CHALMERS
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AI for capacity estimation of overhead transmission lines

A new model proposal for deploying AI to do dynamic line rating

Master's thesis in Data science & AI

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Gothenburg, Sweden 2024
www.chalmers.se

MASTER'S THESIS 2024

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Master's Thesis 2024
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Cover: Picture of overhead transmission lines

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2024

Abstract

Dynamic line rating (DLR) for overhead transmission lines, which estimates the current-carrying capacity based on environmental and operational conditions, presents an opportunity to enhance the efficiency and reliability of electrical grids. This thesis explores the feasibility and application of artificial intelligence (AI) to improve the accuracy and scalability of DLR systems, while also lowering the cost of installation. By leveraging machine learning models, particularly physics-informed neural networks (PINNs), this research aims to lay the foundation of the development of an advanced DLR solution capable of real-time and forecast estimation of the capacity of a transmission line.

The initial phase of the thesis focuses on implementing a weather-based model, based on the IEEE-738 standard, to estimate line ratings based on weather parameters such as temperature, wind speed, wind angle and solar radiation, but also parameters such as the electrical current and conductor specific metrics. This model serves as both a practical tool for immediate deployment and a foundational step towards more complex AI models.

Following the development of the weather-based model, the research transitions to the integration neural networks, with a perspective of utilizing physics informed neural networks. These models combine the data-driven capabilities of traditional machine learning with the robustness of physical laws governing power transmission. The objective is to enhance the precision and reliability of the DLR system, accommodating non-linear relationships and interactions within the data.

The thesis proposes a new model of a DLR system based around the weather model and machine learning. The system consists of several modules that each serve a purpose, *data collection*, *ML model*, *ML training*, *weather model* and *real-time capacity estimation*. The findings demonstrate that AI-based DLR systems is a new, interesting approach that can significantly improve the operational efficiency of electrical grids by providing more accurate and adaptive line ratings. This research contributes to the field of power systems by offering a scalable and innovative approach to dynamic line rating, supporting the transition towards a smarter infrastructure.

The project has gained interest from key stakeholders such as EON, Vattenfall, and Svenska kraftnät, and has been formed in close contact with their respective specialists in DLR systems. The involvement of these industry leaders underscores the practical relevance and potential impact of this type of research in this domain.

Acknowledgements

We would like to express our deepest gratitude to our examiner, Anh Tuan Le, for his guidance and support throughout the course of this project. His expertise and advice have been instrumental in shaping the direction and outcome of our work.

We extend our heartfelt thanks to Ebrahim Balouji and Karl Bäckström from Archeri for their unwavering support and close collaboration. Their insights and assistance have been crucial, particularly in the realm of developing a product with a keen focus on maximizing value both for Archeri and for our customers.

We are also profoundly grateful to the DLR specialists at EON, Vattenfall, and Svenska Kraftnät. Their valuable insights ranged from outlining the ideal technical aspects of a new DLR system to understanding the business perspective of introducing new techniques within power systems. Their contributions have greatly enhanced the quality and relevance of our project.

Thank you all for your dedication, knowledge, and encouragement, which have been fundamental to the success of this thesis.

List of Acronyms

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

ACSR	Aluminium-conductor steel-reinforced
DLR	Dynamic Line Rating
DL	Discrepancy Learning
IEEE	Institute of Electrical & Electronics Engineers
ML	Machine Learning
OHTL	Overhead Transmission Line
PINN	Physics Informed Neural Network
PQM	Power Quality Meter
SLR	Static Line Rating

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

Parameters

α_m	Thermal elongation coefficient of material m
ρ_f	Air density
μ_f	Dynamic Viscosity of air
k_f	Thermal conductivity of air

Variables

I_s	Current at sending end of overhead transmission line
I_r	Current at receiving end of overhead transmission line
V_s	Voltage at sending end of overhead transmission line
V_r	Voltage at receiving end of overhead transmission line
T_a	Temperature of air surrounding the overhead transmission line
T_s	Temperature on the surface of the overhead transmission line

Definitions

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

Ampacity – The maximum amount of Ampere that can flow in a conductor without exceeding the thermal limit of the conductor.

Conductor thermal limit – The maximum temperature of the conductor that is selected to limit line sagging and protect the physical overhead conductor from being damaged.

Creep – The permanent elongation of a overhead transmission line due to stress and tension in the material

Transmission line sag – The vertical distance from the lowest point of the overhead transmission line to the highest point.

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1
Introduction

As electricity demand continues to surge, the reliability, efficiency, and sustainability of the power grid have become paramount. Archeri, a new startup company started at Chalmers university, aims to provide a solution akin to a "GPS" for power grid operators, offering real-time insights into the thermal limits of transmission lines, which can lead to more informed decision-making, reducing energy losses, and ultimately benefiting both consumers and the environment.

The escalating electricity prices and the projection of doubling Sweden's electricity demand by 2035, as stated by Energimyndigheten, highlight the urgency of the situation. Grid operators are struggling to keep up with electrification rates, and despite ongoing digitization efforts, there's a significant gap in understanding grid capacity. This lack of knowledge results in power losses, power outages, excessive maintenance costs, and unnecessary grid expansion. The government organization Svenska kraftnät states in their published report regarding resource adequacy in the power grid that the risk of a lack of power will increase in the years 2024-2028 [1]. This is the case although the power transfer capacity in the grid is increasing. Ultimately, consumers pay for these inefficiencies as prices rise due to stagnant supply and growing demand.

The solution proposed by Archeri hinges on leveraging machine learning and AI-based software to provide grid operators with accurate grid capacity information. This would enable better decision-making made by grid operators, leading to a more efficient use of existing infrastructure, easier integration of renewable energy sources, reduced energy losses, lower energy prices, extended grid lifetime, and decreased maintenance costs. Crucially, Archeri's software aim to accomplish this without the need for additional hardware, setting it apart from competitors and offering a more cost-effective and sustainable solution. The aim for this project is to investigate whether such a solution is plausible in terms of requirements of additional hardware and possible machine learning implementations.

1.1 Background

The Swedish power grid comprises approximately 17 500 kilometers of overhead transmission lines (further described in section 3.1), interconnecting with neighboring Nordic countries as illustrated in Figure 1.1 [2]. Many of these lines carry substantial power over extensive distances, often traversing above villages, roads, and challenging terrain. This poses safety concerns both for the integrity of the power lines themselves and for the environment below. During construction, the sag of the overhead transmission lines is carefully adjusted to ensure safe tension levels and maintain a safe distance between the lowest point of the line and the ground below, as depicted in Figure 1.2.

During operation, power lines are subjected to diverse weather conditions and varying electrical loads, leading to fluctuations in the internal temperature of the line. Consequently, these temperature changes cause the physical dimensions of the line to alter, resulting in an increase in sag, bringing the line closer to the ground. In some scenarios, such as heavy loads on the line, the sag distance may surpass its maximum threshold, posing risks of damage to both the line and the environment underneath.

Figure 1.1: Map of the Swedish power grid [2].

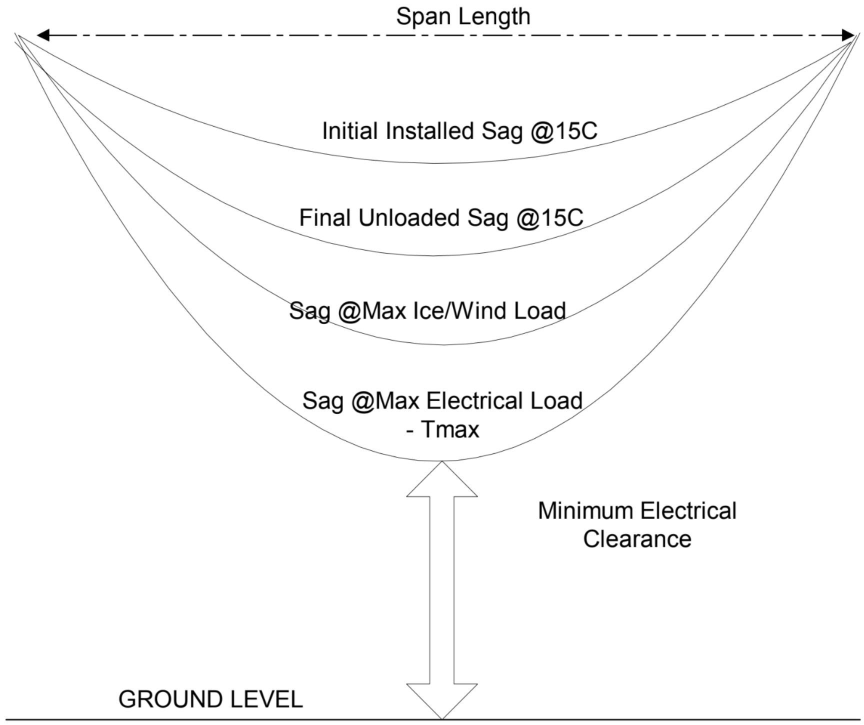


Figure 1.2: Catenary variation with conductor temperature, ice & wind loads, and time after installation, where Tmax is the maximum conductor temperature [3].

The capacity of an overhead conductor is known as its ampacity, representing the maximum amount of current, measured in Amperes, that can be carried by the line without exceeding its maximum sag threshold. However, factors like weather conditions can also contribute to increased or decreased sag in the line, making the threshold (ampacity) dynamic and challenging to accurately determine.

1.2 Market research

In early stage of this project, the objective was to develop a model aimed solely at estimating real-time line capacity. However, through extensive discussions with key stakeholders, particularly Transmission System Operators (TSOs) on the regional level, such as the head of transmission lines at Svenska kraftnät, R&D experts of transmission lines at EON, and transmission line specialists at Vattenfall, a pivotal shift in focus emerged.

The insights gained from these engagements underscored a broader and more pressing need within the industry. It became evident that while real-time capacity estimation is valuable, the potential for forecasting line capacity held even greater promise. This realization prompted us to reevaluate our approach, leading to a decision to pivot our focus, or rather, to split it and revise our objective.

The revised objective instead encompasses the development of a comprehensive system for forecasting line capacity, alongside real-time capacity estimation. This strategic shift is aimed at delivering maximized value for Archeri and addressing the demands of the industry. To achieve this, our research agenda was expanded to encompass two key aspects:

- **Forecasting Line Capacity**
- **Real-Time Line Capacity Estimation**

In summary, our market research has not only informed but also transformed our project's trajectory. By gaining insights from industry experts and stakeholders, we repositioned ourselves to address the need for both capacity forecasting and real-time estimation.

1.3 Problem statement

As mentioned, the escalating demand for power underscores the need for increased power throughput in power grids. Dynamic line ratings (DLR) offer a dynamic approach to assessing transmission line capacity, adapting to fluctuating conditions. Within this context, after market research, two key aspects emerged: forecasting line capacity and real-time capacity estimation.

Forecast of line capacity focus on predicting the maximum allowable current-carrying capacity of transmission lines. To create such a model, relevant external factors impacting a line's capacity must be considered, such as weather conditions and electrical demand. Having an accurate model for forcasting capacity allows grid operators to, in a safe way, operate the transmission lines closer to their maximum capacity, leading to more efficient routing and resulting in minimal power losses when transmitting electricity.

Real-time capacity estimation of a transmission line is the continuous assessment of transmission line capacity during operation. The value of having an accurate model for real-time capacity estimation lies in the possibility of allowing grid operators to easily get an overview of the total grid utilization at the moment. Also allowing for quick, safe and easy rerouting of power transmission in case one or more routes or lines becomes unusable.

Technological advancements, particularly in machine learning, offer promising solutions for the creation of both of the tools mentioned. However, this process is hindered by technical challenges, notably data accessibility. Critical data related to power demand is often securely guarded. Additionally, essential data concerning power usage, weather patterns, and line sag are rarely recorded, hindering the development of precise forecasting models using machine learning. Addressing these challenges is paramount to ensure stakeholders grasp the significance of measuring and collecting comprehensive data.

Crucially, the solution must prioritize minimal additional hardware requirements. The integration of DLR solutions into existing infrastructure should be seamless, minimizing installation and maintenance costs. Furthermore, considering factors beyond hardware, such as software optimization and leveraging existing sensor networks, is also important to ensure cost-effectiveness and scalability.

Addressing the technical challenges associated with forecasting line capacity and real-time capacity estimation, while harnessing technological advancements like machine learning, presents a multifaceted problem in the implementation of dynamic line rating systems. Balancing the need for comprehensive data collection with minimal hardware requirements is essential to develop effective and sustainable solutions for optimizing transmission line capacity in modern power grids. This thesis focus on proposing a new method for deploying a DLR system designed to be operational at installation, generating value for the user right away. Meanwhile, the system should collect neccecasry data to be used to further improve itself over time by leveraging machine learning techniques.

1.4 Purpose of the thesis

The aim of this master's thesis is to explore the feasibility of employing Artificial Intelligence (AI) to assess the capacity of overhead transmission lines, with a focus on real-time estimation and forecasting. Our objective is to demonstrate the development of a model tailored for this task, investigating and highlighting key factors such as weather conditions and line loads and their correlations on a line's capacity. Furthermore, we aim to underscore the significance of data acquisition and measurement by transmission line operator companies, emphasizing the necessity for comprehensive data sets to construct a model capable of delivering optimal estimations.

1.5 Scope & limitations

This master's thesis aims to investigate how the power grid capacity can be estimated using no additional hardware other than existing, only using weather parameters and PQM measurement data. The study will delve into how machine learning methods can be used to estimate real time as well as future grid capacity. It seeks to contribute to the existing body of knowledge in the field of dynamic line rating and add new methods for more precise and effective solutions.

The thesis will be conducted in collaboration with a start-up venture at Chalmers, Archeri, a company with focus on commercializing the developed solution.

Certain limitations will be acknowledged in this thesis. Firstly, the work does not propose or set any safety values, such as the maximum allowable temperature of a line or the maximum allowed distance of a line to the ground. Instead, it is designed to take these values as inputs from its users, preferably transmission line grid operators.

Secondly, this thesis focuses solely on overhead transmission lines and does not consider underground transmission cables, although some parts of the work can easily be extended to accommodate those as well.

Additionally, the thesis considers only external effects on the overhead line, such as thermal effects on the conductor, and does not account for creep or other types of damage, which need to be managed by the grid operators.

Lastly, rain is not considered as a weather parameter in this work. Research of this type of modelling has been done before [4]. Thus, the software is designed to easily incorporate this factor if desired.

2

Literature review

Dynamic Line Rating (DLR) has during the past 20 years emerged as a technique to enhance the efficiency of power grids. Unlike static line rating (SLR) methods, further described in section 3.1.1.1, DLR takes into account real-time environmental conditions and operating parameters to determine the capacity of transmission lines. DLR described in more detail in section 3.1.1.2. This literature review aims to provide an overview of the existing DLR techniques, including its methods, applications and challenges.

The two main approaches to implementing DLR in a power grid are: *measurement methods* and *estimation methods*, and there exists several methods for both approaches. The following sections describe some of the methods that are relevant and used in the industry today.

2.1 Measurement methods

The methods that fall under this category involves measuring the actual sag or temperature of the line in real time using some sort of sensor attached to the line. Although it requires additional hardware installation in the power grid, the results are often more accurate than other estimation methods.

2.1.1 Temperature based

Temperature based solutions entail measuring the OHTL temperature and subsequently computing the line sag by considering line-specific attributes and the measured temperature of the line. Various approaches exist within this domain. One such approach suggests the deployment of a hardware unit affixed to the conductor, which assesses both the conductor temperature and electrical current [5]. While this solution offers a high accuracy, it also requires extensive hardware installation of both the measurement unit and the hardware needed for communicating the data, often resulting in an expensive solution for the grid operator companies. Heimdall Power is a company based in Norway [6] that offers such a solution based around measuring the temperature using hardware mounted on the overhead line.

2.1.2 Tension based

The solution proposed in the paper ”Mechanical State Estimation for Overhead Transmission Lines With Level Spans” [7] propose a solution based around measuring the tension in the line between two towers. The tension in the line is measured with sensors and wirelessly transmitted to a control center. The thermal effect on the line is calculated using some models presented in the IEEE standard 738-1993[8], which is based on external weather parameters and the current in the line. Together with the tension and thermal effect, the state of the line can be estimated. This approach offers a rather extensive combination of both hardware and software solutions for estimation of line capacity.

2.1.3 Vibration based

The paper ”Uprating Transmission Lines through the use of an innovative real-time monitoring system” [9] proposes the base upon the system provided by the company ”Ampacimon” [10] is built. The algorithm proposed in the paper calculates the sag of the line using vibration data, and is said to achieve an accuracy within 2% error margin. The system is based around vibration analysis and does not require any additional information about the line or its surroundings, but is also dependent on hardware installation on the line.

2.2 Estimation methods

Estimation methods involve studying what have an effect on the line, which often involves weather parameters and electrical current. Then, based on physical formulas, trying to estimate how the temperature (and capacity) in the line is affected in different scenarios.

2.2.1 PQM based

By using hardware already installed in the grid, PQM sensors (sometimes referred to as PMU sensors), measurements of the current, phase and harmonics can be a useful data source without installing additional hardware. A solution that utilizes the PQM sensors is presented in the paper ”Online estimation of power transmission line parameters, temperature and sag” [11]. The proposed algorithm can estimate the line parameters, such as resistance, and using that information deduce the thermal effect on the line.

2.2.2 Weather based

Another approach, acting as the base for one type of DLR system used by the Swedish grid operator Vattenfall, considers the external weather parameters in the line’s geographical area, such as wind speed, air temperature and solar heating, which all have an impact on the line’s internal temperature. In the paper ”Dynamic capacity rating for wind cooled overhead Swedish lines" [12], a study done by Vattenfall showed that there exists a large unutilized capacity gap above the static line rating at most times. They noted that this gap in capacity can be addressed by analyzing the wind cooling effects on the line, and started the development of their own DLR systems based on these findings.

3

Theory

3.1 Overhead Transmission Lines (OHTL)

Overhead transmission lines (OHTLs) are the most common in the regional power grid due to their many advantages over underground cables. The advantages of OHTLs include ease of use and construction, as well as economic benefits [13]. The material, design, and height of OHTLs depend on the voltage level and the terrain of the geographical area. The towers carrying the lines over longer distances with higher voltage are often steel structures. In local, smaller power grids with lower voltage levels, the transmission lines may be supported by wooden or concrete poles. These local OHTLs are typically shorter in height and span, reflecting the reduced electrical and mechanical demands compared to high-voltage transmission lines. The design and material choices for OHTLs are influenced by factors such as environmental conditions, line capacity requirements, and cost considerations, ensuring optimal performance and reliability across different regions and applications.

3.1.1 Line rating

An OHTL can be rated from its ampacity, which changes due to several different parameters such as wind, air temperature, solar heating and line current. The line rating can be used to determine how much electrical load the OHTL can handle without exceeding the conductor's thermal limit. There exists different methods on how to determine the rating of an OHTL using more or less complex underlying technologies.

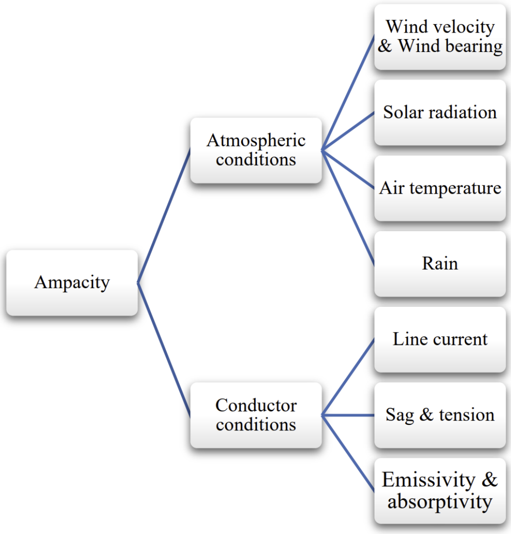


Figure 3.1: Factors influence conductor's line rating [14].

3.1.1.1 Static line rating (SLR)

The static line rating method is not dependent on the present external parameters, but is calculated based on the worst case weather conditions [14]. Since an OHTL can be very long it may be exposed to several different weather conditions and the SLR needs to be derived from the worst possible conditions, hence the static rating will be the same over combined sections in the grid. The weather conditions used for setting the SLR are often in the range of 35 - 40$°C$ for the ambient temperature and 0.6 - 1.0 m/s for wind speed perpendicular to the line.

3.1.1.2 Dynamic line rating (DLR)

DLR is an approach to enhancing the efficiency and reliability of OHTLs by continuously monitoring and adjusting their power carrying capacity in real-time. As stated in the previous section SLR provide a fixed limit to the amount of current that a transmission line can safely carry. In contrast, DLR systems utilize techniques such as sensors, weather forecasting data, and computational algorithms to dynamically assess the actual operating conditions of the transmission line, allowing for a more accurate determination of its ampacity.

One of the key advantages of DLR is its ability to optimize the utilization of existing transmission infrastructure by safely increasing the power transfer capability of the lines during periods of favorable weather conditions or reduced thermal stress. By dynamically adjusting line ratings in response to changing environmental factors such as temperature, wind speed, and solar radiation, DLR systems enable operators to maximize the transmission capacity of the grid without compromising safety limits.

In addition to improving grid efficiency and resilience, DLR also offers benefits in terms of asset management and maintenance. By continuously monitoring the operating conditions of transmission lines, DLR systems can identify potential issues such as excessive thermal loading or conductor degradation, allowing operators to take proactive measures to prevent equipment failures and optimize maintenance schedules [14].

3.1.2 Conductor properties and behaviours

The transmission conductors responsible for power transfer in Overhead High Voltage Transmission Lines (OHTLs) must exhibit qualities of reliability, efficacy, and safety, rendering them integral components within the power grid's design framework. Various types of conductors tailored to specific purposes are available, with regional standards often prescribing particular conductor types for designated applications. Conductor configurations typically fall into two categories: single-material conductors comprising solely one substance, and composite conductors integrating two materials. Composite conductors offer distinct advantages, as the inclusion of a steel core imparts heightened tensile strength, complemented by an outer layer of lightweight and highly conductive aluminum. This composite construction enables an increased span between transmission towers, yielding both efficiency and financial benefits from a grid planning perspective [15].

3.1.2.1 ACSR conductor

The materials of the composite ACSR conductor are aluminum and steel. A commonly used conductor in the Swedish power grid is a steel-reinforced aluminum conductor denoted as Curlew 593(525-AL1/68-ST1A), which is an ACSR (Aluminum Conductor Steel Reinforced) conductor[16]. Figure 3.2 shows a cross-section of the Curlew ACSR conductor, consisting of 26 aluminum wires on the outside and 7 steel wires on the inside [3].

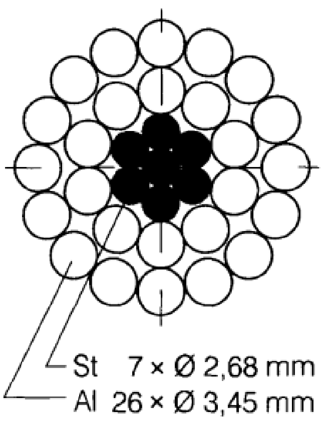


Figure 3.2: Cross section of the ACSR composite conductor 243-AL1/39-ST1A [15]

As a result of using composite conductors, the thermal properties of it depend on the ratio between the two materials. Using equation 3.1, taking into account the thermal elongation coefficient of both aluminum and steel and their respective proportions, a combined thermal elongation coefficient can be calculated, assuming a uniform heat distribution within the conductor.

$$\alpha_a \times \frac{\textbf{No. of aluminium wire}}{\textbf{No. total wires}} + \alpha_s \times \frac{\textbf{No. of steel wire}}{\textbf{No. total wires}} = \alpha_{as} \tag{3.1}$$

Curlew, for example, having 26 aluminum wires and 7 steel wires [15], would therefore, according to equation 3.1 be weighted towards the thermal elongation coefficient of aluminum.

Over its lifetime, the conductor in the OHTL will experience two types of elongations, temporary due to heat and permanent, which cause the length of it to increase or decrease.

3.1.2.2 Elongation

The OHTLs used in power grids will over a longer period of time be exposed to thermal and mechanical stress caused by the tension in the conductor, weather and environment, resulting in a permanent elongation of the conductor. Increased heat in the conductor causes the material to temporarily expand, leading to an increase of the conductor's length. The mechanical stress on the conductor, however, can be caused by heavy wind or ice formations on the line, weighing down the line and creating a higher tension in the line, eventually leading to creep. A factor that contributes to the permanent elongation of overhead transmission lines. Creep is the slow, continuous deformation of materials under constant load over time. In transmission lines, the combination of mechanical stresses and high temperatures can cause the conductors to undergo creep, resulting in a gradual increase in length [15].

The combined wear and tear of these factors can result in a permanent elongation of the material in the OHTL and thus needs to be included when calculating the line-sag for older lines. This thesis focus only on the thermal effects on the material in the conductor, and the permanent elongation will not be covered.

3.1.2.3 Thermal elongation

The increase of heat in the conductor will cause the material to expand, and the difference in temperature, ΔT, is proportional to the difference in length, ΔL, of the conductor as stated in equation 3.2 [12]. As the conductor increases in length, from its original length, L_0 at temperature T_0, the sag of the OHTL will increase and approach the ground to conductor safety limit.

$$\Delta L = \alpha_{as} \times L_0 \times \Delta T \tag{3.2}$$

The difference in temperature of the line depends on several external factors covered in the following sections.

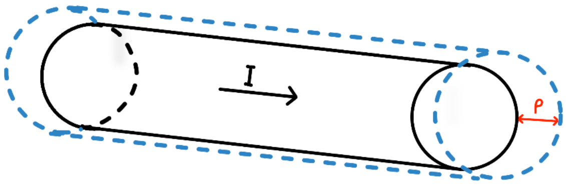


Figure 3.3: The expansion of conductor due to internal temperature of the materials, where ρ is the percentile increase of the conductors dimensions

3.1.2.4 Conductor resistance

The electrical resistance of a bare overhead conductor fluctuates based on factors like its cross-sectional area, power frequency, current, and temperature. However, for this project, methods for directly calculating electrical resistance will not be covered. Instead, we obtain resistance values at high, $R(T_{high})$, and low, $R(T_{low})$, temperatures from established sources, preferably directly from the conductor manufacturer (most often stated in the specifications of the line). Subsequently, the resistance at the average temperature of the wires, $R(T_{avg})$, is derived through linear interpolation using Equation 3.3 below.

$$R_{AC}(T_{avg}) = \frac{R_{AC}(T_{high}) - R_{AC}(T_{low})}{T_{high} - T_{low}} \times (T_{avg} - T_{low}) + R_{AC}(T_{low}) \tag{3.3}$$

For average temperatures, T_{avg}, of the line equal to or below 100°C, a low temperature of 25°C and a high temperature of 75°C are recommended. Conversely, for T_{avg} exceeding 100°C, a low temperature of 25°C and a high temperature of 200°C would give more accurate interpolation.

In the case of AC resistance, which this thesis focus on, the obtained values should consider skin effect and magnetic core effects. However, these effects don't apply to DC resistance. Therefore, it's crucial that the high and low temperature values align with the intended conductor's power frequency. This means using DC resistance values for Equation 3.3 if calculating DC resistance and 50 Hz AC resistance values for 50 Hz AC resistance.

For a frequency of 60 Hz and temperatures ranging from 25°C to 75°C, [17] and [18] provide tabulated values of 60 Hz AC electrical resistance for most sizes and types of bare overhead conductors. Additionally, conductor manufacturers typically offer such resistance values for their products. The AC resistance of a conductor at any temperature must incorporate skin effect and, for one- and three-layer steel-core conductors, magnetic core effects.

3.1.3 Power quality measurement sensor (PQM-sensor)

Power quality measurement units are devices used to monitor and analyze the quality of electrical power in a system. They collect various data points to assess the characteristics of the electrical supply, ensuring it meets certain standards for voltage, current, frequency, and waveform. These units are crucial for maintaining stable and reliable power delivery, especially in overhead transmission lines where power quality can be affected by various factors such as weather conditions, line faults, and electrical disturbances.

Data collected by power quality measurement units typically include:

- **Voltage**: Measurement of voltage levels, including variations, sags, swells, and interruptions.
- **Current**: Monitoring of current flow, harmonics, and imbalance.
- **Frequency**: Analysis of frequency variations from the nominal value.
- **Harmonics**: Identification and quantification of harmonic distortion in the waveform.
- **Transients**: Detection of sudden changes or spikes in voltage or current.
- **Phase Angle**: The relative timing or phase relationship between voltage and current waveforms, which helps determine the power factor and system efficiency.
- **Power Factor**: Evaluation of power factor and reactive power to assess system efficiency.

These measurements help utilities and operators identify potential issues in the power system and take corrective actions to prevent disruptions and ensure the reliability of electrical supply.

In overhead transmission lines, power quality measurement units are often installed at various points along the line to monitor the quality of power being transmitted. This allows operators to detect any anomalies or deviations from the desired parameters and take appropriate measures to mitigate them. The data collected by these units can also be used for predictive maintenance, helping to identify potential faults or failures before they occur.

Providers such as Unipower [19] and ABB [20] offer power quality measurement units designed to perform similar functions. While there may be differences in specific features or capabilities between different providers, the fundamental purpose of these units remains consistent: to monitor, analyze, and maintain the quality of electrical power in transmission and distribution systems. These units are typically installed at substations, distribution centers, or other key points in the power grid where monitoring is essential for ensuring reliable operation.

3.2 Transmission line parameter estimation

The parameters of an OHTL will initially be known, but as the line is affected by weather and electrical current, the parameters will dynamically change. Using the equivalent mathematical model of a long transmission line, a π-section, the parameters of the line can be estimated by analyzing the values of voltage, current and phase at each side of the line. The parameters are shown in table 3.1 below.

Line parameter	**Unit**
R	Ω/m
L	H/m
C	F/m
π-model parameter	**Unit**
R_l	Ω
X	Ω
B	S

Table 3.1: Parameters of the long transmission line and equivalent π-section model

By using measurements of the voltage and current amplitude and phase-shift from each end of the OHTL obtained with a PQM-sensor, combined with the equations for a long line and π-section model, the unknown parameters of the line can be estimated. The equations for a long transmission line are shown below. Sending voltage in 3.4 and sending current in 3.5.

$$V_s = cosh(\gamma l) \times V_r + Z_o \times sinh(\gamma l) \times I_r \tag{3.4}$$

$$I_s = \frac{sinh(\gamma l)}{Z_o} \times V_r + cosh(\gamma l) \times I_r \tag{3.5}$$

The variables used in the equations above are

- Line length, l
- Propagation constant, γ

- Impedance, Z_o
- Sending voltage, V_s
- Sending current, I_s
- Receiving voltage, V_r
- Receiving current, I_r

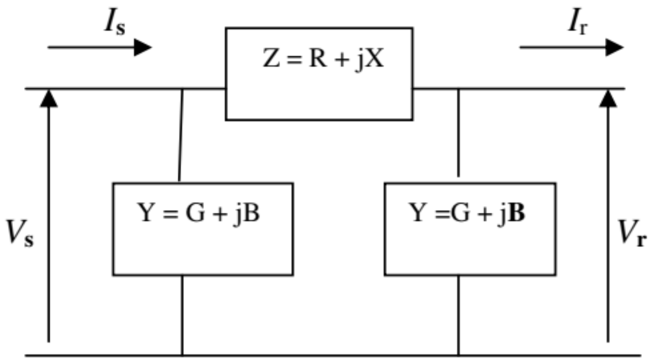


Figure 3.4: Equivalent pi section to a long transmission line [21]

Figure 3.4 shows a π-section that is mathematically equivalent to a long transmission line, where V_s and I_s are defined as

$$V_s = (1 + ZY)V_r + Z \times I_r \tag{3.6}$$

$$I_s = (2Y + ZY^2)V_r + (1 + ZY)I_r \tag{3.7}$$

Where the shunt conductance, G, that is included in Y is neglected and will be in the following calculations. The two imaginary equations 3.6 & 3.7 can be converted into real equations by using the relationship $\theta = \delta - \varphi_s$ from Figure 3.5, with V_r as the reference, and the definitions for Z and Y from Figure 3.4. The four real equations are derived as:

$$V_s \cos\delta = V_r - BXV_r + RI_r \cos\varphi_r + XI_r \sin\varphi_r, \ \triangleq a \tag{3.8}$$

$$V_s \sin\delta = XGV_r - BRV_r + XRI_r \cos\varphi_r - RI_r \sin\varphi_r, \ \triangleq b \tag{3.9}$$

$$\begin{aligned} I_s(\cos(\delta - \varphi_s)) &= 2GV_r + RG^2V_r - RB^2V_r - 2XGBV_r \\ &+ I_r \cos\varphi_r - XBI_r \cos\varphi_r, + RGI_r \times \cos\varphi_r \\ &+ RBI_r \sin\varphi_r + XGI_r \times \sin\varphi_r, \ \triangleq c \end{aligned} \tag{3.10}$$

$$\begin{aligned} I_s(\sin(\delta - \varphi_s)) &= 2BV_r + XG^2V_r - XB^2V_r - 2RGBV_r \\ &+ I_r \sin\varphi_r - RGI_r \sin\varphi_r, + XBI_r \times \sin\varphi_r \\ &+ RBI_r \cos\varphi_r + XGI_r \times \cos\varphi_r, \ \triangleq d \end{aligned} \tag{3.11}$$

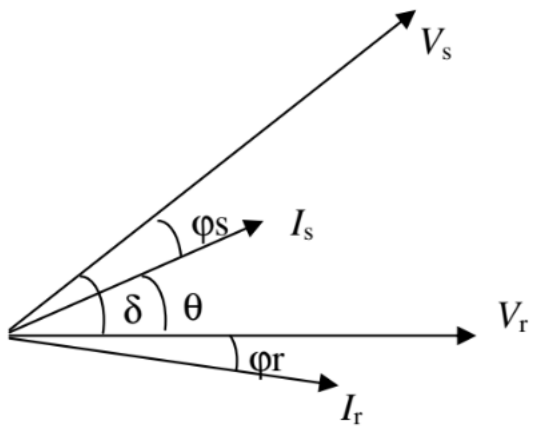


Figure 3.5: Phasor diagram with arbitrary values [21]

The values of $V_s, V_r, I_s, I_r, \theta, \delta, \varphi_r$ and φ_s are all available from measurements with PQM-sensors that exists on each end of the OHTL section. The unknown line parameters X, R, B and δ can be estimated by using the Newton-Raphson method to solve the four non-linear equations. By constructing the four functions $\mathbf{F} = (f_1, f_2, f_3, f_4)$ the problem can be solved by optimizing for $\mathbf{F}(X, R, B, \delta) = 0$, yielding the following:

$$f_1 = -V_s^2 + a^2 + b^2 = 0 \tag{3.12}$$

$$f_2 = -\tan(\delta) + \frac{b}{a} = 0 \tag{3.13}$$

$$f_3 = -I_s^2 + c^2 + d^2 = 0 \tag{3.14}$$

$$f_4 = -\tan(\delta - \varphi_s) + \frac{d}{c} = 0 \tag{3.15}$$

The Jacobian matrix for $\mathbf{F} = (f1, f2, f3, f4)$ is shown in 3.16. The elements of the matrix is further described in appendix A.2.

$$\mathbf{J}(X, R, B, \delta) = \begin{bmatrix} \frac{\partial f_1}{\partial X} & \frac{\partial f_1}{\partial R} & \frac{\partial f_1}{\partial B} & \frac{\partial f_1}{\partial \delta} \\ \frac{\partial f_2}{\partial X} & \frac{\partial f_2}{\partial R} & \frac{\partial f_2}{\partial B} & \frac{\partial f_2}{\partial \delta} \\ \frac{\partial f_3}{\partial X} & \frac{\partial f_3}{\partial R} & \frac{\partial f_3}{\partial B} & \frac{\partial f_3}{\partial \delta} \\ \frac{\partial f_4}{\partial X} & \frac{\partial f_4}{\partial R} & \frac{\partial f_4}{\partial B} & \frac{\partial f_4}{\partial \delta} \end{bmatrix} \tag{3.16}$$

Using the jacobian matrix, $\mathbf{J}$, the stepsize Δx, can be calculated as:

$$\Delta x = -\mathbf{J}(0)^{-1}\mathbf{F}(0) \tag{3.17}$$

Were the next value of x is defined as:

$$x_{i+1} = x_i(0) + \Delta x_i \tag{3.18}$$

$$\cosh \gamma l = 1 + YZ = 1 - XB + jRB \tag{3.19}$$

Using the derivations from the jacobian matrix in Equation 3.16 it can be stated that Equation 3.19 can be used to calculate RLC values of the line, l [21]. As the original RLC are known from the grid construction, variations in these values will be directly related to variation in length of the line, in other words, the variations in RLC values of the line are related to the sagging of the line. Thus, estimation of the RLC values of a line can give an indication of the actual sagging of the line.

3.3 Heat balance equation

As stated in section 3.1.1 and also shown in Figure 3.1 the dynamic ampacity of a conductor depends on several external parameters, which are all critical for predicting the ampacity of the conductor. The resulting change in temperature of the conductor caused by the external parameters is calculated with equation 3.20, which is the dynamic state heat balance equation [22]. The behavior of the temperature is dynamic and will change according to the input parameters, demonstrated in Figure 3.6 where the change in temperature with constant weather parameters and a step change in electrical current is shown.

$$\Delta T_{avg} = \frac{1}{mC_p}\left[R(T_{avg}) \times I^2 + q_s - q_c - q_r\right] \times \Delta t \tag{3.20}$$

Where:

- mC_p is the conductor's specific heat capacity
- T_{avg} is the conductor temperature
- $R_{AC}(T_{avg})$ is the resistance for a specific T_{avg}
- q_s is the solar radiation heating
- q_r is the heat loss from thermal radiation
- q_c is the heat loss from wind cooling
- Δt is the time-step

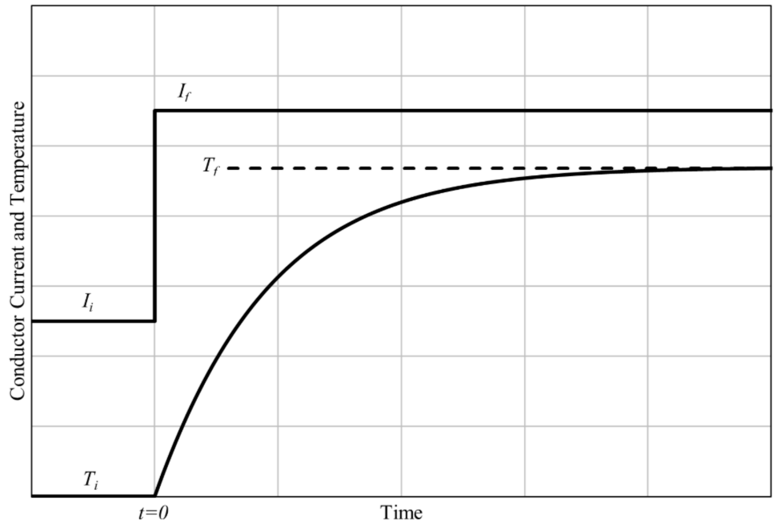


Figure 3.6: The change in temperature after a step in current [22]

Several of the variables used in equation 3.20 are dependent on the conductor, such as the heat capacity and resistance. Theses values are best found in the conductor manufacturer specifications.

The mathematical formulas used to compute the physical effect from the relevant weather parameters are further detailed in the following sections.

3.3.1 Joule heating, q_j

Joule heating, also known as resistive heating, is a phenomenon that occurs when a current passes through a conductor with resistance. It results in the generation of heat within the conductor due to the collisions between charge carriers and the atoms of the material comprising the conductor. These collisions lead to the conversion of electrical energy into thermal energy, causing the conductor's temperature to rise. To calculate the heating of the conductor Joule's Law can be used, which is show in equation 3.21, were q_j is the generated heat in Joules, I is the current in Ampere and R_{AC} is the resistance of the conductor in Ohms.

$$q_j = R_{AC} \times I^2 \tag{3.21}$$

3.3.2 Convective heat loss, q_c

The convective heat loss is a significant factor in the heat dissipation of overhead conductors. It occurs when heat transfers from the conductor's surface to the surrounding air. Convection involves the movement of fluid molecules, in this case, air molecules, which carry away heat from the conductor. The rate of convective heat transfer depends on several factors including the temperature difference between the conductor and the surrounding air, the velocity of the air flow, and the surface area of the conductor. The convection heat loss can be divided into two cases, when the wind speed is zero and when the speed is larger then zero.

$$q_{cn} = 3.645 \times p_f^{0.5} \times D_0^{0.75} \times (T_s - T_a)^{1.25} \quad \mathrm{W/m} \tag{3.22}$$

$$q_{c1} = K_{angle} \times [1.01 + 1.35 \times N_{Re}^{0.52}] \times k_f \times (T_s - T_a) \quad \mathrm{W/m} \tag{3.23}$$

$$q_{c2} = K_{angle} \times 0.754 \times N_{Re}^{0.6} \times k_f \times (T_s - T_a) \quad \mathrm{W/m} \tag{3.24}$$

The first case is calculated with equation 3.22 and the second case is calculated with equations 3.23 and 3.24. In the second case, were the wind speed in above zero, the heated air surrounding the conductor is replaced by new air, creating a cooling effect. In the first case, were the wind speed is zero, the heated air around the conductor will raise due to lower density, and be replaced.

$$N_{re} = \frac{D_0 \times \rho_f \times v_w}{\mu_f} \tag{3.25}$$

The three calculated convection heat losses are compared and the highest number is used.[22]

3.3.3 Radiation heat loss, q_r

As the temperature of the OHTL increases above the temperature of the surrounding air, heat will radiate from the conductor to the air. The thermal energy is transmitted via electromagnetic waves and can be described with the Stefan-Boltzmann law shown in equation 3.26. The rate as which the thermal energy is transferred depends on the difference in temperature between the conductor surface, T_s, and the air, T_a, as well as the conductors emissivity, ε which is the materials ability to emit thermal energy.

$$q_r = 17.8 \times D_0 \times \varepsilon \times \left[\left(\frac{T_s + 273}{100} \right)^4 - \left(\frac{T_a + 273}{100} \right)^4 \right] \quad W/m \tag{3.26}$$

3.3.4 Solar heating, q_s

During the day the OHTL will be subjected to thermal radiation from the sun. The amount of thermal energy depends on the suns position in the sky relative to the conductor, θ, the conductors area and its absorptivity, the date, time and location of the measurement, Q_{se}.

$$q_s = \alpha_c \times Q_{se} \times \sin\theta \times A \quad W/m \tag{3.27}$$

$$\theta = \arccos(\cos(H_c) \times \cos(Z_c - Z_1)) \tag{3.28}$$

where:

- α_c is the conductors absorptivity
- A is the area of the conductor that is projected
- H_c is the angle of the sun above the horizon
- Z_c is the angle of the sun along the horizon with north defined as 0°
- Z_l is the angle of the line with respect to north
- θ is the angle of incidence of the sun to the conductor

Coefficients	**numeric value**
A	-42.2391
B	63.8044
C	-1.9220
D	0.03469
E	-3.61118×10^{-4}
F	1.94318×10^{-6}
G	-4.07608×10^{-9}

Table 3.2: Polynomial coefficients for solar heat intensity as a function of solar altitude corresponding to clear atmosphere[22]

$$Q_s = A + B \times H_c + C \times H_c^2 + D \times H_c^3 + E \times H_c^4 + F \times H_c^5 + G \times H_c^6 \tag{3.29}$$

The amount of solar heating that reaches the earth surface, Q_s, will depend on hos clear the atmosphere is, which depends on pollution, clouds and humidity. Q_s is calculated with equation 3.29 above, using the coefficients for a clear that are displayed in Table 3.2. These coefficients can be altered to represent another type of atmosphere [22].

3.4 Machine learning

Machine learning (ML) is a modern theory in the field of data science that offers a framework for modelling complex problems from the real world. ML is about developing algorithms that enable computers to model and learn to make predictions within a specific area based on patterns. Modern ML techniques can be used for extracting essential features and find complex patterns that initially were unknown. ML models are dynamical in the sense that the model does not need to be modified to learn new data, it can adapt to changes in the data distribution, allowing them to maintain their predictive accuracy even as the underlying dynamics evolve.

DLR is a problem with many parameters, which makes it hard to describe as a mathematical model based on physics principles. Although, the physical formulas for each parameter – such as the solar heating or the joule heating – are available, it is hard to mimic the exact behavior of the OHTL when it is part of a complex system in nature. There exist overlooked or neglected parameters that will have an effect on the line, making the physics-based model less accurate. This is where machine learning comes in to play, more specifically neural networks. If enough data, in this case relating parameters affecting the line's current carrying capacity such as weather and load of it to its capacity (e.g. ampacity) is available, a neural network would most likely be able to model this relationship, even more accurate than any other explicitly formulated model.

However, as mentioned, such data is not widely accessible and may therefore not be sufficient to train a neural network to the point where it outperforms the explicitly formulated weather-based model. To address this and reduce the amount of data needed for the model to achieve the desired results, techniques exist to combine this type of machine learning with the physical knowledge of the system — in this case, physics formulas related to changes in the temperature of the transmission line.

3.4.1 Physics informed neural network

Physics-informed neural networks (PINNs) combine traditional physics-based modeling with the flexibility and learning capabilities of neural networks. They are designed to incorporate known physical laws or constraints into the neural network architecture, thereby enhancing the accuracy and robustness of the model, especially in scenarios where limited data is available, and especially where the physical knowledge of the system is represented as an ordinary differential equation (ODE), which the Heat Balance Equation is. The paper "Structural identification with physics-informed neural ordinary differential equations" [23] demonstrates different ways of incorporating an ODE with a neural network for improved performance.

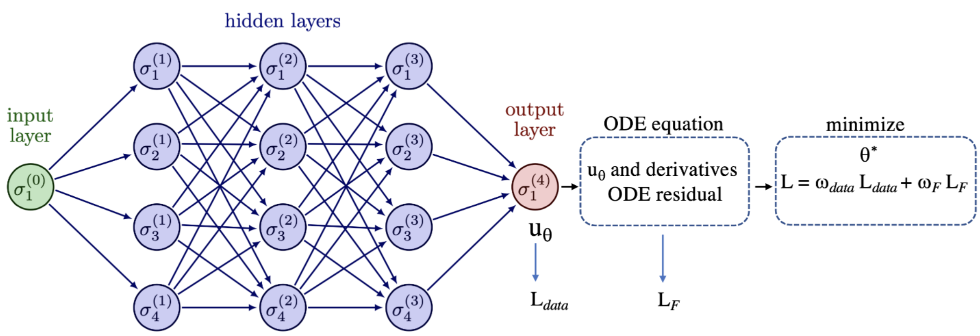


Figure 3.7: Simple model of how a physics-informed neural network may look like (ω - hyperparameters to refine the balance between the losses of the NN and ODE) [24]

Architecture: Generally, PINNs consists of two main components: the physics-informed loss function and the neural network architecture, as shown in Figure 3.7.

The loss function includes terms that enforce the model to satisfy the governing physical equations or constraints, in this case terms such as electrical current, ambient temperature, wind speed, and solar radiation. The neural network architecture is then trained to minimize this loss function. Thus, the PINN ensures that the predicted temperatures of the line are consistent with the physical behavior of the transmission line.

Training: During training, the PINN then learns from both observed data and the known physical laws. It adjusts its parameters to simultaneously fit the data and satisfy the physics-based constraints. This dual learning approach allows the model to generalize well beyond the training data, making it more robust and accurate, especially in regions where data might be sparse.

3.4.2 Discrepancy learning

Discrepancy Learning is an approach used in machine learning and scientific computing to learn the difference or discrepancy between a simulation model and observed data. Unlike Physics-Informed Neural Networks (PINNs), which directly embed known physical laws into the loss function of a neural network, discrepancy learning focuses on minimizing the difference between model predictions and observational data without explicitly incorporating physical equations.

In Discrepancy Learning, the goal is to train a model to accurately replicate observed data while acknowledging that the simulation model may not perfectly capture all aspects of the underlying physical system. This approach is particularly useful when the true underlying physical equations are unknown or challenging to formulate explicitly. Instead of enforcing physical constraints directly, discrepancy learning aims to learn and minimize the discrepancies between the simulation model and observational data.

Discrepancy Learning can complement the Heat Balance formula (Equation 3.20) by refining the model's predictions based on observed data. For instance, in the context of implementing the Heat Balance formula within a neural network framework, discrepancy learning can be used to further adjust the model's predictions to better match real-world observations. By minimizing the difference between the model's temperature predictions and actual temperature measurements from overhead transmission lines, discrepancy learning enhances the model's accuracy and reliability, especially in scenarios where the physical system's behavior deviates from the idealized assumptions of the Heat Balance formula. This approach allows for a more nuanced and data-driven modeling of the thermal behavior of transmission lines, improving the model's performance in practical applications.

4
Methods

This chapter provides an overview of the methodologies employed in this thesis. It encompasses the implementation of the weather-based model, the development of a real-time module, and the methodology for constructing an artificial intelligence (AI) model.

The weather-based model, currently operational, forms the foundation of our project and accounts for various weather parameters and their impact on transmission line temperature and capacity. Additionally, we outline the functionality of the real-time module, how this should be developed with focus on data collection while still being used for live estimation.

Machine learning emerges as a promising tool for addressing the complexities inherent in our problem domain. With numerous variables influencing transmission line behavior, machine learning offers the potential to capture and model these intricate relationships effectively. Through sufficient training, a generalized model may emerge, capable of extrapolating to diverse transmission line scenarios with minimal fine-tuning. This scalability is invaluable, as it enables the application of the model to a wide range of transmission line configurations without the need for extensive retraining.

Despite our partial understanding of the physical relationships governing transmission line behavior, numerous unknown parameters continue to affect line performance. While we possess some knowledge of how conductor temperature influences sag, integrating this knowledge into a machine learning model allows us to incorporate physics-based constraints. By employing Physics-Informed Neural Networks (PINNs), the model can effectively learn the impact of these unknown parameters. PINNs enable us to integrate known physics into the machine learning framework, thereby enriching the model's understanding while simultaneously reducing the amount of data required for training.

4.1 Building the weather based thermal model

In order to accurately forecast line sag, it is essential to consider the interplay between various parameters affecting the temperature of the line. Line sag occurs due to the thermal elongation of the conductive material, caused by elevated temperatures. Thus, to accurately predict line sag, we need to consider a combination of weather conditions, such as ambient temperature, solar radiation and wind speed, along with the electrical load on the line. These factors collectively impact the temperature of the line, ultimately leading to its expansion and consequential sagging.

This model is primarily based on the heat balance formula, as presented in chapter 3. The heat balance formula serves as the foundation for understanding how energy exchanges occur within the system, considering various heat sources and sinks. By integrating this formula into our model, we can effectively calculate the temperature distribution along the transmission line under different operating conditions. This integration enables us to account for both internal and external heat sources, such as electrical losses, solar radiation, and ambient temperature, to accurately simulate the thermal behavior of the line.

4.1.1 Weather based line temperature simulation

The thermal model implemented in this project is derived from the heat balance formula presented in the theory chapter section 3.3. This formula serves as the foundation for understanding the intricate interplay of various factors influencing the temperature of the transmission line.

Initially, the heat balance formula is utilized to compute several key terms essential for temperature estimation. These include convection heat loss, radiation heat loss, solar heat gain, and heat gain due to electrical load (resistance in line). Each term is determined based on specific line characteristics, prevailing weather conditions, and electrical load. By plugging these terms into the heat balance equation 3.20, the model facilitates the estimation of temperature differentials over discrete time steps.

Following temperature estimation, the line's resistance is updated to reflect the newly simulated temperature. This update process employs a linear interpolation technique between reference resistance values corresponding to distinct temperature thresholds, further described in section 3.1.2.4. Subsequently, the simulated time is incremented, and the temperature estimate is stored. This iterative process continues, accommodating potential changes in load or weather parameters until the desired simulation timeframe is attained, typically aligned with the forecast horizon.

The model is formulated as a transient simulation, capturing the dynamic response of the line's temperature over time. By adopting this approach, the model can effectively account for short-term fluctuations in external factors such as weather parameters and electrical load variations. Consequently, transient changes in these

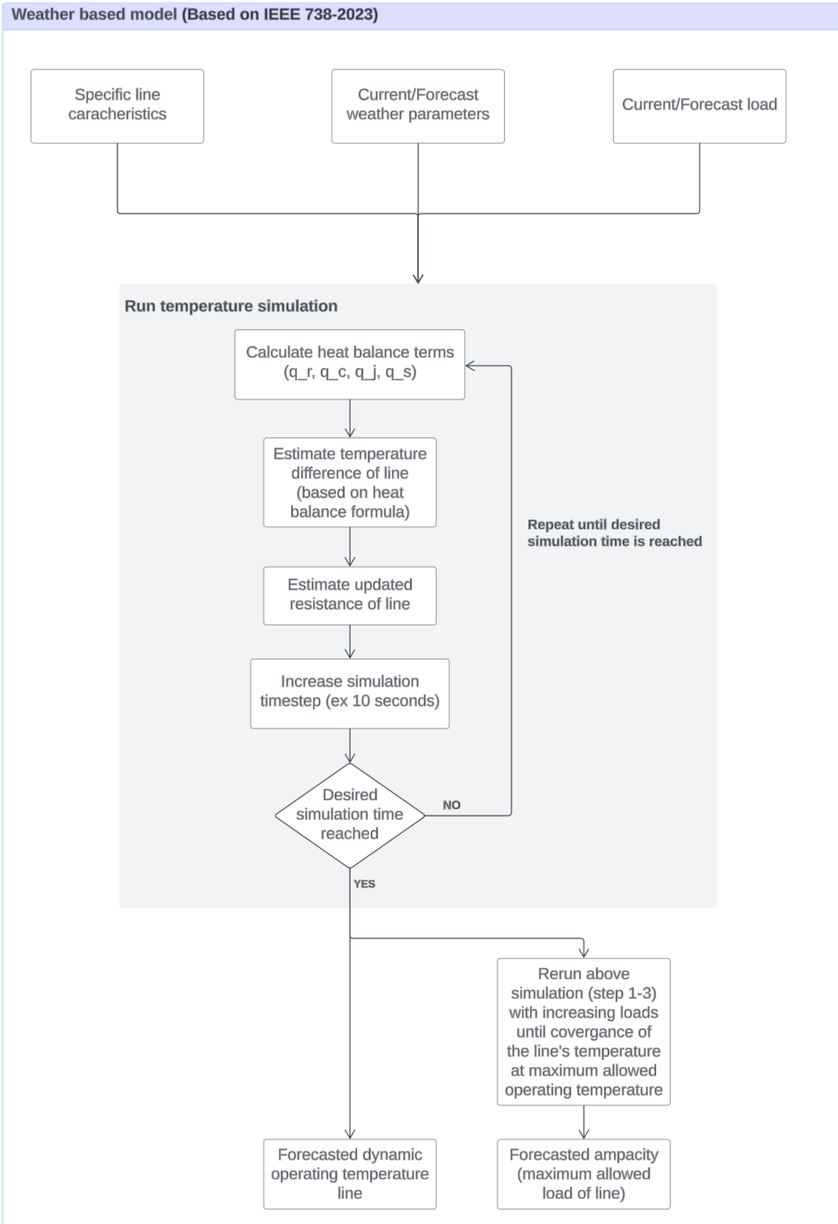


Figure 4.1: Flowchart of weather based simulation of line temperature

parameters have a proportional but moderated impact on the simulated temperature of the line.

Even though the model meant to be used for forecasting, it is also able to handle real-time estimation of line temp. In the real-time mode, the model receives a continuous stream of live load data and weather information, enabling instantaneous temperature estimation for the transmission line. As opposed to when forecasting, where the model is fed forecasted load and weather data, enabling it to project the line's temperature over the forecast horizon.

In addition to temperature estimation, the model offers the capability to forecast the expected ampacity of the transmission line based on anticipated weather conditions. This feature provides operators with valuable insights into the line's load-carrying capacity under varying environmental scenarios. By assessing the proximity to maximum load thresholds, operators can proactively manage load distribution and mitigate potential overloads.

Deployment of the thermal model across multiple sections of an overhead transmission line enables the identification of critical points susceptible to temperature extremes. This information empowers operators to strategize rerouting plans, ensuring optimal line performance and reliability under diverse operating conditions.

4.1.2 Validation

Given the unavailability of specific data correlating weather conditions and load to line temperature or sag, direct validation of the model against real-world conditions is not possible. Without access to a real transmission line, such as through a pilot project with a relevant company, verifying the model in this manner is unfeasible.

Even if data of this nature were to exist, it is classified as critical and inaccessible for sharing without further collaboration with stakeholders (grid operator companies), as noted by a DLR specialist working at Vattenfall. In such cases, validation of this model against real-world conditions can occur through an offline pilot project, where only the data is shared and subsequently analyzed alongside results from our model.

The validation done of the model is against sample calculations provided in IEEE 738-2023, yielding positive results. The agreement between the model's predictions and the heat balance formula's outcomes, as demonstrated in sample calculations, reinforces its accuracy. However, it's important to note that while the model aligns with the equations, the iterative nature of our simulation lacks specific validation examples within the IEEE 738 literature.

Further validation of the IEEE-738 stems from comparisons with studies that test the IEEE standards against real-world scenarios [25]. While these studies may not directly assess the software's performance, their outcomes indirectly endorse the accuracy of our model. By demonstrating consistency with established standards and practices, these comparative analyses contribute to the validation of our software's efficacy.

In summary, while direct validation through real-world data remains a challenge, the model's alignment with established standard and its consistency with comparative studies provide confidence in its accuracy and reliability within the intended operational environment.

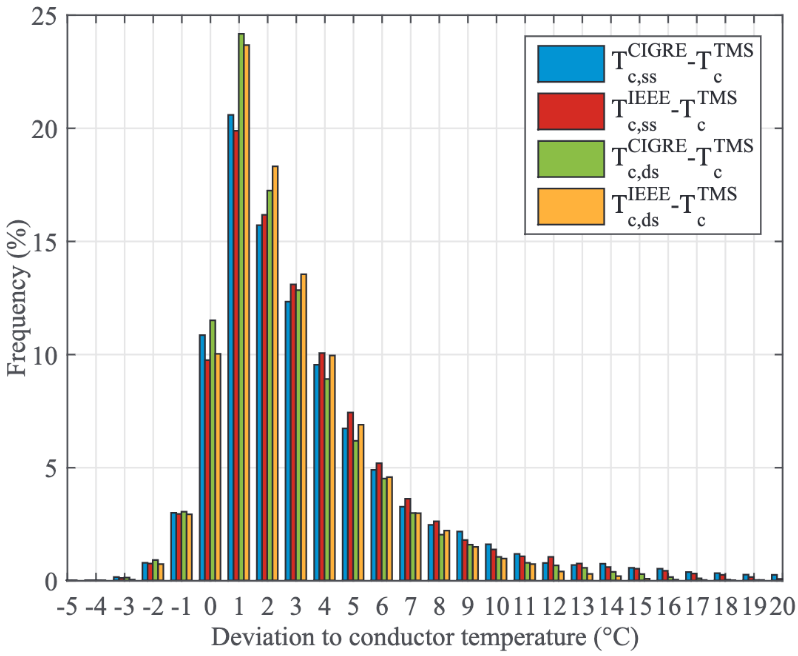


Figure 4.2: Figure showing results from IEEE 738-2012 against real-world measurements [25]

4.2 Real-time estimation

Even though the previously presented weather-based model can estimate a line's real-time temperature — and consequently, an estimation of the line's sag — using weather and load parameters, there exists an alternative method that can provide very accurate results using PQM sensors.

This method is grounded in existing research that leverages real-time PQM data in conjunction with known line-specific characteristics to determine line parameters. The methodology involves using the relationship between a line's length and its Resistance (R), Inductance (L), and Capacitance (C) values, discussed in the theory chapter.

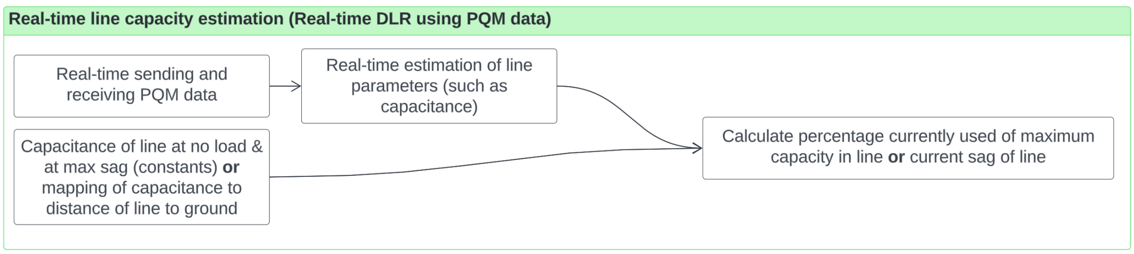


Figure 4.3: Flowchart of real-time estimation module

Continuing from this theoretical foundation, the method for determining a line's real-time sag, or rather currently used capacity, involves estimating the line's real-time RLC values, which is an extension of the theory discussed in 3.2 and listed in Appendix A.2. This method is able to determine capacitance values of the transmission line under a 1% error margin, way more accurate results than what the weather based model is able to, with Figure ?? in mind.

Specifically, the capacitance of a transmission line is important, which is directly impacted by its height above the ground. By analyzing real-time capacitance measurements and comparing them with the line's capacitance specifications at both maximum and minimum sag, one can accurately calculate how close the line is to its maximum allowed capacity.

To elaborate, the capacitance of a transmission line is influenced by its height above the earth due to the changing distance between the line and the ground, which affects its electric field and thus the capacitance. By having an estimation of the line's real-time capacitance, and knowing the capacitance values corresponding to its maximum and minimum sag positions, it becomes straightforward to determine the current sag state of the line. Which is also an estimation of how close the line is to reaching its maximum capacity.

In summary, by utilizing PQM devices to measure real-time line parameters and applying this method, it is possible to achieve highly accurate estimations of a transmission line's sag and capacity usage. This approach enhances the reliability of real-time monitoring and will also be used as a module for data collection, more about this in the results chapter.

4.3 Building the AI-model

The primary objective in constructing our AI model is to develop a system capable of predicting both real-time and forecasted capacity usage of overhead transmission lines. The envisioned model is designed to self-improve over time, continually enhancing its predictive accuracy until the desired performance level is attained. Importantly, the model is intended to operate without the need for additional hardware and to rely on a minimal number of information sources.

As previously discussed, the performance of a transmission line is significantly influenced by parameters such as the electrical load and weather conditions. Consequently, these factors must serve as inputs to the model. Accurate and reliable predictions depend on the model's ability to interpret and integrate these critical variables effectively.

However, a significant challenge arises due to the unavailability of comprehensive data. Data linking weather conditions and electrical load (pqm data) to a line's temperature or sag are often not recorded or accessible. To address this, it is necessary to devise a method for acquiring the required data and training a relevant model. This method will involve innovative data collection strategies and the utilization of existing data sources in novel ways. The specific methodology for data acquisition and model training will be elaborated in Chapter 5.2.1.

By addressing these challenges, we aim to construct an AI model that not only meets the operational requirements but also demonstrates robustness and adaptability. The ultimate goal is to provide a tool that enhances the efficiency and reliability of managing overhead transmission lines, thereby contributing to the overall stability and performance of the power grid.

5

Results and Discussion

5.1 Weather model simulations

This section details the results and insights gained from the weather model simulations, focusing on the simulation results and its relevance for real-time and forecasting DLR. The weather model was tested in extensive simulations to find how the different weather parameters will affect the conductor temperature. If a parameter is static during a simulation is it set to a value shown in Table 5.1.

Static parameter	**Value**
Current [A]	1000
Ambient Temperature [°C]	20
Time of day	12:00
Day of year	182
Wind angle [°]	Parallel/Perpendicular
Wind speed [m/s]	0
Latitude [°]	60
Conductor core diameter [mm]	10.4
Conductor outside diameter [mm]	28.14
Latitude [°]	60

Table 5.1: Static parameters used during simulations.

In Figure 5.1 the wind speed and the angle of the wind relative to the conductor is plotted against the conductor temperature. The plot shows how the wind speed and the wind angle affect the conductor temperature, and it is clear that the wind speed have a significant effect on the conductor temperature. The angle of the wind increases from 0°to 180°and the resulting conductor temperature shows that the angle of the wind angle have a lesser affect. With a parallel wind (0°and 180°) the cooling effect that is a result from the wind angle will be minimized, but still existing, which can be seen in Figure 5.2b, that shows that the cooling effect is existing and increases with wind speed. As the conductor temperature increases above the ambient temperature the conductor will radiate thermal energy and heat up the air around the line, when the wind speed increases the heated air will be replaced by colder air. When the wind angle is perpendicular relative to the conductor the wind will have a larger cooling effect, which is deducted from Figure 5.2.

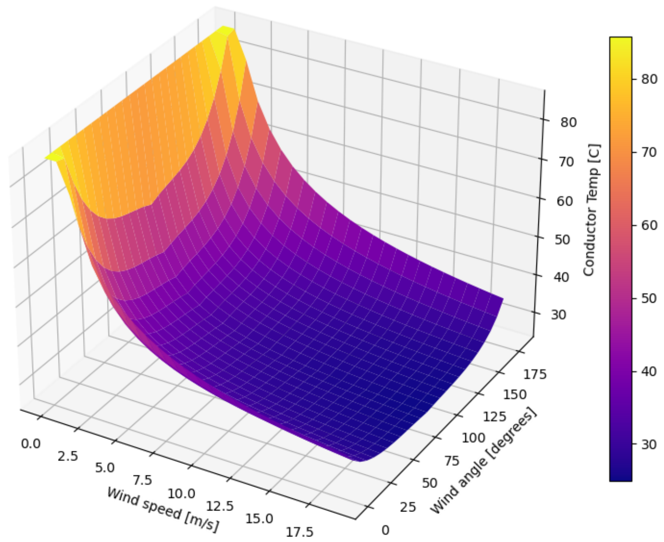
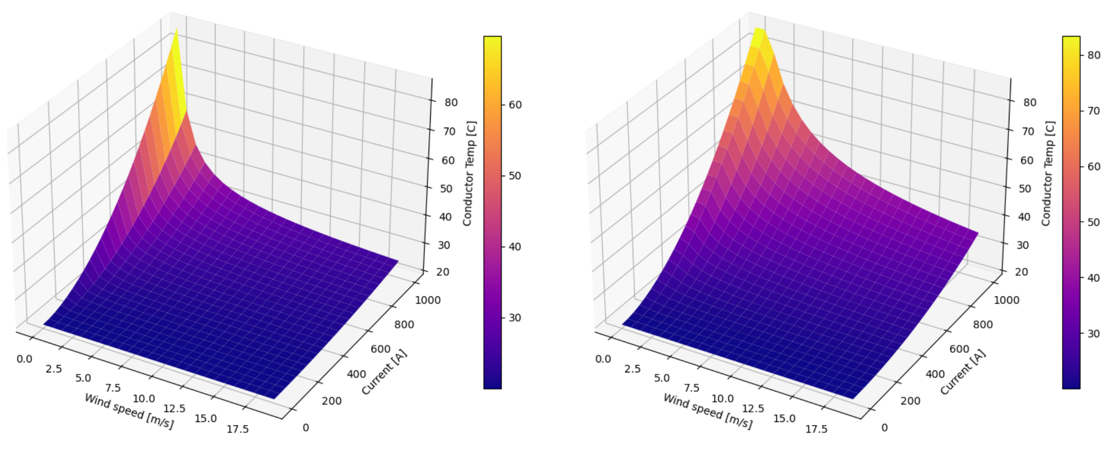


Figure 5.1: This plot is a result of a simulation of wind speed and wind angle relative to the conductor plotted against the conductor temperature. Other parameters where set to static values where, electrical current was 1000 A, ambient temperature was 20° C, time of simulation was set to mid day in the middle of the year and the latitude was set to 60°.



(a) Perpendicular

(b) Parallel

Figure 5.2: Parallel and perpendicular wind angle relative to the conductor. Other parameters where set to static values during the simulation, ambient temperature was 20°C, time of simulation was set to mid day in the middle of the year and the latitude was set to 60°.

In Figure 5.3 below the ambient temperature, electrical current and the resulting conductor temperature is plotted. It can be seen in the figure that the conductor temperature increases linearly with ambient temperature, and exponentially with electrical current. The reason for the exponential relationship is the thermal energy that is created from the current, which is explained in the Theory chapter, section 3.3.1.

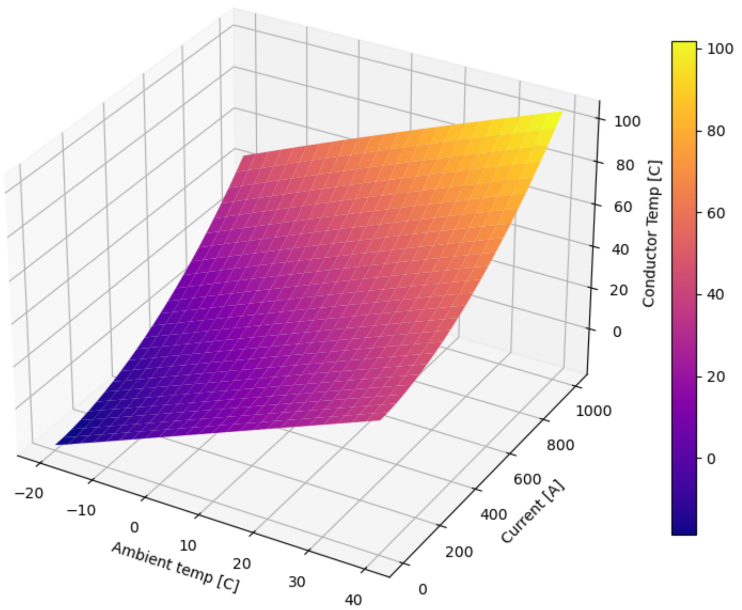


Figure 5.3: Ambient temperature and electrical current plotted against the resulting conductor temperature.

In Figure A.3 found in Appendix, the weather parameters are plotted with arbitrary data that represents the four firsts days of the month of July, together with the calculated ampacity for a conductor with static parameters described in 5.1. As the ampacity is a metric of the maximum electrical load in the conductor before it exceeds its maximum temperature, which is set to 70°C, it increases when the parameters have a cooling effect on the conductor. Resulting in a larger gap between the ampacity and the actual load, allowing the grid operators to increase the load on the production side or allow more electricity to flow in that specific conductor. It can also be seen how the different parameters affect the ampacity and the conductor temperature, and by looking at the second bottom plot in Figure A.1 or A.2 the generated thermal energy from every parameter is shown.

For comparison, the two Figures A.1 & A.2 shows how the resulting metrics act when the wind speed is dropped to zero. It is clear that the lowering the wind speed to zero have a large effect on conductor temperature and ampacity. In this case the the convection cooling effect is higher during zero wind speed, but the radiation cooling decreases, meaning that when the conductor temperature increases above the ambient temperature, the conductor will radiate more heat into the surrounding air.

5.2 New method for DLR

With the insights gained during the research throughout the project and development of the weather model, a system for both training and using a machine learning based model for DLR can be developed. In Figure 5.4 below, the layout of such a system is proposed. The figure shows how the final system would work in practice and how data flows through the system.

The system would consist of a *data collection module*, *Machine learning model*, *Weather based model*, *PQM module* and an *ML training module*. When first initiating the system, no trained ML model exists and the system will make a forecast or real-time estimation using the weather based model or the PQM-based model. It will also collect the data used for estimations, such as weather data, electrical load and line specific information and save it. When a specified amount of data is collected, the ML model will be trained by the training module. Then eventually, when a ”High accuracy ML model” has been achieved. Meaning the point when the ML model performs better than the explicitly formulated modules, this will be used for estimations instead.

The data collection module and ML training module may also be set to run even when the ML model is in use, for possibly even further increased accuracy of ML estimations.

In the following sections, the internal modules of the system are further described.

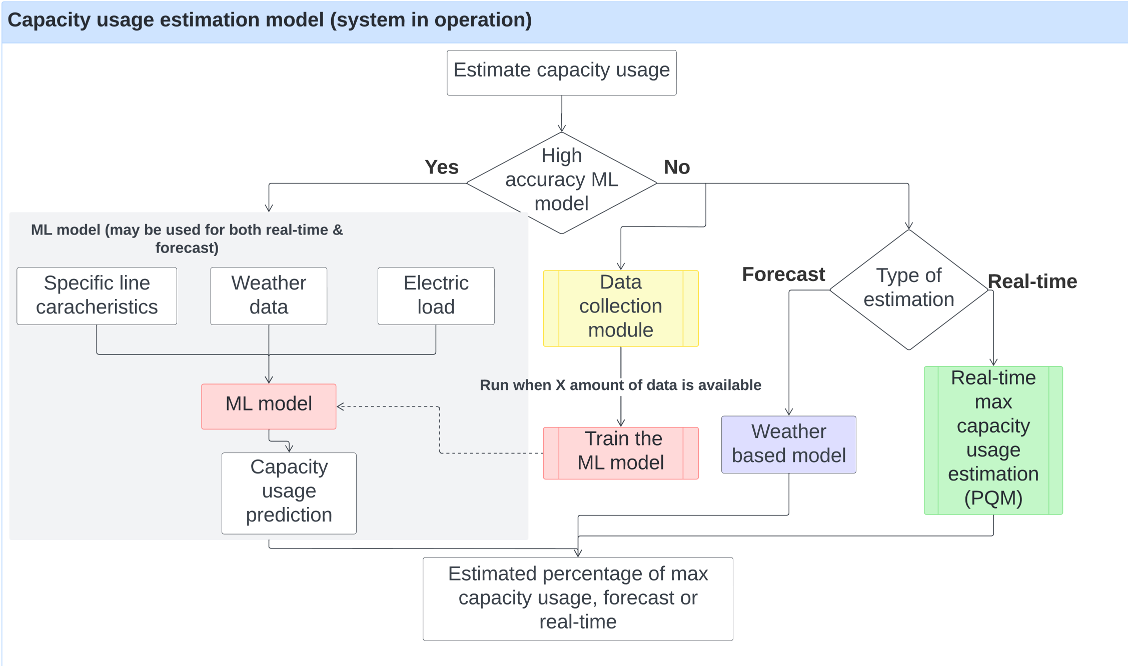


Figure 5.4: Overview of the system and the modules in operation

5.2.1 Data collection module

In Figure 5.5 the data collections module is shown. The function of this module is to collect weather and load data and relevant information about the conductor into a database, mapping all the parameters to the current percentage of max capacity, which is fed by the Real-Time module presented in the Methods chapter. This mapping of data is then used to train the ML model.

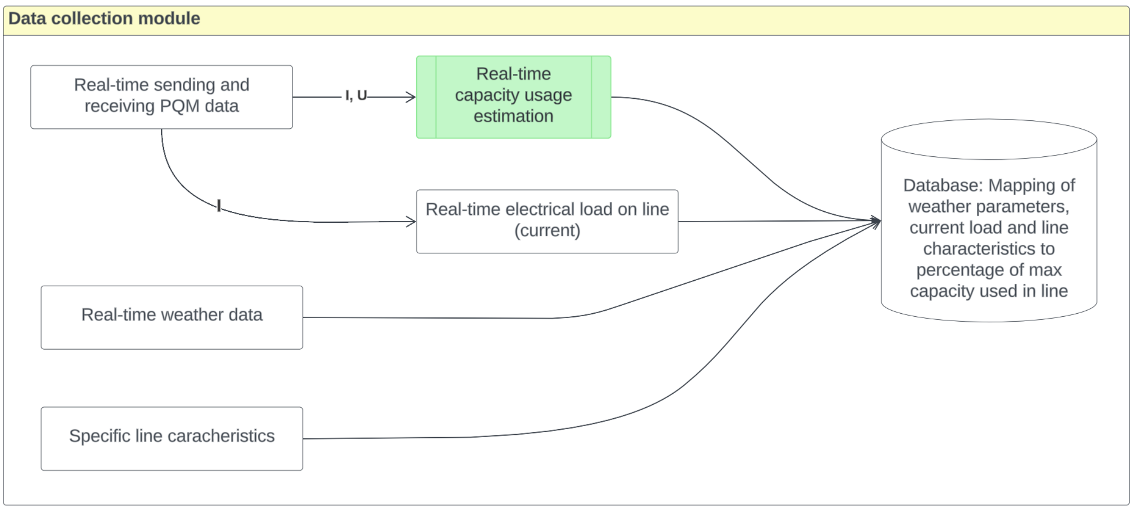


Figure 5.5: Flowchart of the Data Collection module

5.2.2 Training the AI model

Figure 5.6 shows a proposed way of how training an ML model could be done. The specifics of the ML training needs to be developed with respect to the type of ML model used in practice, this layout is therefore an overview and relatively general regardless of ML model used, where the new data is split in two, one training set, and one validation set used for evaluation.

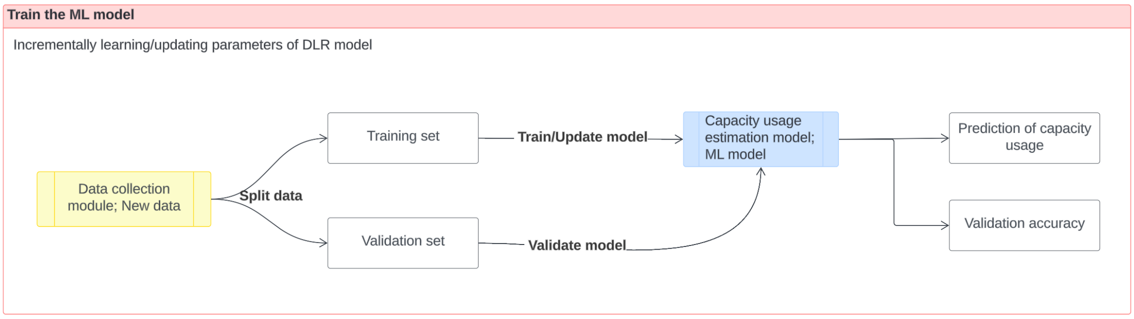


Figure 5.6: Flowchart of the steps in training the AI model

5.3 Context and Challenges in AI-Driven DLR

The utilization of components within contemporary power grids has undergone significant augmentation in recent years. This expansion has engendered a concomitant increase in the complexity of the power grid infrastructure, along with a notable escalation in electrical consumption demands. The proliferation of diverse elements such as solar cells, electric vehicles (EVs), and battery-powered devices has contributed to this phenomenon. These components, whether by generating electricity (e.g., solar cells) or consuming it (e.g., EVs and battery-powered devices), impose an augmented burden on the power grid. Consequently, this dynamic interplay between generation and consumption serves to exacerbate the challenges associated with accurately forecasting energy requirements within the grid.

The proposed model depends on load and weather forecasts, both being sources generally known to be hard to forecast. The results of this thesis states that the wind have a large cooling effect on the overhead lines, which can be seen in Figure A.3 found in Appendix. This raises questions regarding measuring and forecasting the weather, as measurement errors can lead to errors in the estimations. Vattenfall discusses wind measurements in the paper "Dynamic capacity rating for wind cooled overhead lines" [12], where it is stated that there are very few occasions of low wind near the overhead line at the same time as high wind at 100 meters height observed in the measurement data. The measurements of wind speed provided in the paper also shows a clear relationship between winds at 100 meters and winds at conductor height, meaning that to correctly estimate the wind cooling effect the wind does not have to be measured exactly at conductor location. However, this needs to be further validated and is also included in future work for this project.

From conducting market research and reviewing the Dynamic Line Rating (DLR) solutions, it was clear that using AI for DLR was a completely new approach. This poses both challenges and possibilities.

One of the primary challenges is the lack of precedent in the industry. With AI applications for DLR being relatively unexplored, there is limited existing knowledge or case studies to guide the development and deployment of such models. This necessitates a significant amount of foundational work, including the establishment of best practices, validation protocols, and benchmarks for performance. Additionally, there is a steep learning curve for industry stakeholders who may be unfamiliar with AI technologies and their potential benefits for DLR.

Another challenge is the quality and availability of data. Effective AI models require large amounts of high-quality data to train on, yet, as mentioned, data related to weather conditions, electrical load, and their impact on transmission line parameters like temperature and sag are often sparse or non-existent. Developing methods to reliably gather and preprocess this data is crucial, and this process can be time-consuming and resource-intensive.

Despite these challenges, the use of AI in DLR also presents significant possibilities. AI models have the potential to analyze complex and nonlinear relationships between various influencing factors with greater accuracy and efficiency than traditional methods. This capability can lead to more precise predictions of line capacity and, consequently, more efficient utilization of existing transmission infrastructure. By leveraging AI, it becomes possible to dynamically adjust the ratings of transmission lines in response to real-time conditions, potentially increasing the capacity of the grid without the need for costly physical upgrades.

Moreover, AI-driven DLR solutions can enhance grind reliability and stability. By providing more accurate forecasts, grid operators can better anticipate and mitigate potential issues before they escalate into larger problems. This proactive approach can lead to fewer outages and improved service quality for end-users.

Additionally, the scalability and adaptability of AI models mean that, once developed, these solutions can be applied across different regions and types of transmission lines with minimal modifications. This flexibility is particularly valuable in diverse geographical and climatic conditions, making AI a versatile tool for improving grid management globally.

To conclude, while the integration of AI into DLR systems poses significant challenges, it also opens up a realm of possibilities that could revolutionize how transmission lines are managed. The initial hurdles of data acquisition, model training, and industry adoption are offset by the potential for increased efficiency, reliability, and adaptability in power grid operations. As the technology matures and more data becomes available, the impact of AI-driven DLR is likely to grow, offering substantial benefits to the energy sector.

5.3.1 Focus on implementation

When developing the DLR solution, the focus was on implementing the weather-based model due to several reasons. This model provides a foundation for both immediate and future needs, allowing us to demonstrate value quickly while paving the way for more advanced developments.

Firstly, the weather based model is capable of both real-time and forecasting estimations. This enables grid operators to make informed decisions on current operational conditions and plan for future scenarios, enhancing both the immediate and strategic management of the power grid. By starting with this model, we establish a simplified version of the more advanced neural network we plan to implement and train later. This foundational step allows us to quickly demonstrate the value of our solution and build towards more complex implementations.

Another significant advantage of the weather-based model is its adherence to IEEE standards, ensuring that our solution reflects real-world conditions and meets industry benchmarks. This compliance is crucial for gaining the trust and acceptance of stakeholders and regulatory bodies. Leveraging standards-based methodologies enhances the reliability and accuracy of the model, which is essential for the safe and efficient operation of the electrical grid.

Moreover, following discussions with Archeri, we determined that the weather-based model brings the most value for product development and pilot projects. This model offers the quickest path to developing a demonstrable product, which is essential for engaging potential clients and partners early in the project lifecycle. The weather-based model provides a practical and immediate solution that can be used in pilot projects, allowing us to gather real-world data and feedback. This hands-on experience is invaluable for refining the product and proving its efficacy.

Additionally, the formulas and methodologies used in the weather-based model can serve as a foundation for developing physics-informed neural networks (PINNs) combining data-driven approaches with physical laws, enhancing accuracy and interpretability. By starting with a weather-based model, we ensure a smooth transition to more advanced AI models, with the initial model's data and insights directly informing the training and development of the PINNs.

5.3.2 Choice of AI model for DLR system

For implementing the weather-based DLR solution, we can consider several types of AI models, each offering unique advantages and varying complexities.

Linear regression models provide simplicity and transparency, making them ideal for initial implementations. However, they can only capture linear relationships between weather variables and line ratings, which may be too simplistic for our needs. Decision trees and random forests, on the other hand, can handle non-linear relationships and interactions between multiple weather variables, offering robustness and better generalization compared to linear models. These models can also be used to identify the most significant weather factors affecting line ratings, providing insights for further refinement.

Support Vector Machines (SVMs) offer flexibility by handling both linear and non-linear relationships through kernel functions. They are particularly effective for tasks involving complex data patterns and are less prone to overfitting.

However, for the proposed DLR solution, we decided to use neural networks. They can capture complex patterns in the weather data that influence line ratings, linear or non-linear. Starting with these models also sets the stage for developing physics-informed neural networks (PINNs), which would then be based on the already known physics introduced in the weather-based model. PINNs allow the model to be trained effectively with less data than would be needed for training a neural network from scratch.

To further enhance the AI model, ensemble models can be used. These combine multiple models to improve prediction accuracy and robustness by leveraging the strengths of individual models. This approach will be investigated later on.

5.3.3 Risk assessment

Implementing an AI-based DLR solution involves several risks that need to be assessed.

The **data quality and availability** is a large and important part of developing AI, which can have a huge impact on the accuracy and reliability of a model. Since the model will be a product of the data used for training, data that does not represent the affecting parameters correctly will lead to a bad performing model. The **model accuracy** is a result of the data, but also the methods used for training. Training an AI-model is a time consuming operation which often needs to be approach with trail and error for finding the training yielding the best accuracy.

The safety aspects of the grid are important and providing inaccurate line ratings can lead to overheating, equipment damage, or even catastrophic failures. It is therefore important to validate and run extensive testing on a system like the one proposed in this thesis. Using a static line rating together with the provided dynamic line rating can be a way for ensuring that there exists a safety margin in the rating. The provided DLR value should be used in combination with other relevant information to guide the grid operators to make the safest most reasonable decisions, it should initially not be used as a standalone value, more like an additional tool.

5.4 Stakeholder Engagement and Future Prospects

As mentioned, this project has been conducted at the startup company Archeri, where gaining value extends beyond developing the product itself. A critical component of the project's success is identifying and engaging stakeholders interested in the technology. Furthermore, sustaining interest in ongoing research is essential, with the ultimate goal of initiating a pilot project and securing funding for further development. Extensive efforts have been made to achieve these objectives.

The interest gained from potential customers has been achieved through close contact with key stakeholders and extensive market research. By maintaining open lines of communication and actively seeking feedback, we have been able to tailor our development efforts to meet the needs and expectations of our potential customers. This proactive approach has been instrumental in generating enthusiasm and support for our technology, paving the way for its future success and implementation.

Specialists at both Vattenfall and Svenska Kraftnät have shown significant interest in the novel approach of utilizing AI to address the challenges associated with Dynamic Line Rating (DLR). The complexity of the problem, with numerous variables affecting line ratings, makes AI a promising solution. Their interest highlights the potential of our technology to provide innovative solutions in a field where traditional methods are increasingly inadequate.

Presenting our technology has also garnered attention from potential stakeholders. This has resulted in letters of intent and the opportunity to apply for grants in collaboration with major industry players like EON. Such collaborations aim to continue the research and development of our product, underscoring the broad interest and potential impact of our work in the field of DLR and beyond.

6

Conclusion

In this chapter the conclusions from the thesis are presented, involving the key findings, discussion, risk assessment as well as future work.

6.1 Key findings

The findings presented in this section are the most valuable and important results that have emerged from the research and development conducted during this thesis.

- The current existing solutions for DLR used in the industry often relies on additional hardware installation, resulting in expensive and non-scalable solutions. The solutions are often designed for real-time estimations and cannot make long-term estimations, something that is desired by the grid operators.

- Effecting the line's temperature and ampacity heavily depends on the current weather conditions. Thus, providing a DLR solution to handle real-time, but also forecasting estimations will therefore have to include the effects on the line taken from forecasted weather conditions. The developed weather model in this thesis builds on the formulas provided in the IEEE-738 standard [22], recommended by key stakeholders.

- Some of the weather parameters can easily be foreseen since they follow a simple pattern, such as solar heating, but others do not follow a pattern and thus cannot be foreseen to the same extent, such as the wind cooling effect – which also happens to be an important weather parameter –, resulting in a large uncertainty and a need for frequent measuring of the wind.

- Our system can function without any additional hardware installations, using only the already installed PQM-sensors to collect live measurements, and can handle both real-time and forecast estimation. The finished product could therefore provide a cheaper and more scalable solution for DLR.

- The DLR problem is suitable to solve with AI for several reasons: The many parameters that affects the OHTL contributes to the complexity of the problem which makes it difficult to solve with traditional algorithmic solutions, an AI-model could be efficient in finding these patterns and trends. There is a sufficient amount of data available from the electrical grid and weather stations to make the AI-model relevant. There is a clear objective and metrics in the task, making it easy to evaluate the performance of the model and to understand the internal workings. Approaching this problem with AI have a clear economic benefit, both in the sense that no hardware in the grid is needed, but also that the full capacity of the grid can be utilized.

- Using a physics informed neural network is a well fitting solution for this problem, as it uses the existing physics formulas as ground knowledge. In this case, the formals would be the ones presented in the theory chapter. This also reduces the amount of data needed, because the model would not have to learn the formulas completely from scratch, as a simple neural network would have to.

- The solution has a clear value in the industry, but to continue the development a collaboration is needed with a grid operator that can provide testing facilities and more importantly, data.

6.2 Future work

This thesis has presented a framework for an ML based DLR solution that can be used for real-time and forecast estimations of the grid capacity. However, the proposed solution is not ready for deployment and will need further development and validation.

The weather based model that was developed in this thesis and was used for analyzing the effects of weather on the overhead line, needs to be further validated, preferably with real data from the grid. As real grid data is hard to get a hold off, because of classification reasons, the weather based model have only been validated by comparing with IEEE results previously done against the real world.

The modules that not yet have been implemented are the data collection module, ML model, ML training module and the real-time capacity estimation module, which is based on PQM data. The theory and basic layout of these modules have been presented in this thesis, which lay the ground for implementing a working DLR system. The modules would then have to be validated, both as stand alone and in the system as a whole. From discussions with grid operators and DLR industry experts, we have found that the best step forward is to start a collaboration with companies that are interested in developing DLR and have access to the infrastructure needed.

Further down the road, there exist several more implementations that can be done to make the system perform better, such as integrating this solution with existing software used in the grid. This can be software that is used for controlling or analyzing the power flow in the grid.

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A

Appendix

A.1 Code for solving the Jacobian Matrix

```
syms X R B alpha V_s V_r I_s I_r delta varphi_r varphi_s;

% Define function 'a'
a_expr = V_r - B*X*V_r + R*I_r*cos(varphi_r) + X*I_r*sin(varphi_r)
    - V_s*cos(delta);

% Define function 'b'
b_expr = B*R*V_r + X*I_r*cos(varphi_r) - R*I_r*sin(varphi_r) - V_s*
    sin(delta);

% Define function 'c'
c_expr = -R*B^2*V_r + I_r*cos(varphi_r) - X*B*I_r*cos(varphi_r) - R
    *B*I_r*sin(varphi_r) - I_s*cos(delta - varphi_s);

% Define function 'd'
d_expr = 2*B*V_r - X*B^2*V_r - I_r*sin(varphi_r) + R*B*I_r*cos(
    varphi_r) + X*B*I_r*sin(varphi_r) - I_s*sin(delta - varphi_s);

% Define the functions f1, f2, f3, f4
f1 = -V_s^2 + a_expr^2 + b_expr^2;
f2 = -tan(delta) + b_expr/a_expr;
f3 = -I_s^2 + c_expr^2 + d_expr^2;
f4 = -tan(delta - varphi_s) + d_expr/c_expr;

% compute the jacobian
jacobian_matrix = jacobian([f1, f2, f3, f4], [X, R, B, alpha])
```

Listing A.1: Matlab code to compute jacobian matrix used for optimization

A.2 Estimating RLC values

The following calculations originates from the paper "Estimation of transmission line parameters from measurements" [21] where further details explaining each step can be found.

If we let:

$$\cosh \gamma l = \cosh(\alpha + \mathrm{j}\beta) \tag{A.1}$$

Then (hyperbolic cosine of complex number)

$$\cosh \alpha \cos \beta = 1 - XB \tag{A.2}$$

$$\sinh \alpha \sin \beta = RB \tag{A.3}$$

Define:

$$x_1 = 1 - XB \text{ and } \quad y_1 = RB \tag{A.4}$$

eliminate 'α' from A.2 and A.3 we get

$$\cos^2 \beta = \left[1 + x_1^2 + y_1 - \sqrt{\left[\left(1 + x_1^2 + 4y_1^2\right)^2 - 4x_1^2\right]}\right]/2 \tag{A.5}$$

Equation A.2 then gives us:

$$\cosh \alpha = x_1 / \cos \beta \tag{A.6}$$

The value of

$$\gamma l = \alpha + \mathrm{j}\beta \tag{A.7}$$

is thus obtained from Equations A.6 and A.7.

The propagation constant per unit length is then

$$\gamma = \frac{\alpha + \mathrm{j}\beta}{l} \tag{A.8}$$

The characteristic impedance of the line is

$$Z_\mathrm{o} = \frac{R + \mathrm{j}X}{\sinh \gamma l} \tag{A.9}$$

The line impedance per unit length is

$$Z = Z_o \gamma \tag{A.10}$$

The line admittance per unit length is

$$y = \frac{\gamma}{Z_o} \tag{A.11}$$

The line parameters R, L and C of the line are then obtained from Equations A.10 and A.11.

A.3 Effects of change in parameters

The two figures A.1 & A.2 show arbitrary data for every weather parameter and electrical current together with the resulting ampacity, conductor temperature, and the thermal energy generated from every parameter. The change in wind speed demonstrates the effects of wind cooling.

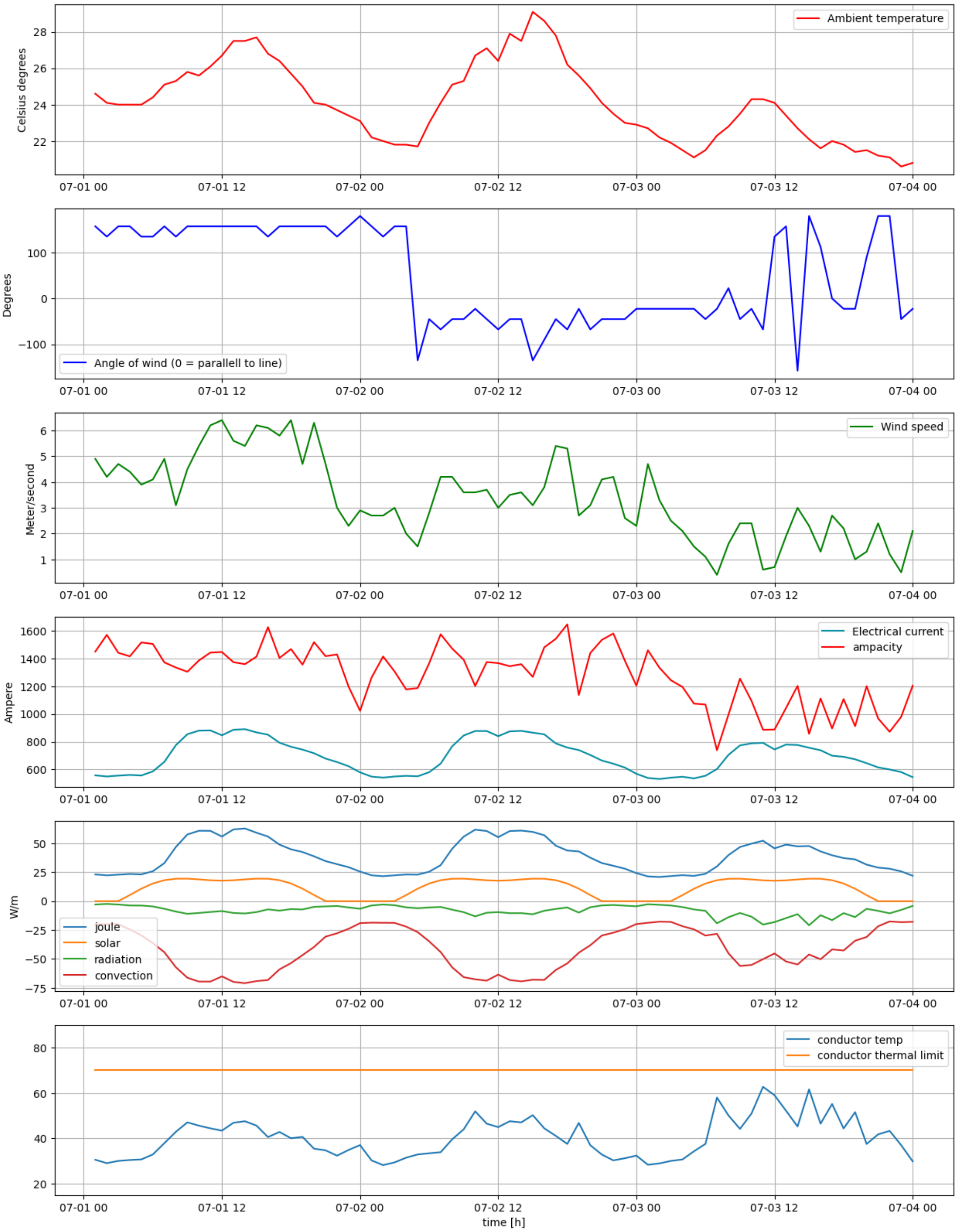
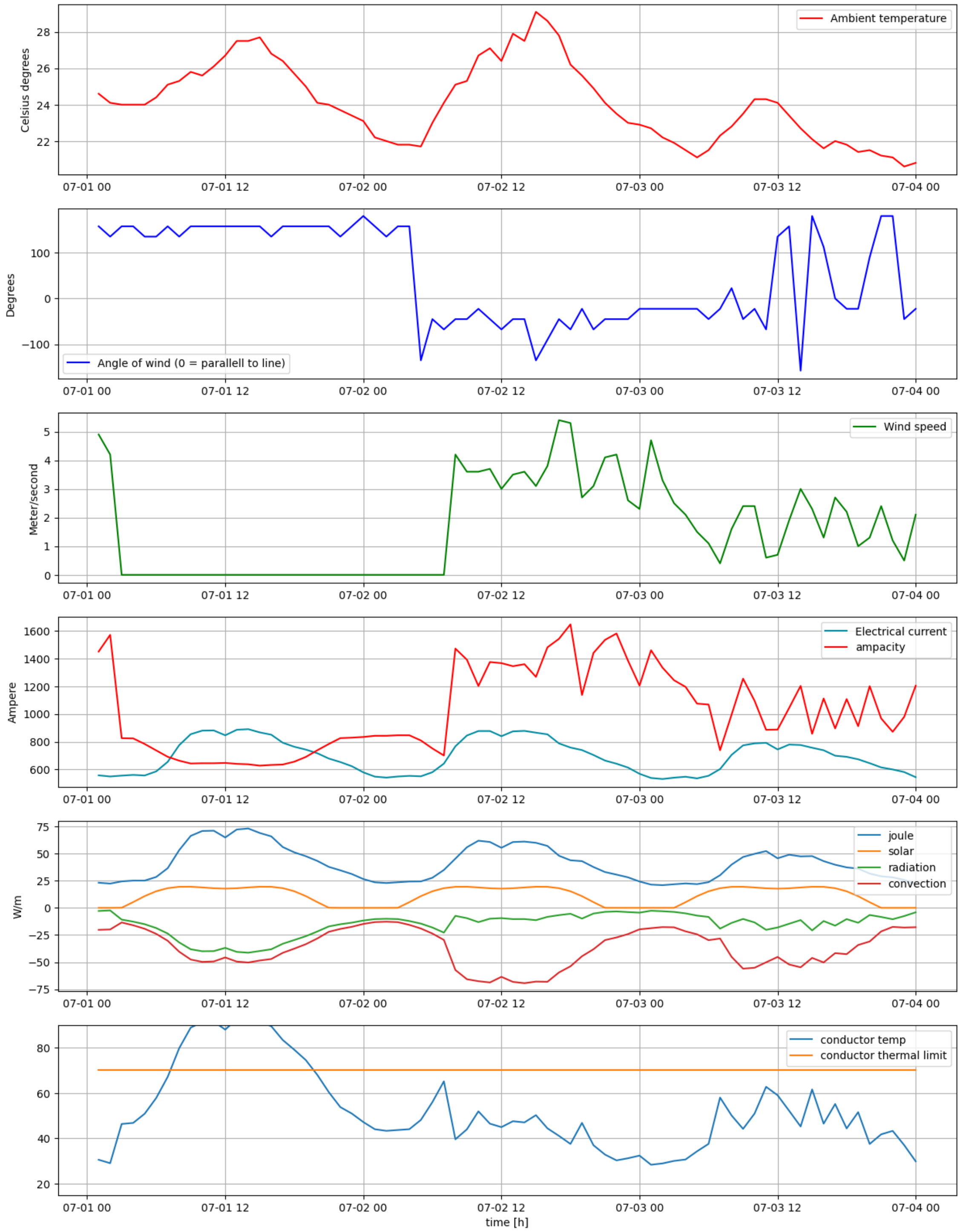

Ambient temperature
Celsius degrees
28
26
24
22
07-01 00
07-01 12
07-02 00
07-02 12
07-03 00
07-03 12
07-04 00
Angle of wind (0 = parallell to line)
Degrees
100
0
−100
Wind speed
Meter/second
6
5
4
3
2
1
Electrical current
ampacity
Ampere
1600
1400
1200
1000
800
600
joule
solar
radiation
convection
W/m
50
25
0
−25
−50
−75
conductor temp
conductor thermal limit
80
60
40
20
time [h]

Figure A.1



Ambient temperature
Celsius degrees
Angle of wind (0 = parallell to line)
Degrees
Wind speed
Meter/second
Electrical current
ampacity
Ampere
joule
solar
radiation
convection
W/m
conductor temp
conductor thermal limit
07-01 00
07-01 12
07-02 00
07-02 12
07-03 00
07-03 12
07-04 00
time [h]

Figure A.2

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1829

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