Resistance Diagnostics in High-Voltage Circuits: From Design to Implementation

A Product Development Approach

Master's thesis in Product Development

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DEPARTMENT OF INDUSTRIAL AND MATERIALS SCIENCE
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2026
www.chalmers.se

Master's thesis 2026

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Master's Thesis 2026
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Cover: Abstract visualization of logic blocks experiencing ranges of heat. Digital art drawn on a tablet.

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2026

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Abstract

In high voltage systems, marginal increases in contact resistance can trigger catastrophic overheating. This thesis aims to apply a product development framework to the challenge of resistance diagnostics within connectors and busbars for heavy-duty automotive applications. The research resulted in a dual-model diagnostic function designed to identify faults before critical temperature thresholds are reached.

The first model utilizes a steady-state thermal equation to establish an expected maximum temperature based on applied current. The second model employs a predictive algorithm that analyzes current and the initial temperature derivative to estimate the actual projected peak temperature. By comparing the theoretical baseline with the predicted real-time peak, the system can detect abnormal resistance in its early stages. This approach enables detection of abnormal resistance in specific components, leading to rapid fault-tracing and enhancing the safety and reliability of heavy-duty electric powertrains.

Keywords: High-voltage system, Resistance diagnostics, Product development.

Acknowledgements

We want to express our gratitude to everyone who has assisted us during this project. The support from both Chalmers University of Technology and Volvo Trucks has made it possible to explore our ideas, provided opportunities and resources to realize them.

Thank you Andrée Ek, Arthur Vidal, Emilio Lobeira and Martin Svensson for being our supervisors at Volvo Trucks. All the time and effort in assisting us is greatly appreciated.

Thank you to our manager Johan Engbom, for having us on the team and giving us an opportunity to complete the project.

Thank you to our professor Andreas Dagman for the academic support of the thesis and for your expertise in product development.

Alice Eriksson, Vera Lundkvist, Gothenburg, May 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ADC Analog-to-Digital Converter
BMS Battery Management System
CAN Controller Area Network
CCS Combined Charging System
CMRR Common-Mode Rejection Ratio
CR Component Resposible
DC Direct Current
ECU Electronic Control Unit
EVs Electric Vehicles
HDVs Heavy-Duty Vehicles
HVIL High-Voltage Interlock System
HVS High-Voltage System
MCS Megawatt Charging System

Nomenclature

Below is the nomenclature of variables that have been used throughout this thesis.

Variables

R	Resistance
V	Voltage
I	Current
Q_a	Rate of accumulated heat
Q_g	Rate of heat gained
Q_l	Rate of heat loss
T	Temperature
m	Mass
c	Specific heat capacity
t	Time
h	Heat transfer coefficient
A	Surface Area
P	Power
C_{th}	Thermal capacitance
T_{ss}	Steady state temperature
τ	Thermal time constant
R_{th}	Thermal resistance
C_{eff}	Effective thermal capacitance

Contents

List of Figures

List of Tables

1
Introduction

This chapter introduces the challenge of diagnosing abnormal resistance in High-Voltage System (HVS) in Heavy-Duty Vehicles (HDVs) and motivates the relevance of solving this problem in the context of increasing electrification. The technical challenges of HVS are described, definitions of research objectives, and the established scope of the case study are presented along with the limitations.

1.1 Background

The transition toward electrification of HDVs introduces new challenges in the design and monitoring of HVS. As power levels and system complexity increase, diagnostic functions and monitoring become increasingly important to ensure safe and reliable operation. In particular, high power levels in these systems make them sensitive to small deviations in electrical resistance, since even minor increases can result in considerable heat generation.

Electrical resistance plays a critical role in HVS, as it determines the level of power losses, which are dissipated as heat within the system. The generated heat is directly related to both the electrical resistance and the current flowing through the component. As a result, components exposed to higher power levels or increased resistance experience higher temperature rises and reduced efficiency. This makes conductive components sensitive to both manufacturing variations and operational conditions.

Resistance-related faults can be difficult to localize, as the resulting heat may spread throughout the system. Depending on the system's complexity, multiple components may contribute to the observed temperature increase, making it challenging to identify the root cause. Additionally, sensors dedicated to directly detecting resistance in HVS are typically not available. The reason is that it requires having a sensor for each component, junction and bus bar, and such sensors require great precision for the task.

This project explores the possibilities of implementing a diagnostic function for detecting abnormal resistance in a high-voltage circuit, where no resistance sensor is currently available. Hence, providing new opportunities to implement diagnostic functions where this was not previously possible. This could warrant a revised approach to introducing diagnostic functions in HVS, in a later stage of the design process or even after a product has entered the market.

1.2 Aim

The project aims to investigate the feasibility of developing a diagnostic function for detecting resistance-related faults in HVS of HDVs, using a product development approach.

1.3 Limitations

The diagnostic function developed in this thesis is for detecting resistance-related faults, implemented and evaluated in the case study, mentioned in Section 1.4.5. Other types of faults, such as sensor faults, software faults in the system, and battery pack-level faults, are outside the scope of this project. Furthermore, the applicability of the proposed solution is not validated on other vehicle platforms or high-voltage systems other than the HVS in the case study.

As the aim is to develop a fault diagnostic, focus will not be on how to solve said fault, but rather on how to identify it. Due to the expected scope of the project, the implementation is limited to a conceptual design, and testing is restricted to demonstrating a proof of concept. Therefore, long-term real-world vehicle testing will not be performed, as it cannot be justified at this stage.

These limitations should be considered when interpreting the results, as they may affect the maturity of the implementation and the applicability of the results to other systems or system configurations.

1.3.1 Research Questions

The following research questions guide this thesis:

- **RQ1:** What are possible resistance diagnostic methods for HVS?
- **RQ2:** What are the criteria for the HVS and its components to implement a method for diagnosing resistance?
- **RQ3:** What types of diagnostic solutions are feasible to implement in a HVS, to address resistance abnormalities?
- **RQ4:** Which solution meets the requirements and is most suitable for implementation in the system?
- **RQ5:** What is the effect of applying a product development process to the development of a software-based diagnostic function?

1.4 Case Description

To provide a concrete basis for the design and development of a diagnostic function for abnormal resistance in high voltage circuits, the HVS of an electric truck was studied at Volvo Trucks. Hence, the implementation is developed following the constraints of the case HVS and in accordance with Volvo's diagnostic framework. The system, its constrains and the diagnostic framework are described in this section. Since the solution is intended to be applicable to other systems, the criteria for implementation and the process is presented in Section 4.1.2.

1.4.1 Volvo Trucks

The case study is conducted at Volvo Trucks, a global manufacturer of heavy-duty trucks powered by combustion engines and electric drivetrains. In recent years, the company has invested and focused on the development of electric trucks, as electrified heavy-duty vehicles represent an emerging technology area that continues to evolve (Volvo Group, 2026).

1.4.2 Diagnostics

Diagnostic functions for road vehicles follow standards and regulations, which are presented in Section 2.2.2. The implementation and design is however, up to each company and developer. For this case, Volvo's diagnostic framework and process were used.

The diagnostic functions are implemented as code in the software of an ECU. The ECU handles communication with sensors and other controllers through CAN and these signals can be inputs for the diagnostic function. Depending on the purpose of the diagnostic function, it can trigger messages to inform the vehicle operator, workshop personnel, or record data for the engineer.

1.4.3 High-Voltage System

The HVS of a heavy-duty vehicle consists of several key components, including energy storage units (batteries), charging systems, power distribution units, converters, junction boxes and electric motors. Electrical power is distributed throughout the system via cables, which are connected with bus bars, pins and contactors. These connection points are particularly exposed to outside factors, meaning they are susceptible to experiencing increased contact resistance.

1.4.4 Problem Areas

There are a few challenges with implementing a diagnostic function that detects abnormal resistance in HVS. Ideally, the resistance in connection points should be small to reduce thermal losses during power transfer. With a high current, even minimal resistance differences can have a large thermal impact and can risk the components to overheat and take damage. However, these resistance variations can be difficult to detect with sensors and even with calculations.

The heat generated by an abnormal resistance tends to spread quickly throughout a casing of a component, since it is usually sealed and well insulated. This poses challenges when trying to pinpoint where in the circuit the fault is coming from, especially in a component that contains many connections and parts that can generate heat, both from internal and external sources.

1.4.5 Case Study Component

The component that is studied in the case is a bus bar responsible of carrying the entire load of the energy transfer during charging, located in the charging inlet of the truck, see Figure 1.1 for a simplified overview. The charging process starts by connecting the truck's charging inlet to a charging station. There are mainly two types of charging stations, combined charging system Combined Charging System (CCS) and Megawatt Charging System (MCS). The difference between the two cases are the power capacity where CCS can deliver between 50-400 kW of Direct Current (DC) power and MCS delivers more power with the potential of reaching 1 MW of DC charging in the future (Engdahl, 2025). As a result, the bus bar is one of the components that experiences the most amount of electrical current in the system and is therefore particularly sensitive to variations in electrical resistance.

During charging sessions longer than 40 minutes, the bus bar will reach its maximum temperature. The system operates under two different power levels, but exclusively with DC. The bus bar is housed within an insulated enclosure together with other components, which influences its thermal behavior and limits heat dissipation.

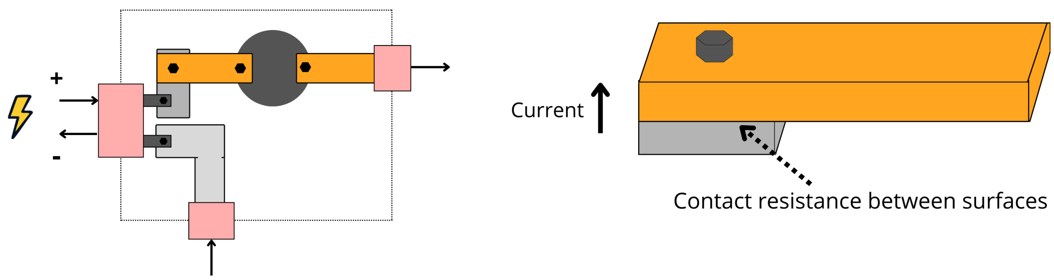


Figure 1.1: Example of system receiving power with bus bars and junctions, and close up of a bus bar.

1.5 Outline of the Thesis

The thesis was conducted with a product development approach, investigating the methods of resistance diagnostics, designing a solution and implementing it a high-voltage system of a heavy-duty vehicle. The work includes the investigation of resistance diagnostic methods, high-voltage systems and product development methodologies, described in the theory chapter. The methodology then describes the development process and methods used throughout the project. Following this, the result chapter presents the developed concepts during the iterative design process and lastly the final implementation of the diagnostic function.

Finally, the thesis concludes with a discussion of the results, the research questions, and considerations related to ethics and sustainability, before presenting the conclusion and suggestions for future work.

2

Theory

The theoretical topics in the thesis are general background regarding HVS, resistance and fault diagnostics and product development tools and processes. The introductory section presents the product development framework applied throughout the development process. The possible failure modes of an HVS along with standards and regulations are the basis for the diagnostic concepts later presented. These include the types of readable effects resistance has on a system, in addition to different applicable diagnostic types.

2.1 Product Development Process

A product development process aims to in a structured way design, plan and manufacture products with the expected performance of the user. It is useful in terms of product planning, coordination, management, quality assurance and future improvements. The framework is presented in *Product Design and Development* by Ulrich and Eppinger, 2012 and is the basis of the information in this section.

2.1.1 Identifying Customer Needs

When starting the development process, a key factor is identifying customer needs. In this context, "the customer" encompasses a broad spectrum of stakeholders, including end-users, regulatory bodies and industry standards as well as the current market. Several qualitative methods can be employed to identify these requirements. Semi-structured interviews with users and subject-matter experts provide insights into user behavior and perceived value. For a diagnostic application, the needs include standards of the software, safety requirements of the HVS, as well as developers and service providers interacting with the function.

2.1.2 Requirement Specification

A requirement specification acts as a technical translation of customer needs into verifiable and testable requirements. To ensure each customer need is accounted for the relationship between qualitative needs and quantitative metrics is mapped where each requirement is linked to a need. Recognizing that not all requirements carry equal weight, a prioritization framework can be applied. This makes a difference between requirements (must-haves) and desires (good-to-haves).

2.1.3 Concept Generation

The aim of the concept generation is to provide several viable options, guided by the established customer needs and requirements, moreover it ensures a wide range of alternatives are explored. This reduces the risk of superior concepts emerging late in the development process when it is no longer economically or logistically feasible to pivot. The concept generation method is divided into five steps by Ulrich and Eppinger (2012), visualized in Figure 2.1

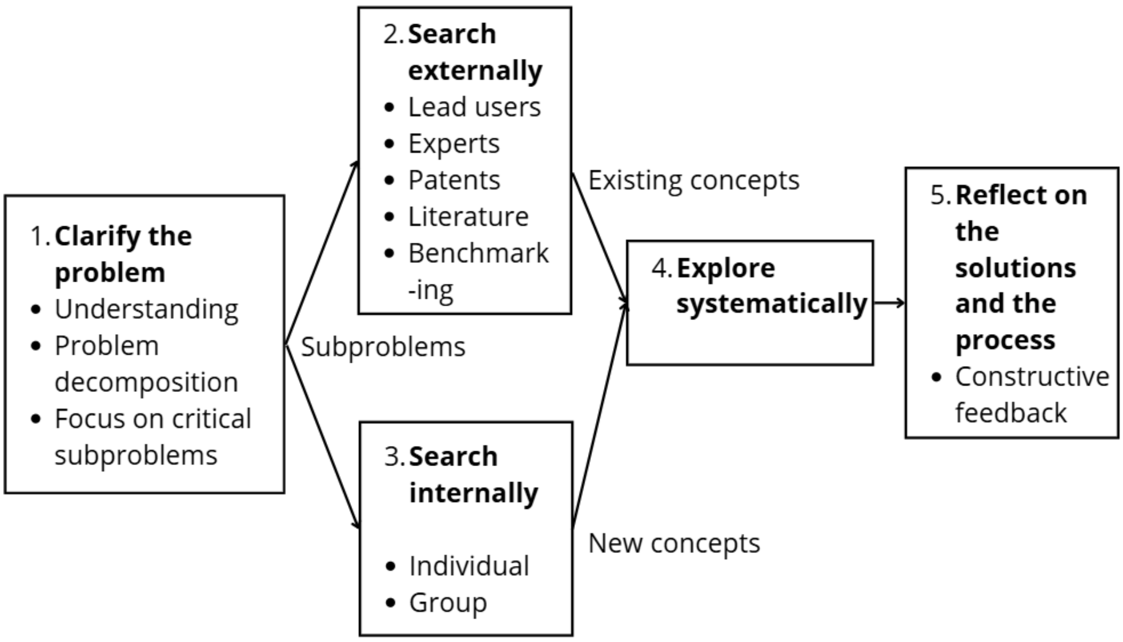


Figure 2.1: Five steps of concept generation method.

As illustrated, the process begins with understanding the problem and dividing it into several sub-functions, describing what functions work together to deliver the total functionality of the product. By searching externally for existing solutions and internally for new ideas and contributions, a range of concepts are discovered. The process will generate solutions that are not feasible, and step 4 of the method aims to systematically explore solutions in order to focus resources and time on the most promising concepts. The last step is to evaluate if, during the process, avenues have not been explored, or focus has been skewed on certain problems, and establish whether the development can continue to concept screening and selection.

2.1.4 Concept Screening and Selection

To methodically evaluate concepts and their performance a screening and scoring process is applied. Initially, to ensure only solutions where all requirements are reached, an elimination matrix can be used. A small-scale example is presented in Table 2.1 where hard requirements (not wishes) from the requirement specification are evaluated against each concept. A perfect score fulfilling every requirement is necessary to qualify for further review. In the example, this would be Concept 1 and Concept 4.

Table 2.1: Elimination Matrix Example

Requirement \ Concept	Concept 1	Concept 2	Concept 3	Concept 4	Concept 5
Requirement 1	Yes	No	Yes	Yes	No
Requirement 2	Yes	No	Yes	Yes	No
Requirement 3	Yes	No	No	Yes	No
Requirement 4	Yes	No	Yes	Yes	No
Requirement 5	Yes	Yes	Yes	Yes	Yes
Requirement 6	Yes	Yes	Yes	Yes	Yes
Requirement 7	Yes	Yes	Yes	Yes	Yes

The next step in the process is to compare the concepts against each other in order to further evaluate and discard less promising ones. One method to do this is using a Pugh matrix. This makes one concept a reference point, and each of the other concepts are compared on each requirement. This establishes how the concepts perform next to the reference and gives them a score based on the results. In the example in Table 2.2, the reference is Concept 3, and based on the score, Concept 4 is eliminated, and 3 and 2 are combined, based on conclusions likely reached through discussions.

Table 2.2: Pugh Matrix Example

Requirement \ Concept	Concept 1	Concept 2	Concept 3 (Reference)	Concept 4	Concept 5
Requirement 1	0	-	0	-	0
Requirement 2	0	-	0	0	+
Requirement 3	0	0	0	+	+
Requirement 4	0	0	0	-	-
Requirement 5	0	0	0	-	0
Requirement 6	+	+	0	-	0
Requirement 7	+	-	0	0	0
Sum +'s	2	1	0	1	2
Sum 0's	5	3	7	2	4
Sum -'s	0	3	0	4	1
Net score	2	-2	0	-3	1
Rank	1	4	3	5	2
Continue?	Yes	Combined	Combined	No	Yes

To further the selection process concept scoring is introduced. This aims to narrow down the solutions more, and review any new combinations or ideas from earlier processes. The idea is similar to the Pugh Matrix, here however the requirements are weighted, based on importance. This ensures the high-performing metrics of the concepts are taken into consideration, while less important characteristics are not as significant in the results, as seen in Table 2.3

Table 2.3: Kesselring Matrix Example

		Concepts					
		Concept 1 (Ref)		Concept 2/3		Concept 5	
Requirements	**Weight**	**Rating**	**Score**	**Rating**	**Score**	**Rating**	**Score**
Requirement 1	5%	3	0,15	3	0,15	4	0,20
Requirement 2	10%	3	0,30	4	0,40	3	0,30
Requirement 3	15%	2	0,30	3	0,45	5	0,75
Requirement 4	25%	3	0,75	3	0,75	3	0,75
Requirement 5	15%	2	0,30	5	0,75	3	0,45
Requirement 6	20%	3	0,60	3	0,60	2	0,40
Total Score		**2,40**		**3,10**		**2,85**	
Rank		3		1		2	
Continue?		No		Develop		No	

The objective of this stage is to isolate one or two concepts for further optimization and testing. The final selection depends on both time constraints and the inherent uncertainty of each design. If significant technical unknowns remain, it is often beneficial to retain more concepts to gather additional data, rather than premature elimination. The tools presented are, in most cases, applied when there are several possible solutions. In the case of diagnostics concept generation requires some development and testing in order to perceive performance and screen accurately. This process can result in fewer concepts generated depending on the time frame. In those cases, screening methods can still be applied, however the tools focusing on sub-functions can be more applicable and decision-making matrices may play a smaller role, with a limited amount of viable concepts.

2.2 High-Voltage Systems

The HVS of an electric vehicle consists of all components that require or enable high voltage to be used in the system. These are components that connect the batteries, which are the high-voltage power source, to the electric motors to propel the vehicle forward. In addition to the batteries and electric motors, the HVS typically includes DC–AC and DC–DC converters. It also includes on-board chargers and auxiliary devices such as cabin heaters and climate compressors (Gupta et al., 2021; Mueller & Heinrich, 2013).

HVS in Electric Vehicles (EVs) contain several safety functions which are primarily driven by standards and regulations, addressed in more detail in Section 2.2.2. To shield from arcing and access to dangerous voltage, EVs are generally equipped with a High-Voltage Interlock System (HVIL). It consists of a separate closed low-voltage circuit and is designed to be mate-last and break-first to identify connector mating, disabling the high voltage accordingly (Schauer et al., 2024).

To ensure that the system is protected against electrical faults, a function known as insulation resistance monitoring continuously measures the resistance between the HVS and the chassis ground. If a drop in resistance is detected, a diagnostic fault is set and, depending on the severity, appropriate actions are taken (EV Engineering Online, 2026).

Another safety function in the HVS is the Battery Management System (BMS). The BMS is responsible for monitoring the batteries and protecting them by ensuring reliable and safe operation of the cells. This system also calculates the remaining charge of the batteries (state of charge, or SoC) and the degradation (state of health, or SoH) (Hauser & Kuhn, 2015).

Galvanic isolation is a fundamental safety function in HVS to separate the high-voltage and low-voltage power grids. This is necessary as the battery monitoring and the vehicle's low-voltage electronics have different ground potentials. This implementation also ensures safe operation of communication and power interfaces (Hauser & Kuhn, 2015).

2.2.1 Failure Modes Relevant to Resistance Diagnostics

Over time, insulation materials can degrade due to moisture, mechanical stress, or aging of the material. The severity of this isolation loss is less critical to the operation of the system, while it could be a potential hazard to operators coming into contact with the system (Lechner, 2023).

In addition to degradation of insulation, other components, such as bus bars and electrical interconnections, can experience resistance-related faults. These components are sensitive to environmental factors, including moisture and corrosion, which may lead to surface degradation and increased contact resistance (Lu et al., 1999). Since electrical isolation is not necessarily affected by this type of degradation, such faults may remain undetected by isolation resistance monitoring functions alone (EV Engineering Online, 2026).

2.2.2 Standards and Regulations

Diagnostics for electric vehicles are required to meet certain standards. Some are particularly relevant from a high-voltage diagnostics perspective:

- **ISO 26262-10:2018 Road vehicles — Functional safety — Part 10: Guideline on ISO 26262** provides guidelines and examples of implementing functional safety concepts defined in ISO 26262. This standard describes the ability of diagnostic functions (International Organization for Standardization, 2018). It indirectly enforces the use of a battery management system, addressed in Section 2.2.
- **ISO 6469-3:2021 Electrically propelled road vehicles — Safety specifications — Part 3: Protection safety** addresses protection against electric

shock. These electrical safety standards establish requirements that must be met when developing HVS for EVs, including the implementation of diagnostic functions such as periodic isolation resistance monitoring (International Organization for Standardization, 2021). The standard indirectly enforces galvanic isolation and the HVIL, mentioned in Section 2.2.

- **UN Regulation No. 100: Uniform provisions concerning the approval of vehicles with regard to specific requirements for the electric power train** defines isolation resistance as a verifiable requirement to approve a vehicle for the market (United Nations Economic Commission for Europe, 2022).
- **ISO 6469-1:2019 Electrically propelled road vehicles — Safety specifications Part 1: Rechargeable energy storage system (RESS)** handles the requirements for the battery system. This includes what type of monitoring and actions are required to ensure a safe battery system (International Organization for Standardization, 2019). The standard enforces the use of a battery management system, addressed in Section 2.2.
- **SAE J1939-73: Application layer — Diagnostics** is the standard used to structure diagnostic messages over the CAN bus for HDVs (Society of Automotive Engineers, 2022).

2.3 Resistance and Fault Diagnostics

To investigate and research solutions for resistance abnormalities in specific components in the HVS, other applications were explored. In the area in which the thesis is based, there are not many diagnostic functions publicly available, and the research in this area is not yet extensive. Some common fault diagnostics that are well researched and currently very relevant are within battery health. There are strong motivations for resistance diagnostics connecting to lithium-ion battery packs, and they may be applicable to the project.

Other applications where resistance abnormalities are a concern are cables for power distribution. Being able to monitor and diagnose where faults impact the performance is of priority, and there may be solutions that can be modified to the HVS.

The contact resistance of conductive components may increase due to environmental factors or surface degradation. Between copper and aluminum conductors, even nano-scale oxidation layers, from $0.4\,nm$, can cause a significant increase in resistance. For example, the resistance increases from close to $0\,\Omega$ to around $100\,\mu\Omega$ at $0.5\,nm$, and $500\,\mu\Omega$ at $0.6\,nm$ (Oberst et al., 2019).

2.3.1 Resistance Measurement

The way resistance is traditionally measured is with a multimeter, or ohmmeter. This functions by applying a known current to the component being measured, and reading the resulting voltage and uses a two-wire measurement method. Ohm's law will then give a calculated resistance (Edwards, 1971):

$$R = \frac{\Delta V}{I} \tag{2.1}$$

For this to be a viable method there needs to be controlled voltage and current through the component, which means it is rarely used while in use, rather a manual quality assurance of components. It is most suitable and accurate for large resistances, as the resistance of wires and connection have an impact, skewing results of low resistances (Zhang, 2023).

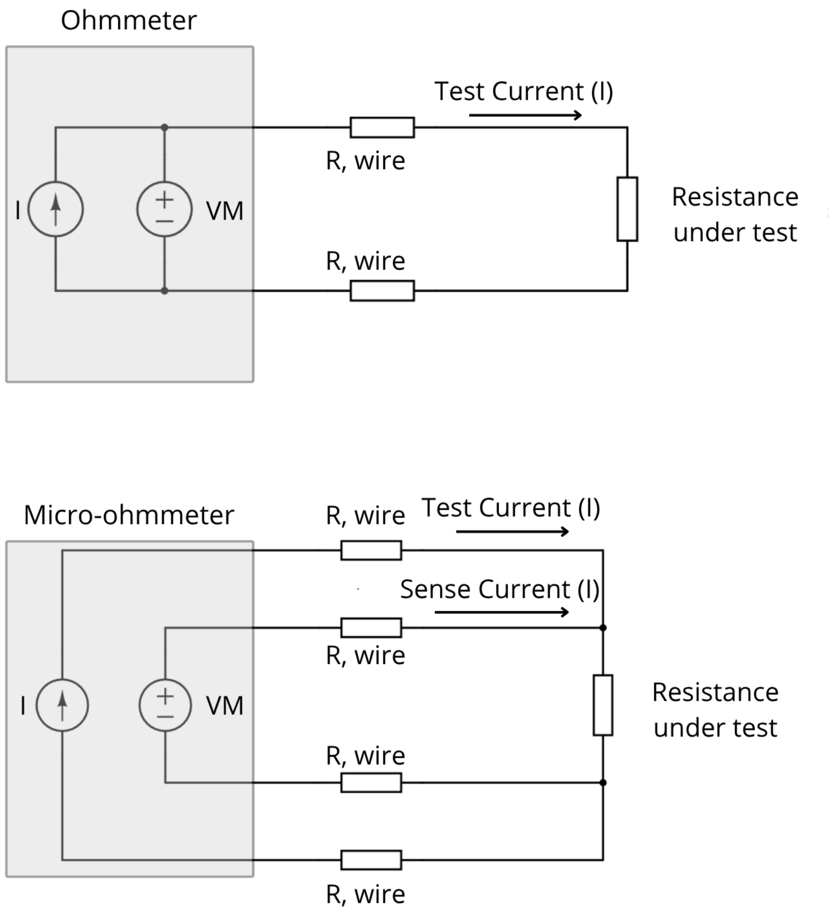


Figure 2.2: Schematics of a 2-wire and 4-wire measurement circuit, based on Zhang, 2023

In the cases where very small resistances need to be detected, a common method is a four-wire resistance measurement. Typically, this ohmmeter has a range that spans down to $1\,\mu\Omega$ (AEMC Instruments, 2026) or less in some cases using this method. As shown in Figure 2.2, the difference between two-wire and four-wire measuring is that the latter has separate lead wires to the resistance under test. This means the voltage circuit is disconnected from the high current and therefore measures the true voltage (Zhang, 2023) over the resistance with very little current passing through. This leads to very little voltage drop from the wires and an ability to give accurate readings of resistance.

2.3.2 Voltage Drop Measurement

One way to estimate the resistance of a component is by measuring the voltage drop across it and applying Ohm's law 2.1 as the voltage is directly proportional to resistance. A voltage deviation beyond a predefined threshold may therefore indicate abnormal resistance. This method requires precise differential voltage measurements across the specific component. Considering a component experiencing early degradation, the increase in resistance may be minimal, at around $40\,\mu\Omega$. With a current of $500\,A$, this corresponds to a voltage drop of approximately $20\,mV$, as given by Ohm's law:

$$\Delta V = R \cdot I = (40 \times 10^{-6}) \cdot 500 = 20\,mV \tag{2.2}$$

In practice, a differential measurement configuration would be used locally to measure the voltage drop across the component. It is important that the measurements are close to the component so as not to include voltage contributions for multiple components (Scott Wayne, 2021).

The large contrast between the differential signal of interest and the supplied voltage, with one in the millivolt range and the other up to 800 V, introduces measurement challenges. It is technically feasible to use two voltage sensors and calculate the difference between them. However, when large voltages are measured independently and subtracted to obtain millivolt differences, the result may be dominated by sensor offsets and quantization errors. The accuracy is also affected by the resolution of the component that converts the signal from an analog voltage signal into a digital value, namely the Analog-to-Digital Converter (ADC) (Wagdy, 1987). For instance, a 12-bit ADC with a $5\,V$ reference provides a resolution of approximately $1.22\,mV$ per least significant bit. Consequently, a differential voltage smaller than the least significant bit cannot be resolved without additional amplification. The voltage resolution of an N-bit ADC is given by:

$$\Delta = \frac{V_{ref}}{2^N} = \frac{5}{2^{12}} = 1.22\,mV \tag{2.3}$$

Instead of calculating the difference between the two measured voltage signals, a differential amplifier can be introduced to improve measurement accuracy. This component amplifies the voltage difference between two input nodes while suppressing voltage components that are common to both inputs. The ability to suppress these common signals relative to the desired signal is characterized by the Common-Mode Rejection Ratio (CMRR) (Geramirad et al., 2020). Since the common-mode voltage in high-voltage electric vehicle systems may be several hundred volts, while the desired differential signal remains in the millivolt range, a high CMRR is essential to prevent unwanted signals from corrupting the measurement.

2.3.3 Temperature Measurement

Although the resistance variations caused by degradation may be small, they can result in a significant rise in temperature, detectable by temperature sensors. This thermal impact of resistance can be modeled by the heat balance equation presented by Herrejón-Escutia1 et al. (2017) and :

$$Q_a = Q_g - Q_l \tag{2.4}$$

Where Q_a represents the accumulated heat, defined by the thermal mass and rate of temperature change:

$$Q_a = mc\Delta T \tag{2.5}$$

The heat generated, Q_g, is governed by Joule's Law, while the thermal loss to the environment, Q_l, is governed by Newton's Law of Cooling:

$$Q_g = I^2 \cdot R \cdot t \tag{2.6}$$

$$Q_l = hA(T_s - T_a) \cdot t \tag{2.7}$$

To calculate ΔT for each time step, the following equation is then used, based on the model:

$$\Delta T = \frac{1}{mc}(Q_g - Q_l) \tag{2.8}$$

In these expressions, m is the mass, c is the specific heat capacity, I is the current, R is the resistance, h is the heat transfer coefficient, A is the surface area and T_s and T_a represent the surface and ambient temperatures, respectively. The end result is a value for temperature based on the time passed.

Thermal energy, Q, and power, P, are related as seen in Equation 2.9, where P represents the rate of heat transfer, while Q denotes the total energy transfer over time. The derivative of Q is therefore P:

$$Q = Pt \Rightarrow P = \frac{dQ}{dt} \tag{2.9}$$

Using this expression in the formulas above, the following equations are given: Heat transfer rate:

$$P_a = P_g - P_l \tag{2.10}$$

$$P_a = mc\frac{dT}{dt} \tag{2.11}$$

Generated heat rate:

$$P_g = I^2 R \tag{2.12}$$

Heat loss rate:

$$P_l = hA(T_s - T_a) \tag{2.13}$$

The temperature evolution is obtained by integrating the net heat transfer rate divided by thermal capacitance C_{th} where $C_{th} = mc$:

$$T(t) = \int_0^t \frac{P_g - P_l}{C_{th}} dt \tag{2.14}$$

To demonstrate the effect of these resistance variations, a $0.200\,kg$ copper bar with a heat capacity of $385\,J/(kg \cdot K)$ is considered. The contact resistance is assumed to be $1\,\mu\Omega$ for a non-oxidized copper bar, $40\,\mu\Omega$ for early degradation and $500\,\mu\Omega$ for an oxidized bar. The current is set to $500A$ and the temperature increase over time is presented in Figure 2.3.

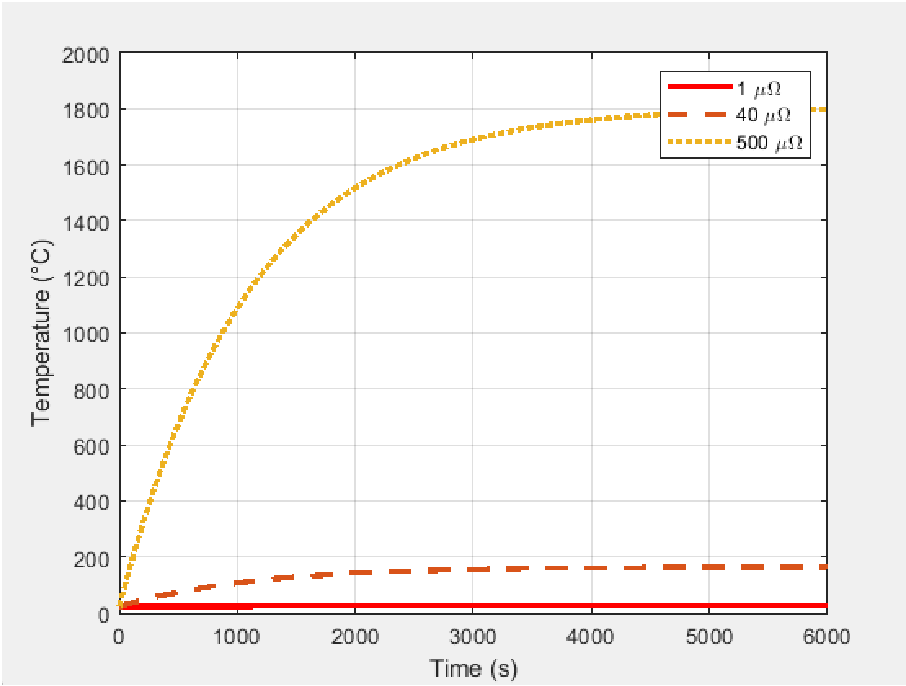


Figure 2.3: Temperature increase over time with varying resistance

Relatively small changes in resistance can result in large increases in temperature, making this a viable method for detecting small resistance variations. However, a challenging aspect of tracking the temperature is that the thermal inertia leads to a delayed reaction to resistance changes (Bergman & Levine, 2019). The component could therefore already be damaged before the temperature indicates the fault. Another important consideration is that the temperature of the component does not increase indefinitely, as heat is continuously dissipated to the surrounding environment. According to Newton's law of cooling, heat transfer to the surroundings increases with the temperature difference between the component and the surroundings. Eventually, the component reaches a steady-state temperature when the generated heat equals the dissipated heat (Bergman & Levine, 2019). Combining Joule's law with Newton's law of cooling gives the following expression for the steady-state temperature:

$$T_{ss} = T_{amb} + \frac{I^2 R}{hA} \tag{2.15}$$

The transient temperature response can furthermore be estimated using a first-order thermal model, where the temperature approaches the steady-state value exponentially with a rate determined by the thermal time constant (Bergman & Levine, 2019). The thermal time constant is given by thermal resistance R_{th} times thermal capacitance C_{th}:

$$\tau = R_{th} \cdot C_{th} \tag{2.16}$$

$$T(t) = T_{ss} + (T_0 - T_{ss})e^{-t/\tau} \tag{2.17}$$

2.3.4 Threshold-based Diagnostics

Threshold-based fault detection is a diagnostic method based on comparing a signal with a predefined limit value. A fault is indicated if the monitored value exceeds (or falls below) the limit, triggering a fault condition (Stoustrup et al., 2003). Since the method relies on measured signals, its performance is closely related to measurement accuracy.

In the context of resistance diagnostics in HVS, threshold-based detection can be implemented in several ways. The monitored parameter can, for example, be derived from measuring resistance, voltage or temperature.

2.3.5 Model-Based Diagnostics

Model-based methods are based on represented physical systems that model an expected result. When real-life values and measurements from sensors deviate from expectations, there is an indication that there is a fault (Movahedi et al., 2026). In applications regarding battery health there are several methods being researched. One instance is a model-based application using inputs from bus bar voltage, input current and cell temperature. The research by Movahedi et al. (2026) investigated the use of an IMM- Interactive Multiple Model when investigating short circuit resistance. It works by running two scenarios, on with a healthy working battery, and the other is a failure scenario where one cell is short-circuited. The algorithm uses real-time data from temperature sensors and total voltage. During the course of a fault, it will calculate the probability of a short based on the deviation of the expected value compared to the measurement. When a short is diagnosed, the system switches to an algorithm where, based on the incoming data, the resistance is estimated based on the model.

2.3.6 Data-Driven Diagnostics

Data-driven approaches to fault detection and diagnostics are currently being researched rigorously because of their broad applications. By identifying fault patterns that are subtle and easy to overlook when using traditional methods, machine learning and deep learning can be powerful tools (Polat et al., 2026). An advantage to relying on AI in diagnostics is that it requires no models or algorithms based on physics or thermal equations. The method is completely driven by pattern recognition, which only requires data to be trained on, using simulations and real data.

2.3.7 Combined Approaches

Combined, or hybrid approaches as they are often called use data-driven methods with applications from model-based methods as well. This typically entails physical constraints and limitations coupled with a data-driven approach which in early research shows more precise diagnostics than each method separately (Polat et al., 2026). This has applications in Lithium-Ion batteries as well, where a method by Jin et al., 2024 uses a hybrid approach to diagnose battery internal resistance, and distinguish these from a sensor fault. The method uses an observer that is based on the expected behavior from the battery (model-based), which monitors any changes that would indicate a fault. It does not collect any data until this fault is connected and therefore does not occupy much of the communication in the computer. When a fault is detected, a data-driven approach is applied to compare the real-time data to the typical behavior of a normal internal resistance. The differences are slight and develop over time, making them challenging to diagnose with conventional diagnostic methods.

3

Methodology

To establish a robust foundation for the project, research and understanding of the issue was conducted as a first step. Identifying the current problems and the applications required, as well as how a solution can be implemented on a larger scale, was key. Technical benchmarking of internal and external landscapes was conducted and semi-structured interviews with subject matter experts. This alongside the product development framework that was applied throughout the project and final implementation will be presented in the Methodology chapter.

3.1 Overview of Approach

The project was carried out with planned steps to reach the goal of implementing the solution and to evaluate its applicability in other HVS. The process is visualized in Figure 3.1 and the steps are as follows:

1. Gain an understanding of the system and its components in the Case Study. This included any history of previous issues and current diagnostic solutions.
2. Research HVS and perform a literature review. The research provided the theory behind the possible solutions.
3. Select a specific component for which to develop a diagnostic function based on the data available, the relevance for a diagnostic function and the potential to perform meaningful tests.
4. Generate a list of requirements for the solution based on the pre-study.
5. Generate concepts.
6. Screen concepts.
7. Design-build-test cycle.
8. Implementation.
9. Evaluation.

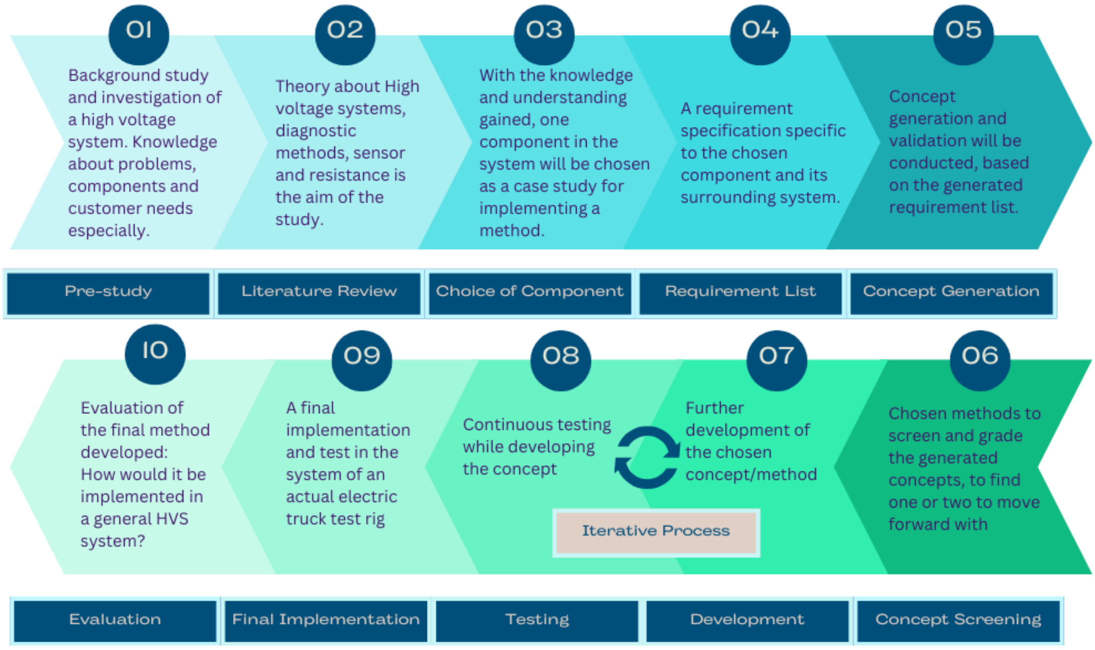


Figure 3.1: Work flow of project from literature and initial to final implementation and evaluation.

3.2 Interviews

Two rounds of interviews were conducted with different aims. The interviews were generally specific to the system where the case study was conducted, with some questions more generally applicable. Initially, an interview was conducted to gain an understanding of previous problems of a related nature as well as insight into the HVS as a whole. The experts present were software developers working within diagnostics, during a group interview to encourage discussion. The following questions were asked, along with relevant follow-up questions:

- How does the diagnostic system work?
- Can you explain the drive train?
- What are some components that are part of the HVS?
- Are there previous examples of resistance-related faults? If so, how were they detected?
- What are the challenges of detecting abnormal resistance?

Understanding the HVS where the case study was based required knowledge of the system architecture and component functions. This information was gathered through interviews with experts responsible for the respective sub-components of the HVS, titled Component Resposible (CR). The aim was to define the scope of the project, specifically by identifying the systemic areas most suitable for a representative case study and pilot implementation. Six CRs were interviewed, each responsible for a separate component. Some examples of components are ways to handle charging, junctions and power conversions. All interviews followed a similar structure, with the following questions:

- What does the sub-components do?
- What other components are affected/affect this component?
- What internal components (such as bus bars, junctions connectors etc.) are likely to cause abnormal resistance?
- What sensors are available close to said components?
- Is the data available for diagnostics? Or does it have its own confidential diagnostics from a third party?
- Are there testing possibilities for the component, either on the hardware itself or by simulation?

3.3 Software and Tools

The diagnostic function was developed and implemented in Simulink using Targetlink for code-oriented modeling. The simulation data was acquired through recorded energy transfer logs, which were processed and analyzed in CANalyzer and ATI Vision. This development approach aligns with Volvo's diagnostic framework, which has guided the selection of software and tools used in this project to allow the finished function to be implemented and tested during the case study.

The functionality of the software is described in general terms to provide an understanding of the design process, as well as to outline a development framework that can be applied when implementing similar diagnostic functions using alternative software environments.

3.3.1 Matlab Simulink

All concepts were generated using Matlab Simulink, a modeling and simulation environment. The software is used to visually represent equations and allows for the study of dynamic systems. The models are later translated into C-code using Targetlink, which produces efficient code optimized for limited memory typical for an on-board ECU. Simulink was the main tool in the development of concepts as well as testing and verification.

During the development phase, the input data consisted of recorded measurement data organized as matrices, collected from sensors during energy transfer sessions. This enabled testing with realistic simulated input signals. The model outputs were monitored and analyzed to evaluate the performance of the model.

In the final implementation, the simulated inputs are replaced with real sensor signals, and the outputs are used either as fault indicators or for data storage for monitoring.

3.3.2 CANalyzer

A significant portion of the final testing and verification phase was based on data collection and analysis. To translate real logs collected from on-board testing into viewable data, CANalyzer was used. CANalyzer is a tool for analyzing communication on the Controller Area Network (CAN). It gives the possibility to log and observe signals in the CAN bus and not just the end message through diagnostic functions. The raw data collected is vital for developing functions based on those same signals.

3.3.3 Vector Vision

The extracted signals from CANalyzer were analyzed in ATI Vision to assess their quality and determine if they are suitable for Simulink model testing. Vision provides an interface for viewing selected signals as graphs, where parameters such as range and resolution can be adjusted.

The data sets deemed suitable for simulation were converted into Matlab matrix files to use as input for the Simulink models.

3.3.4 Software Testing

To test the function in the intended software, the model was integrated to run in the software of the electric truck. Bench testing was done to ensure the model ran in the expected way. This entails uploading the software to an Electronic Control Unit (ECU) and simulating charging.

The final test was conducted in an electric truck, where the software was uploaded onto the onboard ECU and the vehicle was charged at high power to confirm that the model would run as expected.

3.4 Product Development Process

As presented in Section 2.1, the product development process is a series of tools and frameworks to aid the decision-making process. This process was applied throughout the project using applicable tools when needed.

3.4.1 Requirement Specification

The pre-study and knowledge gained through the conducted interviews served as a base for the requirement specification, as well as complementary information gathered in the literature study. The criteria were sorted into Desires and Requirements, indicating if they are a mandatory requisite or a target goal. The criteria were ranked based on importance, guided by the interviews, and justifications were added to connect the requirements to stakeholders. The initial specification was used and changed throughout the development process when further development and research indicated the feasibility and necessity of each requirement.

3.4.2 Concept Generation

The concept generation process was executed in three stages. The initial generation was done using a brainstorming session and was reliant on the literature study. At that stage, the focus was on what type of measurement the solution could rely on. Sub-functions and corresponding solutions were investigated as well, however the following decision-making was regarding the type of measurement.

The second stage of concept generation focused on sub-functions, based on the chosen measurement method. The process relied on verification and some implementation and testing as opposed to general brainstorming. This methodology was implemented as the solutions were not screenable as conceptual ideas. Some implementation and testing were needed, using the provided data for simulations, in order to judge performance and possible issues.

The last concept generation stage focused on developing and implementing the final, complete diagnostic model. This included using the results from the second concept generation and screening. Additionally, the model was prepared for implementation in the intended system by refining it to conform to the system structure.

3.4.3 Concept Screening

The screening process was made in two stages. The requirements from the specification guided the choice of measurement method using an elimination matrix to ensure only viable solutions were further evaluated. This resulted in only one solution fulfilling all criteria. The measurement method chosen was then the basis for further development and solutions.

The second stage of screening involved evaluating several concepts representing sub-functions, where each concept was rated both with respect to its intended functionality and its suitability for implementation within the final diagnostic model. The concepts that were rated high and had potential to be included in the final concept were kept to the last concept generation stage.

3.4.4 Testing and Verification

Testing was conducted throughout the development process of the sub-solutions, as well as on the final concept to evaluate performance and enhance calibration. The models were in the majority of cases tested on real data logs from situations where the function would be applied. The aim was to judge accuracy as well as applicability and function. The early tests were simulations in Simulink to enable easy debugging and changes. Later tests used a test rig, and a final test was conducted on a truck in the system. The test rig consisted of an ECU as the only physical component with simulated signals. This test was conducted to see if the integration into the software had been successful. The last test, in the truck, was also performed to confirm successful software integration with the added complexity of the physical components in the truck, such as real sensors and signals.

3.4.5 Implementation

When the development of the final concept was concluded in Simulink, the model was prepared for implementation and conversion into Targetlink. All functions and tools used were investigated to ensure compatibility with the system, and naming standards as well as model structure were adjusted in order to adhere to regulations from working within the software. The necessary outputs and inputs were adjusted for the function to be functional in the system and speed was considered for implementation in the on-board computer.

4
Results

This chapter presents the results of the stages of development. The initial interviews serve as a basis for the project, guiding the problem formulation and requirement specification. The results from the product development process follow, with several iterations of concept generation, concept screening and testing. The final concept and further implementation are then presented, including the final steps to integrate the diagnostic function into the software of the case study.

4.1 Interviews

The results of the interviews conducted in this chapter are organized by themes and area of use. The main contents and takeaways are initially about the problem, and challenges of resistance diagnostics, generally as well as case-specific. Using this knowledge, interviews to gather information about components within the HVS were conducted. The aim was to gain an understanding of what hardware, measuring capabilities and problems were present in each of the components in the system in order to choose a basis of the case study. The interview process illuminated further what would be needed for an implementation and guided what prerequisites a component needed for an implementation of the solution.

4.1.1 Problem Formulation

The interviews conducted with software developers specializing in diagnostics led to a broader understanding of the problem at hand. The possible obstacles to diagnosing the fault were also examined, and why the fault needs a specific solution beyond the implementations currently in place. A list of obstacles is presented below.

Proximity to other heat-generating components An obstacle to fault tracing in heat-generating components and joints is that the origin of the heat can be difficult to trace. The exceeding temperature may have many different causes.

Complex system with many components Similarly, a known fault of high resistance can be difficult to trace simply because of the number of joints in close proximity to each other.

Unanticipated failures In places where there has been no history of temperature increase or resistance faults there may be a gap in diagnostic function as well as measurement capabilities. Newly arisen issues are therefore difficult to pinpoint and diagnose.

Insulated casing The casing of a component is typically insulated, making the heat generated from specific joints inside spread more easily and limiting heat dissipation.

4.1.2 Component Research

Through interviews with experts specializing in different components in the HVS, the CR, several significant findings emerged. The result was a list of requirements for a component or area in the system in which to base the case study. The interviews were also a basis for investigating where in the system these requirements were fulfilled. The following became the criteria:

Temp. sensors close to connection It is common to have temperature sensors close to components that are likely to generate heat. It is important for the solution that there is a way to detect temperature in proximity to the connector that is to be monitored.

Several temp. sensors inside the component Some methods could require several measurements of temperature in order to establish a source of the increase of heat in the area.

Data from sensors available The components in a propulsion system are not always developed and manufactured in-house. This may mean that the component has its own diagnostic functions, as well as classified data from sensors. This makes it unsuitable for developing diagnostic functions.

Voltage and current sensors For the ability to compare the amount of electrical energy through the connector with the heat generated.

Simulations possible The component is available to simulate in local software.

Physical testing possible The component has a possibility to test the actual fault of a connector with high resistance in a physical lab with high resistance.

4.2 Requirement Specification

The pre-study resulted in the requirement specification in Table 4.1. The result was requirements and desires summarized by five categories: Cost, general diagnostic requirement, complexity, capabilities and constraint.

Table 4.1: Requirement Specification

Criteria	Description	Importance	Justification
	1. Cost		
D1: Zero BOM impact	The existing components are sufficient for full implementation	4	Hardware architects
D2: Developmental cost	The concept can be completed within the hours of the thesis	2	System developer/ R&D management
	2. General diagnostic requirement		
R1: Zero false positive rate	The system shall only trigger in response to valid events.	5	End user
R2: Triggers one fault	The function triggers exactly one fault, the one being the correct diagnostic function for the cause of the issue.	5	Repair service provider
R3: Useful info from diagnostic	The diagnostic function produces clear messages to end users.	5	Repair service provider
R4: Reliable result	Function that can handle inconsistencies in sensors, for example.	5	High safety in practice
	3. Complexity		
D1: Minimize data collection	Data collection strains the memory capacity and is a privacy concern.	2	Legal department/ System architects
D2: Implementable in existing system	The method can be implemented in trucks already on the market.	4	After market value
	4. Capabilities		
R1: Resistance specific	Can specify that the fault is specifically caused by high resistance.	5	System developer/ Repair service provider
D1: Pinpoints specific faulty component	Can pinpoint what specific component is faulty.	4	Repair service provider
R2: Pinpoints specific faulty area	Can pinpoint in what area the fault originates from.	5	Repair service provider
D2: Generally applicable in HVS	Implementation that can be used in other systems if the necessary prerequisites are present	3	R&D management
D3: Detects aging over time	Be able to detect aging of a component	1	Maintenance management
	5. Constraint		
R1: Geometrically feasible in the subsystem	The function is physically implementable in its designated area, considering the spatial constraints.	5	R&D management/ Hardware developer

4.3 Concept Generation 1

The first iteration of concept generation focused on what indications, or measurements, could be used for a possible solution. The process resulted in five main solutions, presented in Figure 4.1.

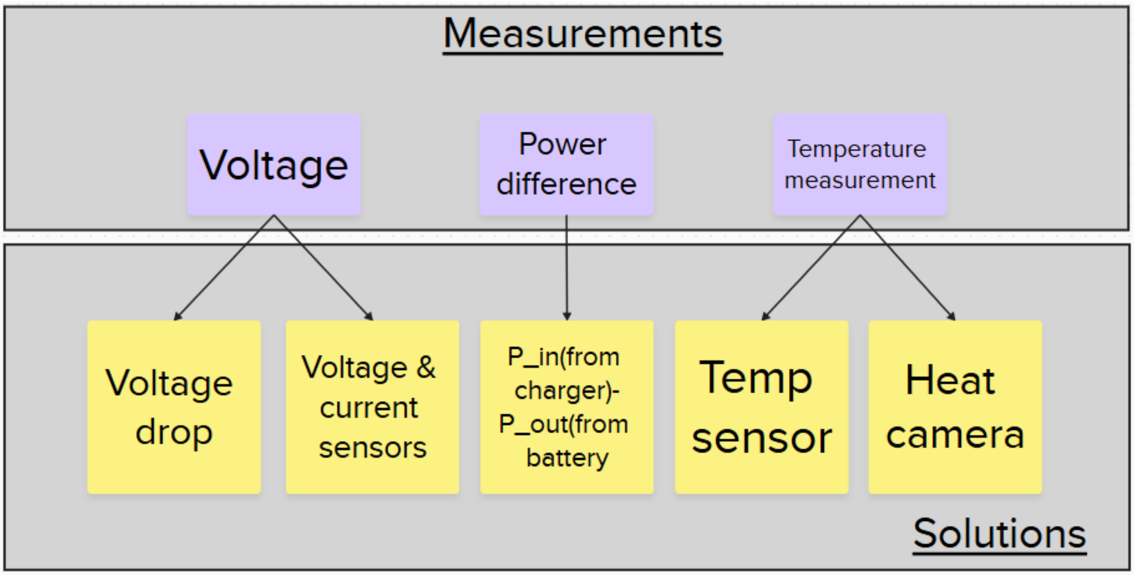


Figure 4.1: Concept Generation Process

The five solutions for the measuring method can be summarized as:

Power difference By measuring known values of the power from the charger and the power that reaches the battery, the loss due to resistance can be calculated:

$$P_{in} - P_{out}$$

Temperature measurement By measuring the effect of high resistance from temperature sensors there are several possible implementations.

Voltage and Current Sensors Using Ohm's law, a known voltage and current can be used to calculate the resistance of any given point.

Voltage drop The voltage drops across a component directly proportional to its resistance, assuming constant current.

Several added voltage sensors The sensors need to be in close proximity to the studied component for the measurement to be accurate. If the system is equipped with voltage sensors throughout the circuit, an estimation of resistance can be done in several areas to compare and use the difference to pinpoint the fault.

Heat camera For tests Thermal imaging can be used in test scenarios to map the typical behavior of the system. This data can serve as a baseline for comparison within a diagnostic function.

Inside component To accurately identify the source of the temperature increase, thermal imaging can be performed continuously during operation. This could point to which component is behaving abnormally.

Additional functionalities and solutions were theorized for later development steps and are presented in Figure 4.2, where possible functions and their corresponding solutions are organized into two different categories: Failures and Precision.

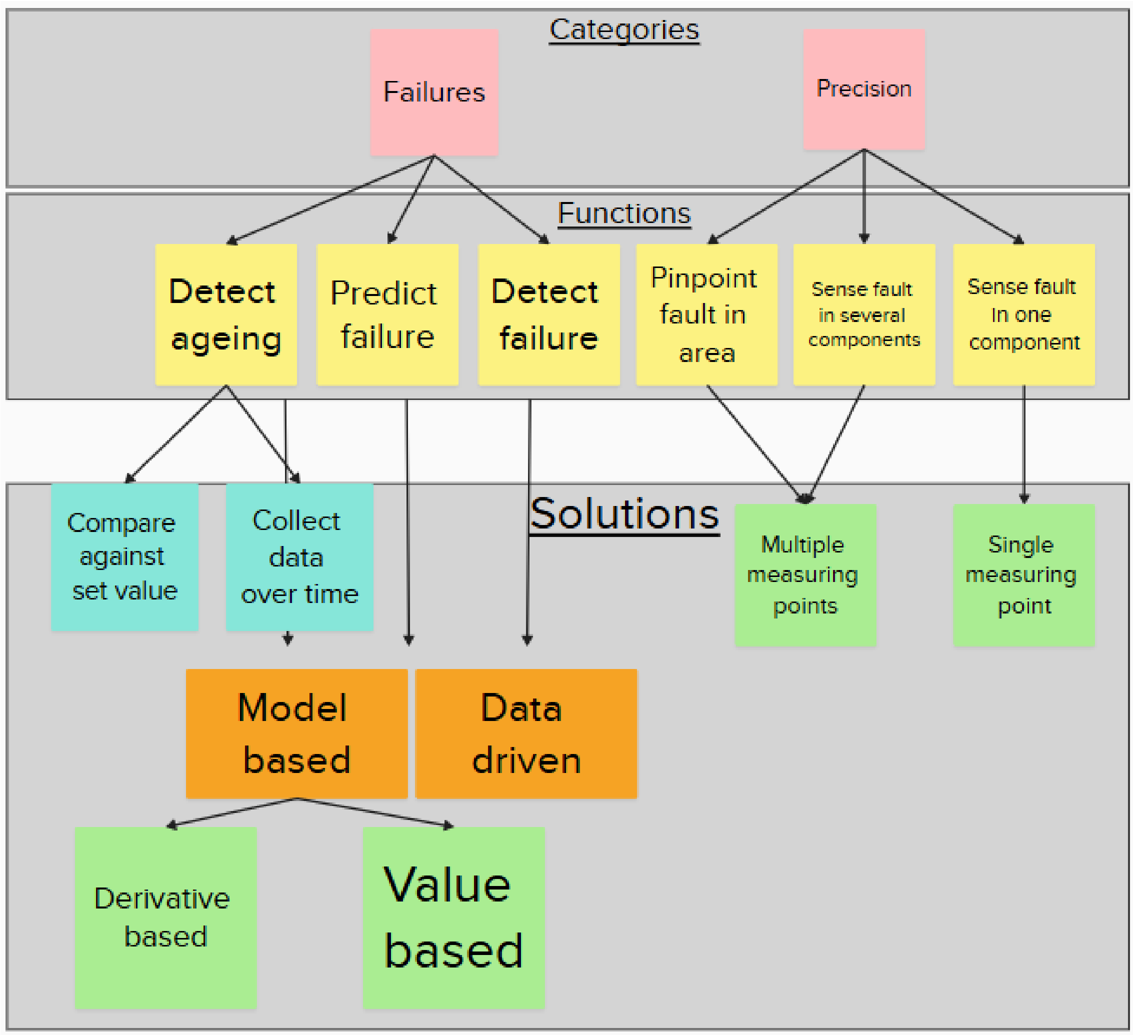


Figure 4.2: Additional Functionalities - development process

The failure category is as follows:

Detect Aging Wear over time can be diagnosed, and a component's failure can be caught before it happens.

Detect Failure The fault is diagnosed as it happens, with no predictive capabilities.

Predict Failure The potential fault of a component can be caught before the full effect has happened with a predictive solution.

All of the potential failures have the ability to be solved with both model-based approaches and data-driven solutions, as presented in Section 2.3. A model-based method is possible to base both on a value, as well as a derivative. For example, how much the temperature has increased vs how rapidly it is increasing.

The aging detection could be solved by data collection over time, as well as using a set value to compare against for a less complex solution.

The category Precision includes the following functions:

Pinpoint fault in area This means pointing to an area with a fault, but not in which specific component.

Detect fault in one component The solution is able to point to one specific component that is faulty

Detect fault in several components The solution can monitor and detect faults in several components.

To detect a fault in one component, one single measuring point would be enough, but to detect an area or several components, the solution needs to contain multiple points of measurement.

4.4 Concept Screening and Scoring 1

To select the most fitting approach of measurement, all methods were evaluated in relation to the requirement specification and compared with each other. The three main methods based on the case study were resistance measurement, voltage drop measurement and temperature measurement. In addition to the case study, the concept generation yielded two more methods: heat camera and power difference. The screening was done using an elimination matrix.

Table 4.2: Elimination Matrix - Method of Resistance Estimation

Method / **Requirement**	Heat Camera	Power Difference	Resistance Measurement	Temperature Measurement	Voltage Drop
Zero false positive rate	Yes	No	Yes	Yes	No
Triggers one fault	Yes	No	Yes	Yes	No
Useful info from diagnostic	-	-	-	-	-
Reliable result	Yes	No	No	Yes	No
Resistance specific	Yes	Yes	Yes	Yes	Yes
Pinpoints specific area	Yes	No	Yes	Yes	Yes
Geometrically feasible	No	Yes	Yes	Yes	Yes

Based on the elimination matrix, the temperature measurement is the only method that satisfies all the requirements. Evaluating the other methods reveals drawbacks:

The heat camera was eliminated because of the geometric constraints of achieving a complete view of the system internally. Both the power difference and the voltage drop methods were excluded as they handle large-scale measurements affected by numerous components, affecting the accuracy and precision required for a reliable result. Finally, the resistance measurement was eliminated due to the necessity of integrating additional voltage and current sensors in specific areas of the system.

4.5 Concept Generation 2

In the second concept generation, several models were generated with temperature as the basis of the diagnostic. At this stage, the models are subfunctions that can be implemented in a diagnostic function in different ways, and can in some cases be combined. Figure 4.3 is an example of the placement of the temperature sensors used.

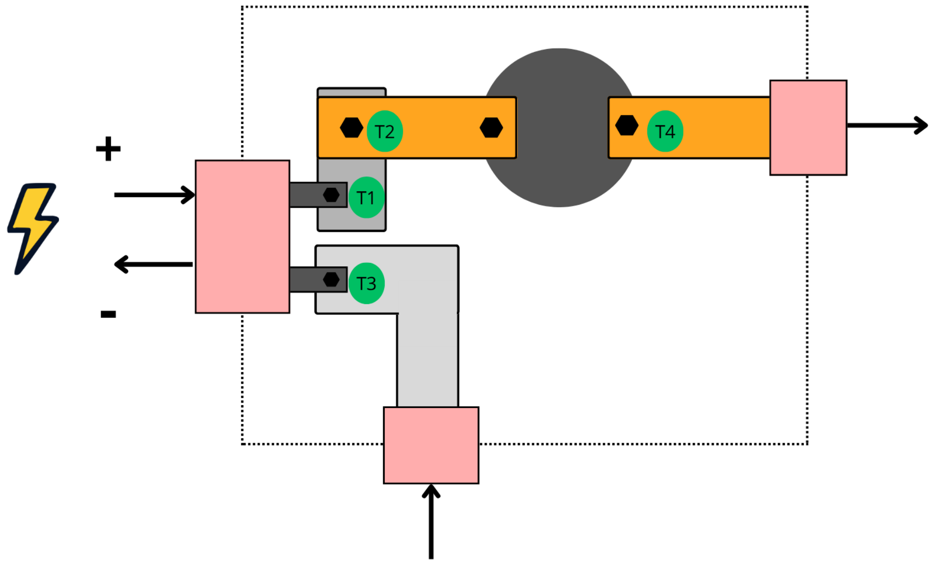


Figure 4.3: Temperature placement in component, example

4.5.1 Concept 1

The first concept uses a model-based approach, using a thermal model to model an expected temperature based on the current as input. The model is adapted to each temperature measurement, needing manual calibration to 'fit' the temperature increase of each specific placement. The result is the expected temperature increase over time based on the current, using Equation 2.8 from Chapter 2:

$$\Delta T = \frac{1}{mc}(Q_g - Q_l) \tag{4.1}$$

The equation is translated into a discrete Simulink model, with the power in based on the current representing the heat gain, and the cooling constant representing heat loss. The 1/mc constant is multiplied by this result and integrated.

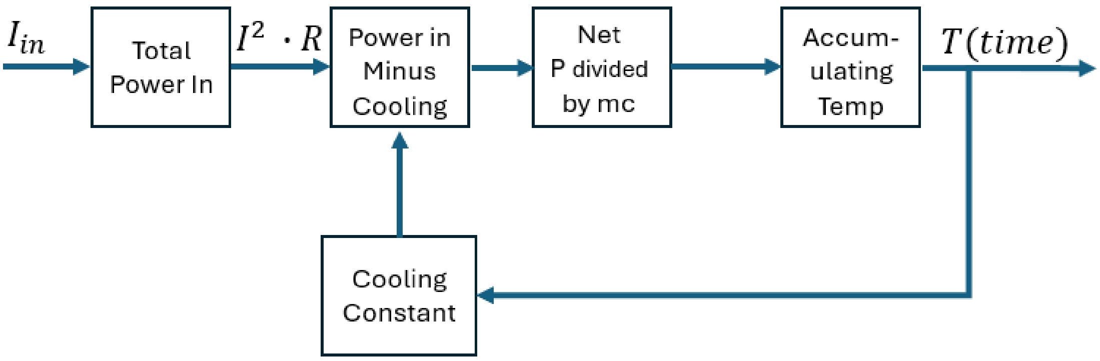


Figure 4.4: Concept 1 - Simplified Simulink model

The model is based on existing data from previous logs, where the adjustment of the cooling constant and 1/mc, seen in Figure 4.4, calculates the expected temperature of different junctions by different temperature sensors.

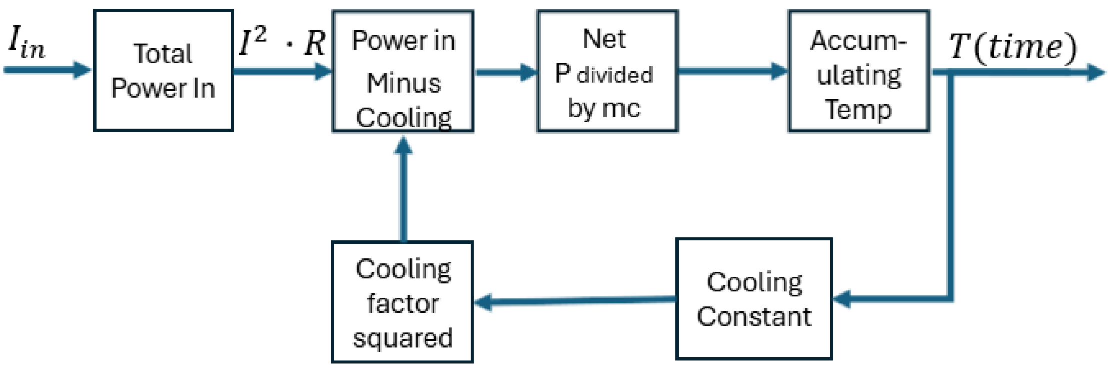


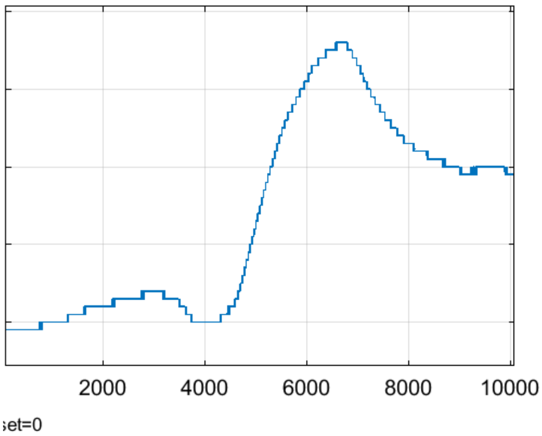
Figure 4.5: Concept 1 with squared cooling factor - Simplified Simulink model

The component has several temperature signals at different connectors and junctions. For this reason, the temperature increases differently. In some areas, an increased effect of cooling was found, showing an exponential effect on the temperature. A modified model was implemented in these areas for an accurate result, as seen in Figure 4.5. The cooling constant is squared to reflect the increased effect of heat loss. The model represents the following equation:

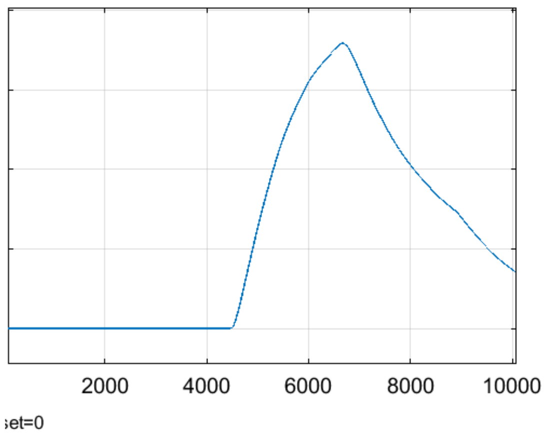
$$T = \int \frac{1}{mc}(Q_g - Q_l^2)dt \tag{4.2}$$

The model has several possible implementations in a diagnostic function. An expected increase in temperature can be compared to the actual increase, giving an indication that the resistance is higher than expected. Similarly, for a more predictive approach, the initial derivative of the expected curve can be compared to the derivative of the curve from the temperature signal.

Examples of the results for Concept 1 are presented in Figure 4.6 and 4.7

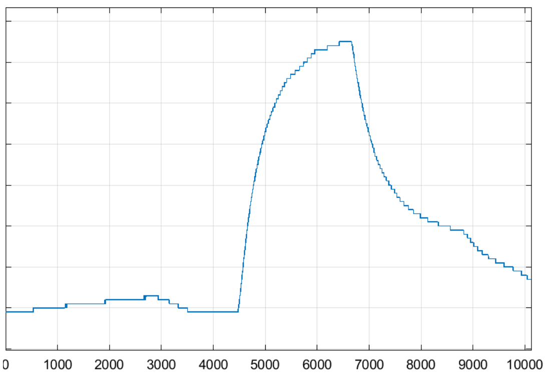


(a) Real temperature signal

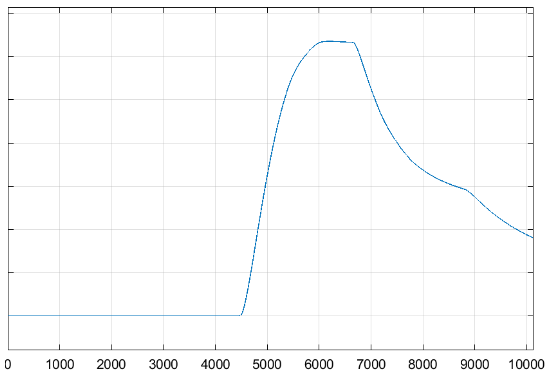


(b) Simulated temperature signal

Figure 4.6: Results from model in Figure 4.4 of Concept 1



(a) Real temperature signal



(b) Simulated temperature signal

Figure 4.7: Results from model in Figure 4.5 of Concept 1

4.5.2 Concept 2

The second model aims to plot the temperature curve for the system based on sensor input, reflecting the actual thermal behavior of the system. To obtain the correct temperature slope in a system where the internal component properties are not fully known, an effective thermal capacitance, C_{eff}, is calculated using current input data. This parameter represents not only the physical heat capacity of the system, but also accounts for effects such as heat distribution and internal cooling.

The concept is based on Equation 2.10, expressing the accumulated power in the system. The model uses input power P_{in} as the generated heat rate P_g. P_{in} is based on the measured current and voltage. The heat loss P_{out} represents the heat loss, expressed as P_l in Equation 2.10. To simplify the expression for heat loss rate, $\frac{1}{ha}$ is replaced with thermal resistance R_{th}. The expression is as follows:

$$P_{out} = \frac{T_n - T_{ref}}{R_{th}} \tag{4.3}$$

Since the internal properties of the system are not explicitly known, R_{th} was estimated by studying the graphs from recorded logs. For the same reason, the effective thermal capacitance is estimated from measured data during the initial temperature rise, expressed as C_{eff}. At this stage, the cooling influence is limited, allowing a simplified approximation of Equation 2.11:

$$C_{eff} \approx \frac{P_a}{\frac{dT}{dt}} \tag{4.4}$$

The temperature is obtained by using Equation 2.14, including the previous temperature T_{t-1}, P_{in}, P_{out} and C_{eff}, expressed as:

$$T(t) = T_{t-1} + \int_0^t \frac{P_{in} - \frac{T_n - T_{ref}}{R_{th}}}{C_{eff}} \tag{4.5}$$

Since the temperature appears on both sides, this model is solved numerically. In the implementation, this is done by updating the temperature stepwise based on the current rate of change, as seen in Figure 4.8 below:

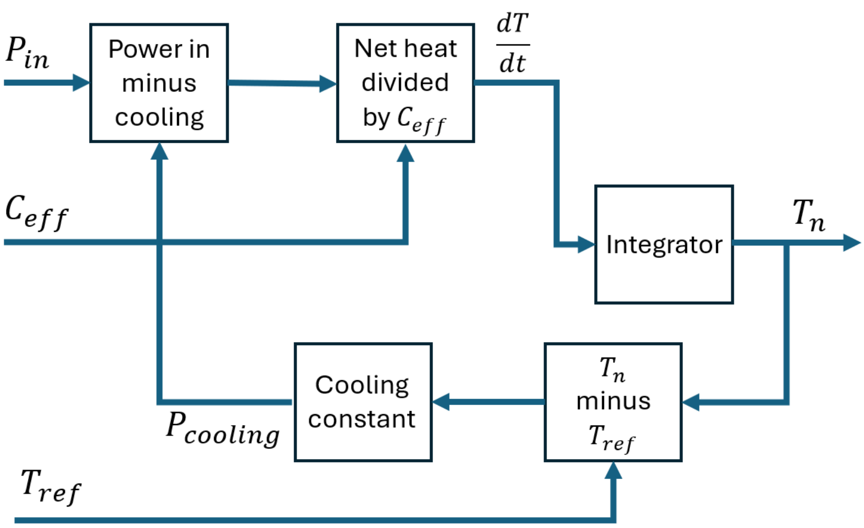


Figure 4.8: Simplified Simulink model - Temperature Curve Prediction

The implementation of C_{eff} in SimuLink is modeled after the equation seen in Figure 4.9.

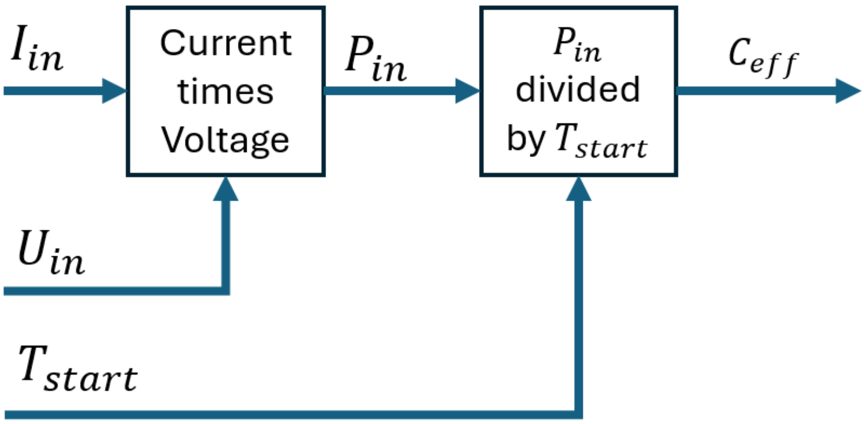
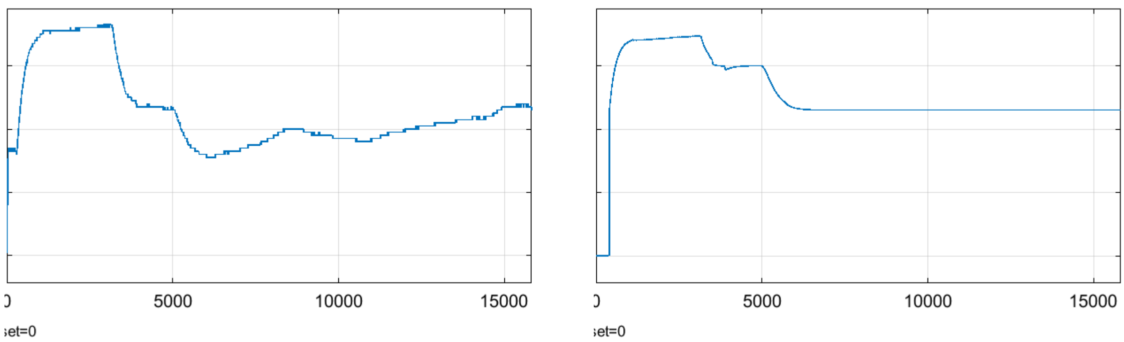


Figure 4.9: Simplified Simulink model - Thermal Capacitance Estimation

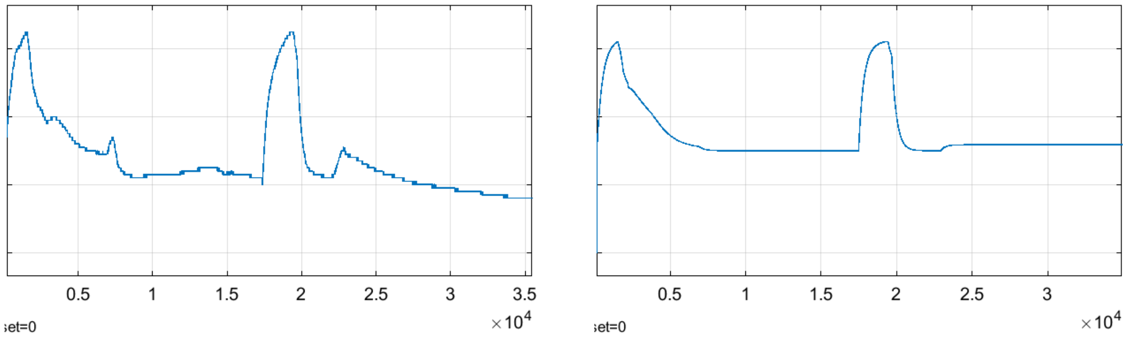
Using recorded logs of energy transfer, the resulting outputs for the models were as seen in Figure 4.10 and 4.11 below. They are simulations from two different logs. For both images, the graph to the left is the input temperature signal and to the right is the predicted temperature curve. As seen in both simulations, the models are not calibrated to perform the correct temperature decrease as the real signal. It is possible that this could be corrected, but since the important output from the model is what maximum temperature the component will reach, it was not a focus point for improvement.

The maximum temperatures for the real curve and the predicted curve are similar in these simulations, which is the goal for the model. This is, however, not the case for all simulation attempts. The reason for this is partly because more calibration is needed with the constant and enable windows. Another reason could be the quality of the logs and the circumstances of the charging.



(a) Real temperature signal **(b)** Predicted temperature curve

Figure 4.10: Results from model in Figure 4.8 of Concept 2



(a) Real temperature signal **(b)** Predicted temperature curve

Figure 4.11: Results from model in Figure 4.8 of Concept 2 with another log

4.5.3 Concept 3

The third concept extends the previous concept to enable early prediction of the maximum temperature. Instead of continuously evaluating the temperature over time, the model uses the same Equation 4.5 to simulate the future temperature behavior.

In the SimuLink implementation, the input values for power and thermal parameters are locked, allowing the model to iteratively simulate the temperature development. This iteration is performed internally and does not follow the real-time evolution of the system. The number of iterations is defined based on the thermal time constant of the system, see Equation 2.16.

By setting t as a multiple of the time constant τ, it ensures that the number of iterations is sufficient to reach the maximum value for the temperature. Looking at equation 2.17, if $t = 4\tau$ the estimated temperature will be $e^{-4} \approx 1.83\%$ from the maximum temperature.

By setting t as a multiple of the thermal time constant τ, the transient temperature response can be estimated sufficiently close to steady-state conditions. From Equation 2.17, setting $t = 4\tau$ gives $e^{-4} \approx 1.83\%$, meaning that the temperature is within approximately 98% of its steady-state value. This was considered an acceptable value for the model.

The model is structured using a counter that runs a for loop for the set amount of times, 4τ, seen in Figure 4.12:

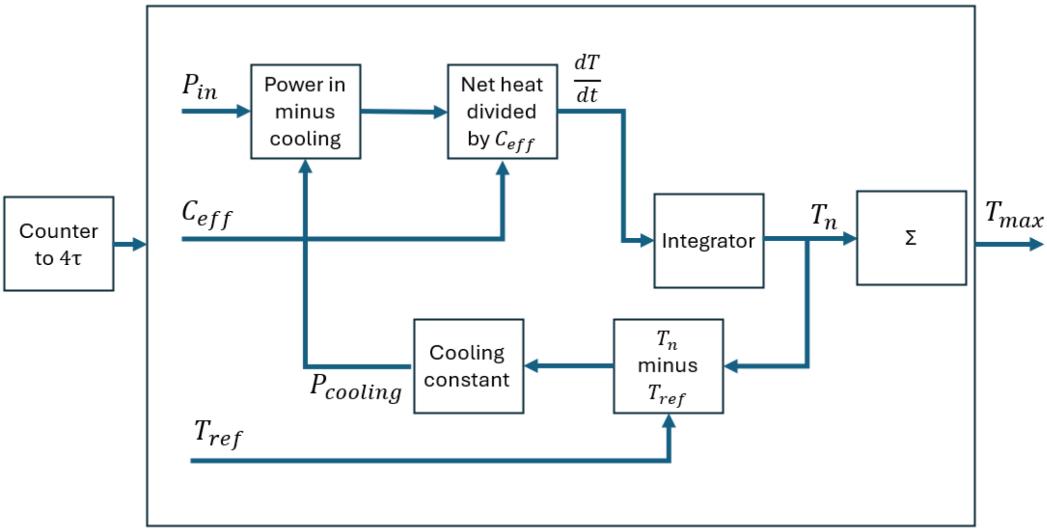
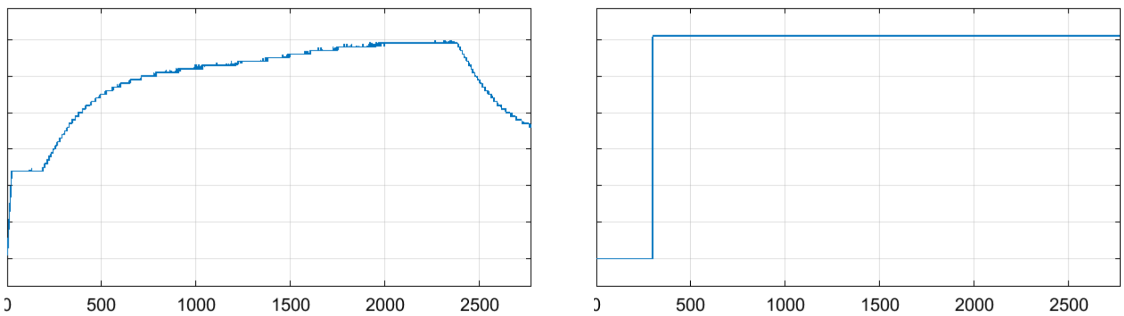


Figure 4.12: Predicted maximum temperature model inside for loop, iterated with counter.

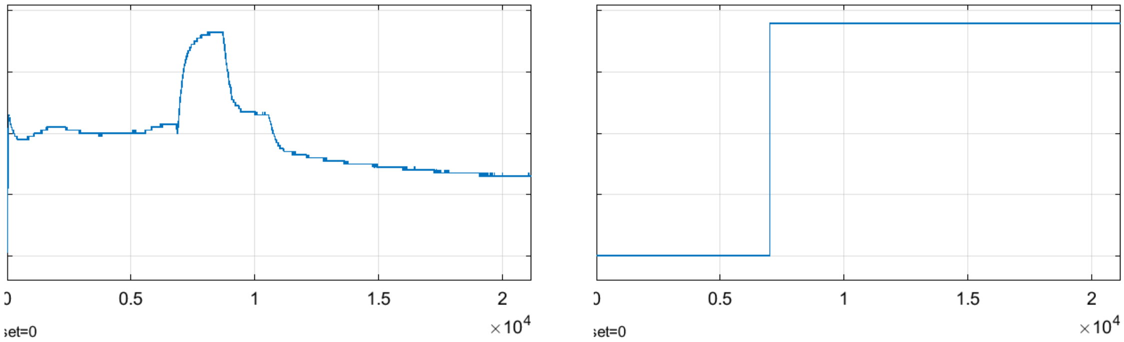
The output, predicted maximum temperature, is shown in Figure 4.13 and 4.14 together with the real temperature curve to the left. Due to the nature of the formula used, the model will only predict the maximum temperature generated by the derivative in the early stages of the temperature increase. This means that the predicted maximum only represents the temperature generated by the component and is not affected by the heat from surrounding components.

The model predicts a maximum temperature before the real temperature reaches its maximum. As seen in the graphs, the temperature prediction is within $\pm 5°C$. However, much like Concept 2, further testing and calibration need to be done, as not all simulations result in predictions within a reasonable temperature span.



(a) Real temperature signal **(b)** Predicted maximum temperature

Figure 4.13: Results from model in Figure 4.12 of Concept 3



(a) Real temperature signal

(b) Predicted maximum temperature

Figure 4.14: Results from model in Figure 4.12 of Concept 3

4.5.4 Concept 4

The fourth potential concept is based on patterns observed when studying logs from several different temperature sensors. It was observed that several temperature measurements increased in pairs, meaning the curve was almost identical. Considering the measurements are from different connectors and junctions, the temperature reading could be independent enough that anomalies could be identified in a comparison between those two temperatures.

4.6 Concept Screening and Scoring 2

Since the concepts in the second generation cycle provide different types of outputs, a direct comparison using a traditional elimination was not considered appropriate. Instead, the concepts were evaluated on their individual characteristics, together with their potential contribution to a complete diagnostic function.

In Table 4.3 below, each concept is assessed in terms of their suitability for integration into a final diagnostic model. Since the concepts represent sub-functions rather than complete solutions, they cannot be evaluated as finalized systems. Instead, they are assessed on their potential to contribute with additional sub-functions or further development.

The evaluation criteria are defined as follows: simplicity reflects implementation complexity, applicability describes how well the concept can be implemented in a diagnostic model, generalisability indicates the potential for use in other systems, and testability is how well the concept can be tested to verify its reliability.

Concepts 2 and 3 perform similar functions and can therefore be directly compared. Concept 3 achieves equal or higher ratings across all criteria, which is expected since it represents a refined and improved version of Concept 2. Thus, Concept 3 is deemed the more suitable alternative of the two.

Concept 1 performs a different function and is therefore evaluated primarily on its own. While the model is simple, it requires some further development to be integrated more efficiently into a complete diagnostic model. For example, it would benefit from providing an estimated maximum temperature instead of a temperature curve to enable early detection of abnormal temperature. The usage of constants limits the generalisability and testability as the constants need to be configured.

Concept 4 represents a simple approach but is highly dependent on the layout of the system, requiring sensors in specific positions. This makes generalisability very difficult. Testability is also uncertain as the behavior of each sensor and component needs to be studied in detail to develop a working model.

Table 4.3: Concept screening 2 - rating matrix

Concept	Function	Simplicity	Applicability in Diagnostic Model	Generalis-ability	Testability
Concept 1	Ideal temp curve estimation	High	Medium	Medium	Medium
Concept 2	Actual temp curve estimation	High	Medium	High	High
Concept 3	Actual max temp prediction	Medium	High	High	High
Concept 4	Multiple temp comparison	High	Medium	Low	Low

The results of the concept screening indicate that Concepts 2 and 4 are not suitable for further development, while Concepts 1 and 3 show potential to be refined for final implementation.

4.7 Concept Generation 3

The objective of the third concept generation cycle was to develop a complete diagnostic function. To achieve this, the model had to be capable of detecting abnormal temperature increases caused by increased electrical resistance and reliably link such deviations to the resistance itself.

Following the second concept screening, two concepts were selected for further development. However, both concepts required additional refinement to enable comparison between their outputs and either ideal or actual temperature.

Since the individual concepts provide either an estimation of the ideal temperature or a prediction of the actual temperature, the possibility of combining the models was therefore explored.

4.7.1 Final Concept

The final concept is based on combining an ideal temperature estimation model with a model predicting the actual temperature to identify when there is a deviation. In practice, it means comparing two maximum temperatures, an ideal estimation and a predicted real temperature before the component has reached its maximum. To achieve this, Concepts 1 and 3 were refined to create the solution presented in Figure 4.15.

The ideal temperature estimation model, Concept 1, was developed to output a maximum temperature. For this solution, the iterative model was replaced by a steady state equation, Equation 2.15, in order to minimize the required computational power.

The predictive model, Concept 3, was already improved in the last generation cycle and was ready to be combined with Concept 1 into one complete diagnostic function. The first step was to create joint enable conditions for the models. A few of the conditions regulating the time window that decides when the models analyze and freeze input signals differ for each sub-function.

The next step in the implementation was to add the feature that compares the two maximum temperatures to see if the actual temperature differs from the ideal estimation. This is implemented by taking the difference between the two outputs and comparing it with a set threshold. If the difference is higher than the threshold, that is, if the actual temperature is estimated to be X degrees higher than the estimated ideal, the diagnostic function will set a fault.

There are additional functions added in the diagnostic model, not connected to the fault evaluation. These functions are a status evaluation that sends out a message about whether the evaluation is ongoing, not started, finished, or failed.

There are two possible power levels, P_{high} and P_{low}, with two different connectors and temperature signals. To distinguish which power level is being applied, the model utilizes an input signal: P_{index}, that establishes which signal to analyze.

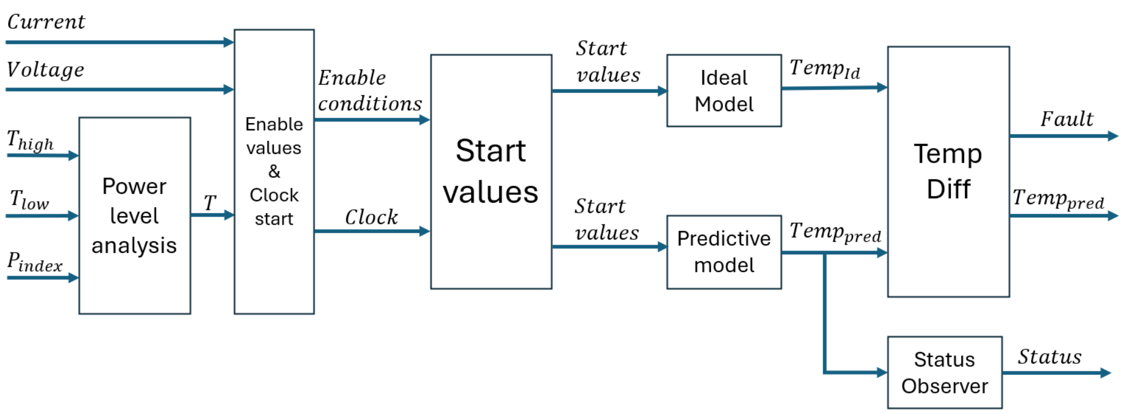


Figure 4.15: Simplified Simulink model - Final Concept

5 Discussion

The applicability of the product development approach is discussed below in the context of developing a diagnostic function. Following that, the research questions are discussed with the knowledge and results yielded after the study. The results themselves are discussed with a final note about ethical and environmental concerns.

5.1 Process

The product development framework used provided the project with a wide knowledge base initially. The interview process was a solid foundation to investigate the HVS and vital information for later steps in the development process, such as testing possibilities. There were also several steps of screening and decision-making guided by matrices, aiding both in the decision-making process as well as serving as a clear tool as to why certain selections were made.

However, the concept generation process was quite time-consuming and each possible function was developed in order to test and verify the performance and capabilities. This meant the number of concepts was low, and extensive screening through multiple matrices was deemed inefficient in this application. A variation of decision-making matrices was utilized, including fewer steps. This approach was more suited for the time available, but a more thorough approach in the screening process could have presented a clearer picture of the process and why each sub-function and final concept was selected.

The decision to save time in the decision-making process gave more time to develop the final concept. That led to final testing and implementation into the intended vehicle being possible in order to conduct charging tests. The successful testing acted as further proof of concept than simulation results.

In the testing and validation process of the final implementation, one hindrance was the difficulty collecting meaningful and applicable data. This became apparent as the final concept was to be verified, late in the process. The testing required a measured maximum temperature value reached during stable charging over a long period of time in order to validate the function. An improved approach would have collected this type of data earlier in the process, either through databases or by running the needed tests to control the conditions.

5.2 Research Questions

The study has explored and aimed to answer five research questions presented in Section 1.3.1.

For RQ1, the possible resistance diagnostic methods for HVS were investigated, including voltage, power and temperature measurements. The literature study showed a variety of applications using thresholds, models, or data-driven approaches. There were however, limited implementations of these in a component-based setting and the majority of research is based on battery-health applications.

RQ2 was investigated through thorough interviews to establish criteria for the HVS and its components to implement a method for diagnostic resistance. The results were presented in Section 4.1.2 and indicated the availability of sensors and data inside the component. It also specified the ability to test and simulate the component in order to develop and verify solutions. The full list of criteria was, however, not possible to generate until the solution was finalized, as different implementations and concepts had differing needs.

In Section 4.5 RQ3 was researched, exploring what types of diagnostic solutions were feasible to implement in a HVS in order to address resistance abnormalities. The second concept generation resulted in several sub-functions viable to predict or detect abnormal resistance. To create a solution that meets the set requirements and answer RQ4, these sub-functions were combined to reach the necessary performance in the final concept, presented in Section 4.7.1. This resulted in a predictive function, comparing the max temperature that should be expected, and the max temperature actually being reached. This process was largely limited by the time available. Several sub-functions were developed, but there were options that were not explored due to the time constraint. The time required to develop skills in the software, as well as knowledge gaps in what implementations were possible, was a contributing factor to the limited amount of concepts generated.

Finally, RQ5 aimed to investigate the effect of applying a product development process to the development of a software-based diagnostic function. The result was a wide collection of knowledge at the beginning of the project and systematic and clear decision-making. The drawback of the framework is the amount of time each concept requires in the case of software development. This results in fewer potential concepts to choose from, which means the framework was applied less towards the end of the project, as only one viable concept was developed in the end.

5.3 Results

The study aimed to develop a diagnostic function that could indicate a specific component's abnormal resistance with a method that is precise, robust and generally applicable. The result is a model with predictive capacity to detect faults in specific components. Although the output does not specify a resistance value, the effects of high resistance are detected and evaluated.

Evaluating the solution with the requirement specification fulfills the cost requirements well, as zero added components were needed, with a slightly added cost for development in terms of testing and calibration. The complexity requirements were fulfilled as the solution does not use data collection and is implementable into trucks already on the market, and is geometrically feasible as well. The solution also has the capability to be resistance specific and pinpoints a specific affected component. The solution is in an early development stage and the possible performance and accuracy require further testing in the intended environment. Until these tests are performed the overall robustness and reliability related to the general diagnostic requirements in the specification can not be evaluated.

The current limitations of the solution are mostly a sensitivity to stable energy transfer as well as an inability to evaluate an already heated component. Since the function relies on analyzing the rate of heat increase when a certain current is applied, the results are somewhat skewed if the current varies considerably. The formula the evaluation is based on assumes the component is in the early stages of heating. Therefore, a component that has gone through recent heating and not yet cooled will provide inaccurate results.

5.4 Ethical and Environmental Concerns

The ethical concerns throughout the project have partly been concerning data collection infringing on the right to privacy. The solution does not, in the end, collect data in order to detect abnormal resistance. In order to detect aging of a component, however, a record of historic heat increase ought to be traced if it were to be implemented. This would not necessarily collect user data or charging and driving behavior, but should be under consideration in the development process.

The safety of the function is also a consideration, as dangerously high heat increases that are missed are a threat to the end user and service workers. The importance of rigorous testing is therefore crucial before implementation as well as an added level of security, observing real-time temperature increase that will stop charging if limit values are reached.

In applications where a large amount of current is applied, the environmental impact could be positive, as detecting abnormalities could mean that faulty components are replaced the energy transfer is more effective. On a larger scale, less energy is lost through heat and the power is used more efficiently.

During this process, AI has been used mainly as a tool to work in software such as Matlab Simulink. The application has mainly been fault tracing and debugging models to quickly move forward in the process. AI also aided in providing documentation for specific functions, how they were utilized and ways to translate mathematical equations into Simulink models.

6
Conclusion

In conclusion the aim to investigate the feasibility of developing a diagnostic function for detecting resistance-related faults in HVS of HDVs, using a product development approach was largely successful. The applied product development process of the study was a useful tool in the software development of a diagnostic function. Some modifications made in the process for this study that were deemed promising were to divide the decision-making and concept generation, initially choosing a method of measurement to base the next round of concepts on. This can be applied in instances where several measurement options are available, and quickly focuses the development towards the most viable options. The usage of matrices like Pugh or Kesselring, which were in this case omitted, could be applied in cases where several solutions solving the same sub-functions are generated. This could be the case if a developer is already aware of the performance and limitations of a concept, or perhaps the solutions are less complex and time-consuming to validate.

In conclusion, the rigorous pre-study and knowledge gathering at the start provided a base for the next steps, and adjusting the product development process for the type of development and amount of concepts was an effective use of time. As the end goal was a tested implementation, all of this resulted in a promising final concept with a successful charging test and proof of concept.

6.1 Future Work

There are steps still needed for the function to be reliable and robust. The recommendation for future work is to investigate a reliable baseline of what an expected temperature increase entails, and establish that the result is consistent enough in all vehicles. This would include specific testing to record the maximum temperatures reached under known conditions.

Intentional testing with abnormal resistance to test the predictive model's ability to detect faults is also needed. Based on these findings and mapping the function's accuracy, the level of sensitivity can be calibrated. If the results are trustworthy, the allowed difference between the expected and predicted value can be narrowed without running the risk of false fault detections.

The known limitation of the model is that it requires the component to be entirely cooled since the last charge. This is a prerequisite the model is based on and will continue to be the case. It is, however, something that should be flagged before running the model, to indicate that the model's results are to be disregarded. Before putting the function in use, further development should be directed in this area.

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