fig 3.1, where for didactic reasons we consider only two subsystems. The system dynamics of the centralized system 2.6b can be rewritten as $x(t) = [x_A(t), x_B(t)]^\top$, and the state and control vectors stacked as $f(\cdot) = [f_A(\cdot), f_B(\cdot)]^\top$ and $u(t) = [u_A(t), u_B(t)]^\top$, respectively. The dot $(\cdot)$ notation is used to represent a function that depends on more than 2 variables. Subsystem dynamics are described as:

$$\dot{x}_A(t) = f_A\left(x_A(t), u_A(t), d_A(t), x_B(t)\right) \tag{3.7}$$

$$\dot{x}_B(t) = f_B\left(x_B(t), u_B(t), d_B(t), x_A(t)\right) \tag{3.8}$$

where x_A and u_A are the state variable and control variables of subsystem A and x_B and u_B are the state variable and control variables of subsystem B. These subsystems' dynamics are coupled, as subsystem A requires information from subsystem B to solve its dynamics, and vice versa.

The dynamically coupled OCP for the centralized MPC scheme can be decomposed into individual subsystems using dual decomposition in conjunction with an augmented Lagrangian formulation [51]. This decomposition is facilitated by introducing local copies of the coupling variables and additional coordination variables. These steps allow the augmented Lagrangian to be expressed in a decomposable form, enabling a distributed solution approach based on the ADMM.

The local copies are defined as

$$l(t) = [l_B(t), l_A(t)]^\top \tag{3.9}$$

where l_B represents a vector of the local copy of states x_B for subsystem A and l_A represents a vector of the local copy of states x_A for subsystem B. Using these local copies we can rewrite the subsystem dynamics (3.7) and (3.8) as follows:

$$\dot{x}_A(t) = f_A\left(x_A(t), u_A(t), d_A(t), l_B(t)\right) \tag{3.10}$$

$$\dot{x}_B(t) = f_B\left(x_B(t), u_B(t), d_B(t), l_A(t)\right). \tag{3.11}$$

Since each subsystem only has access to copies of the true variables from the other subsystem, a negotiation process is required to reach a consensus on the common values of these local variables [51]. This negotiation is facilitated by introducing coordination variables c_i for each of the local copies and imposing consistency constraints

$$c_i(t) - x_i(t) = 0, \quad i \in \{A, B\}, \tag{3.12a}$$

$$c_i(t) - l_i(t) = 0. \tag{3.12b}$$

For simplicity, in the following, the dependency of variables on time t and the planning horizon $\tau \in [0, T]$ is omitted from the notation. Furthermore, to streamline the notation, we introduce the stacking notation for the coordination variable $c = [c_A, c_B]^\top$ and for multipliers $\lambda = [\lambda_i]_{i \in A,B}$ with $\lambda_i = [\lambda_{c_i}, \lambda_{l_i}]^\top$. Based on (3.3), we can express the augmented Lagrangian for this decomposition as

$$L_\rho(x,u,l,c,\lambda) = J(x,u) + \sum_{i\in\{A,B\}} \int_0^T \Big(\lambda_{c_i}^\top (c_i - x_i) + \frac{\rho}{2}\|c_i - x_i\|^2 \\ + \lambda_{l_i}^\top (l_i - x_i) + \frac{\rho}{2}\|l_i - x_i\|^2\Big)\, \mathrm{d}\tau \tag{3.13}$$

where the consistency constraints in equations (3.12) are incorporated into the cost function using the dual variables λ_{c_i} and λ_{l_i}, which correspond to the constraints (3.12a) and (3.12b), respectively.

The augmented Lagrangian can be discretized for each subsystem over the time horizon $\tau \in [0,T]$, resulting in the following NLP for subsystem

$$\min_{u_A, l_B} L_\rho\left(x(k), u(k), l(k), c(k), \lambda(k)\right)$$

$$\text{s.t.} \quad x_A(k+1) = \tilde{f}_A\left(x_A(k), u_A(k), d_A(k), l_B(k)\right), \tag{3.14}$$

$$x_A(k) \in [x_{A,\min}(k), x_{A,\max}(k)], \quad \forall k = 0,1,\ldots,N \tag{3.15}$$

$$u_A(k) \in [u_{A,\min}(k), u_{A,\max}(k)], \quad \forall k = 0,1,\ldots,N-1 \tag{3.16}$$

$$g_A\left(x_A(k), u_A(k)\right) \leq 0, \quad \forall k = 0,1,\ldots,N-1 \tag{3.17}$$

$$x_A(0) = x_{A,\text{init}}. \tag{3.18}$$

where k denotes the discretized time steps. Similarly, for subsystem B,

$$\min_{u_B, l_A} L_\rho\left(x(k), u(k), l(k), c(k), \lambda(k)\right)$$

$$\text{s.t.} \quad x_B(k+1) = \tilde{f}_B\left(x_B(k), u_B(k), d_B(k), l_A(k)\right), \tag{3.19}$$

$$x_B(k) \in [x_{B,\min}(k), x_{B,\max}(k)], \quad \forall k = 0,1,\ldots,N \tag{3.20}$$

$$u_B(k) \in [u_{B,\min}(k), u_{B,\max}(k)], \quad \forall k = 0,1,\ldots,N-1 \tag{3.21}$$

$$g_B\left(x_B(k), u_B(k)\right) \leq 0, \quad \forall k = 0,1,\ldots,N-1 \tag{3.22}$$

$$x_B(0) = x_{B,\text{init}}. \tag{3.23}$$

To solve these NLPs efficiently, an ADMM-based iterative solution process is employed, which allows for effective coordination between subsystems while ensuring convergence to the optimal solution. The overall solution process involves solving the NLPs for Subsystems A and B iteratively, as outlined below:

1. **Initialization**: Begin with initial guesses for the control variables u_A and u_B, the local copies l_A and l_B, and the coordination variables c_A and c_B and initialize the dual variables λ_{c_i} and λ_{l_i} for each subsystem.

2. **Local Optimization**: Independently solve the NLP for each subsystem (3.14) and (3.19) to minimize the augmented Lagrangian with respect to the control variables u_A and u_B, as well as the local copies l_A and l_B.

3. **Dual Variable Update**: Update the dual variables λ_{c_i} and λ_{l_i} based on the latest solutions of the local copies and coordination variables.

4. **Coordination Variable Update**: Minimize the augmented Lagrangian with respect to the coordination variable using new values from step 2.

5. **Consensus Check**: Evaluate the consistency constraints to determine whether convergence has been achieved. If the constraints are satisfied within a specified tolerance, the algorithm converges; otherwise, return to the local optimization step.

6. **Iteration**: Repeat the local optimization, dual variable update, and coordination variable update steps until convergence.

A similar approach is utilized for the FTEM system considering the battery coolant circuit and refrigeration circuit as subsystems, where the dynamics are coupled. This is explained in detail in the *Distributed MPC* section of paper B.

CHAPTER 4

Summary of included papers

This chapter provides a summary of the included papers.

4.1 Paper A

Prashant Lokur, Nikolce Murgovski, Mikael Larssonn
Control-oriented Model for Thermal Energy Management of Battery Electric Vehicles
.

This paper presents a control-oriented model for a novel architectural Thermal Energy Management (TEM) system in Battery Electric Vehicles (BEVs) and evaluates energy-saving strategies, including the use of predicted passenger information while meeting all thermal demands of the system. The research addresses the challenge of developing a model suitable for real-time control that balances simplicity with accuracy, enabling efficient control strategies to minimize energy consumption. The model, specifically designed for the TEM system in BEVs, balances computational simplicity and the accuracy required for real-time control. Validation against high-fidelity GT-SUITE simulations shows a root mean square error of 1.54 % for cabin air temperature and 0.70 % for battery temperature. The model is leveraged to explore energy reduction strategies, demonstrating a 5.7 % reduction in energy consumption during a cool-down scenario in high ambient temperatures. The methodology involves developing a control-oriented model based on the governing physical laws of the system, with key simplifications to ensure real-time feasibility. This model captures the dynamics of critical components such as the compressor, fans, pump, battery thermal system, and cabin thermal system. The model is validated against a high-fidelity simulation tool for both accuracy and behavior and is subsequently employed in an optimal control problem to explore various energy-saving strategies, demonstrating its effectiveness for optimization.

4.2 Paper B

Prashant Lokur, Nikolce Murgovski, Kristian Nicklasson
Distributed Model Predictive Controller for Thermal Energy Management System of Battery Electric Vehicles
Published in 2023 62nd IEEE Conference on Decision and Control (CDC), pp. 8363-8368, Jan. 2024.
©2023 IEEE DOI: 10.1109/CDC49753.2023.10384273 .

This paper presents a Distributed Model Predictive Controller (DMPC) for the TEM system in BEVs using the ADMM. The primary challenge addressed is the complexity of real-time TEM control in BEVs, arising from the inherent nonlinearities and high computational demands of centralized control approaches. To overcome this, the paper proposes a DMPC approach that decouples the TEM system into separate battery and HVAC subsystems. By leveraging the ADMM method, the approach enables efficient parallel computations and significantly reduces implementation complexity, making real-time control feasible while enhancing energy efficiency. The DMPC strategy results in a 2.21 % energy savings compared to a conventional rule-based method. The paper also develops a distributed optimization framework tailored to the nonlinear TEM system, demonstrating how to decouple the interdependent dynamics of the battery and HVAC subsystems using local copies of coupled variables. An ADMM-based DMPC algorithm is applied to iteratively solve the optimization problem, with coordination variables ensuring subsystem consistency. The proposed approach is validated through simulations under extreme temperature conditions, showing superior performance and effectiveness compared to centralized MPC and rule-based strategies.

CHAPTER 5

Concluding Remarks and Future Work

This thesis addresses the critical challenge of optimizing TEM systems for BEVs by developing and implementing a distributed control approach for a novel TEM architecture. The research focuses on enhancing energy efficiency while maintaining system performance, particularly under varying environmental conditions. Through the introduction of a control-oriented, system-level model tailored to a state-of-the-art FTEM system, the framework developed in this thesis can be extended to various TEM systems.

The core contribution of this thesis lies in the development of a holistic control-oriented model and the application of distributed optimization techniques, specifically leveraging MPC and ADMM. The distributed approach effectively addresses the computational complexity associated with real-time control in TEM systems. By decoupling the problem into smaller subproblems, the proposed method facilitates parallel processing across multiple ECUs, thereby enhancing scalability and modularity. This approach not only reduces the computational burden but also improves the system's flexibility, allowing for the seamless integration of new technologies and components.

Simulation results validate the effectiveness of the proposed distributed MPC method, demonstrating its ability to achieve substantial energy savings while maintaining thermal comfort within the vehicle. The thesis also explores the potential for further energy optimization through the integration of predictive information, such as vehicle occupancy, which has shown promising results in reducing energy consumption in autonomous vehicle scenarios.

In conclusion, this research contributes to the broader goal of advancing zero-emission transportation by developing a distributed TEM control framework that optimizes energy usage in BEVs. The findings of this thesis pave the way for future research focused on extending the distributed control approach to other FTEM subsystems, exploring hierarchical control structures, and integrating predictive data for even greater energy efficiency. Ultimately, the methodologies developed here offer a significant step forward in making BEVs more energy-efficient, reliable, and attractive to consumers, thereby supporting the transition to a more sustainable transportation ecosystem.

The current research, conducted in the attached papers, considered only hot climatic conditions and a few driving scenarios. A natural extension of this work would be to broaden the framework to accommodate various climatic conditions, ensuring that the controller remains robust and stable across diverse environments. Additionally, exploring alternative methods within distributed optimization could further enhance system performance or reduce implementation complexity for real-time applications. Finally, incorporating more advanced predictive data, such as weather forecasts and climate conditions along travel routes, will enable the controller to better anticipate and adapt to environmental changes, ultimately improving energy efficiency and overall system performance.

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