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Development, validation and simplification of component models for DigitalEnergyTwin

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Abstract

English

To reach the Paris Agreement, the global CO₂ emissions need to reach zero by 2050. The energy sector is the biggest contributor to emissions, an increase in efficiency in this sector is necessary to achieve the emission goals. One way to improve this and to increase the share of renewable energy sources is the Digital Energy Twin (DET). The following methods were used to create models and simulations for the DET.

Co-Simulation of an industrial energy system: A physical model of a thermo-hydraulic system and a data-driven model of a photovoltaic system were combined to a Co-Simulation model. It was shown that this can produce meaningful results and the PV system can reduce the usage of the gas-powered kettle. In the second part, the practical part that included work in the laboratory, an electroplating process was conducted. The aim of the experiment was mainly to create a data-set for the creation of a data model. The experiment was conducted successfully and the created data-set was modeled with different machine learning algorithms such as neural networks.

Deutsch

Um das Pariser Abkommen zu erreichen, müssen die globalen CO₂-Emissionen bis 2050 auf null sinken. Der Energiesektor ist der größte Verursacher von Emissionen, eine Effizienzsteigerung in diesem Sektor ist notwendig, um die Emissionsziele zu erreichen. Eine Möglichkeit, dies zu verbessern und den Anteil der erneuerbaren Energiequellen zu erhöhen, ist der Digital Energy Twin. Die folgenden Methoden wurden verwendet, um Modelle und Simulationen für den DET zu erstellen.

Co-Simulation eines industriellen Energiesystems: Ein physikalisches Modell

eines thermohydraulischen Systems und ein datengetriebenes Modell einer Photovoltaikanlage wurden zu einem Co-Simulationsmodell kombiniert. Es wurde gezeigt, dass damit aussagekräftige Ergebnisse erzielt werden können und die PV-Anlage den Verbrauch des gasbetriebenen Kessels reduzieren konnte. Aufbau eines Galvanik-Experiments: Im zweiten Teil, dem praktischen Teil, der die Arbeit im Labor beinhaltet, wurde ein Galvanisierungsprozess durchgeführt. Ziel des Experiments war es vor allem, einen Datensatz für die Erstellung eines Datenmodells zu erzeugen. Das Experiment wurde erfolgreich durchgeführt und der erstellte Datensatz konnte mit verschiedenen maschinellen Lernalgorithmen wie neuronalen Netzen modelliert werden.

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List of Abbreviations

DT	Digital Twin
DET	Digital Energy Twin
CPS	Cyber Physical System
PV	Photovoltaic
PLM	Product Lifecycle Management
FMI	Functional Mockup Interface
FMU	Functional Mockup Unit
DE	Discrete Event
CT	Continuous Time
DC	Direct Current
NN	Neural Network
ML	Machine learning
IoT	Internet of Things
AR	Augmented Reality
VR	Virtual Reality
IEA	International Energy Agency
OPEC	Organization of the Petroleum Exporting Countries

1. Introduction

In the shadow of the Covid-19 pandemic, one may forget the challenges to come, that need all combined effort to deal with. Some prominent examples are climate change, increasing energy demand, the extinction of species, the shortage of resources, increasing human population. These aspects are closely connected and often influenced by each other. In the following part, the focus is put mainly on the growing energy demand and its connection to greenhouse gas emission and climate change. To give an overview, in this introduction two recently published reports are further investigated. Firstly the World Energy Outlook 2020, published by the International Energy Agency (IEA) [1] and secondly the World Oil Outlook 2045, published by the Organization of the Petroleum Exporting Countries (OPEC) [2].

1.1. Motivation

1.1.1. Current Position and Paris Agreement

The greenhouse gas emissions have been rising during the last decades, as can be seen in Figure 1.1. To keep the effect of global warming below 2°C, all countries of the world signed the Paris Climate Agreement [3]. By doing so, the countries committed to the Paris Climate goals, to keep the effects of global warming to a minimum. To reach these goals, the development of the CO₂ emissions have to develop as is shown in Figure 1.1.

One can see in Figure 1.1 that the goals are ambitious and major changes in all CO₂ emitting processes have to be made. To stay below 1.5°C temperature change - which is the goal of the Paris Agreement - carbon neutrality has to be reached by 2050 and net negative emissions have to be made after 2050.

1. Introduction

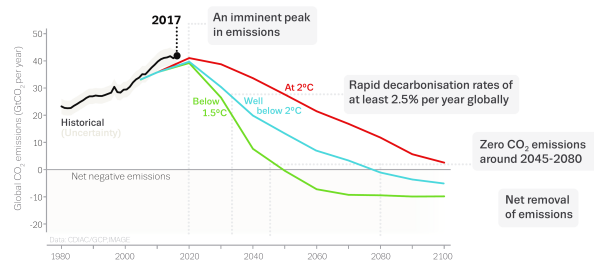


Figure 1.1.: Historic CO₂ Emissions and future projected global CO₂ Emissions that meet the Paris Agreement Temperature Goal. [4]

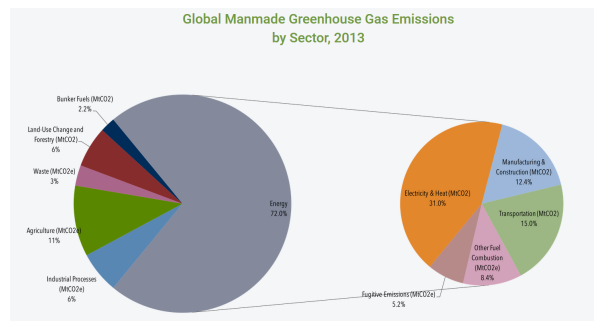


Figure 1.2.: The Greenhouse Gas Emissions per Sector. One can see that Energy is the main Factor. [5]

Looking at the emissions, one can see in Figure 1.2 that the emissions related to the energy sector make up the biggest share of the greenhouse gas emissions. To reach the Paris Agreement goals, major reductions are necessary for this sector.

1.1.2. Outlook

The next discussed point is the predicted development in the energy sector, the demand, and the form of production. In Figure 1.3, one can see the development and the prediction for the final energy consumption for the EU by fuel and by sector. The reference for this graph is 2016, until 2050 the numbers are predictions. The report was published by the European Commission and considers many factors in the creation. The projection indicates a change in

1.1. Motivation

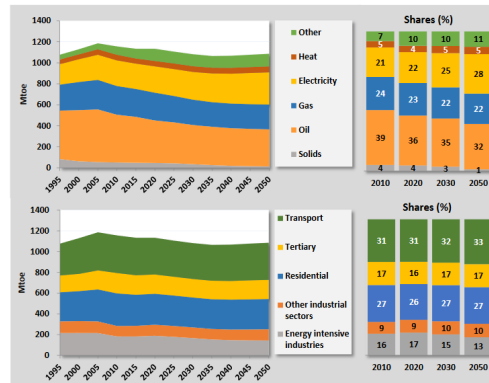


Figure 1.3.: Final Energy Consumption for the EU by Fuel and by Sector.[6]

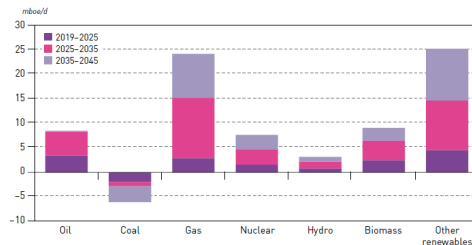


Figure 1.4.: Growth in Primary Energy Demand by Fuel-Type on a global Level, 2019–2045[2]

the fuel mix of energy consumption in favor of renewable energy sources. This shift is driven by the emission targets the members of the EU made and energy efficiency policies until 2030 as well as the emission trading system. Even though the share of oil decreases, it remains at a high level, mostly because transportation is projected to remain dominated by oil.

Due to factors like the increasing population and increasing energy demand per person, on a worldwide level the final energy consumption is expected to rise, as can be seen in Figure 1.4. Renewable energy sources have the biggest increase, but this does not reduce the CO_2 emissions if the energy produced by fossil fuel is not reduced.

The vision shared by OPEC paints a picture of the future that is not too optimistic regarding climate goals. If the form of production is not expected

1. Introduction

to change that much, a decrease in demand is necessary. The digital twin can help to increase the efficiency of industrial processes and help to achieve this goal by increasing the share of renewable energies used in industrial processes.

1.2. Project Description

The goal of the project is the creation of a Digital Energy Twin (DET) for the printed circuit manufacturer AT&S. Large scale energy systems can only react slowly to fluctuations in the energy demand and energy supply because they are created for a single supply system. To overcome this limitation and increase the flexibility, the operation of demand and supply needs to be optimized. This optimization can lead to better integration of volatile energy sources. These sources could be renewable energies like solar power or other sources like waste heat could be used. By better integration the dependence on conventional energy sources can be reduced.

To summarize, the DET is a software tool that supports in optimizing the operation and set-up of energy systems on an industrial scale. Different data sources, such as production data, predictions of the system as well as historical data is used in the process. The DET aims to provide solutions to problems related to energy fluctuations, volatile energy supply and increased efficiency. [7] The following statements conclude the major goals of the DET.

- create optimization algorithms and software tools
- apply digital twin methodology to energy systems
- service provision of augmented and virtual
- development of energy models
- development of a concept for data security
- standardized and simplified models reality (AR/VR)

The work can be split into three main parts, all of which have in common that they are steps in the development of component models for the Digital Energy Twin.

1. The physical modeling of an industrial heat bath and the co-simulation of the heat bath with a data-driven photovoltaic system
2. The assembling of an electroplating process and the creation of a data set
3. The creation of a data model using the data obtained in the electroplating process

As can be seen from these three parts, physical models, data-driven models and the combination of these two is the central part of the thesis. Physical models have many advantages, they describe the system with equations, and using programs like Modelica, systems can be constructed easily and in high detail. Unfortunately, often it is the case that the construction of a physical model is not possible, either because the model is too complex or too little information is available. Then a data-driven approach can be chosen, one uses the available data of a system to create a model, without knowing what happens behind the scenes. These concepts are described in more detail in section 2.5.

1.2.1. Co-Simulation of an Industrial Energy System

The physical model created in the first part is the first approach in the creation of a model of the bath system, an important part of the Digital Twin. With the co-simulation of the data-driven photovoltaic system, which was developed by Schranz et al. [8], it was shown that this is a promising approach for further implementation. The basic idea is that parts that can not be modeled physically are described by a data model, the different models can be connected via Co-Simulation, a main tool in the creation of the DET.

1.2.2. Setup of an Electroplating Process

In the second part, the practical part that includes work in the laboratory, an electroplating process was conducted. The experiment setup is explained in more detail in section 3.2. The aim of the experiment was mainly to create a data set for the creation of a data model. The electroplating experiment was designed in a simple way but with as much similarity to the process at AT&S as possible.

1.2.3. Data-model of the Electroplating Process

In the third part, the data obtained in the second part was used to create a data model of an electroplating process. Different algorithms were used, the main focus was however on neural networks. Different architectures were applied, it was also investigated how to increment physical knowledge and how to include physical constraints into the network. Because the accurate physical modeling of an electroplating process is very difficult, a data model is a key strategy. This approach is the first step in this direction, to test if it is an promising approach and to set the boundaries for further development.

2. Literature Study

2.1. Overview

In this chapter, the concept of Digital Twins and Cyber physical systems is explained as well as their differences. A analysis regarding the number, topic and distribution of publication to DT and CPS was created.

2.2. Digital Twin

2.2.1. Introduction

Digital Twins are virtual copies of real processes and physical systems. NASA defines DTs as "integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin" [9]. Since its conceptual introduction by Michael Grieves in 2002 , the concept has evolved to model not only discrete production but also continuous production processes, information processes, and transport systems.[10]

The idea of the Digital Twin has not changed drastically since its creation, but the terminology has changed. The concept is still valid today and the idea, that by using the digital information of a physical system to construct a digital entity on its own has not changed. As the creator of the Digital Twin mentioned, it is of special interest to link the twin to the physical system during its whole lifecycle. [11]. The Digital Twin concept model is shown in Figure 2.1.

2. Literature Study

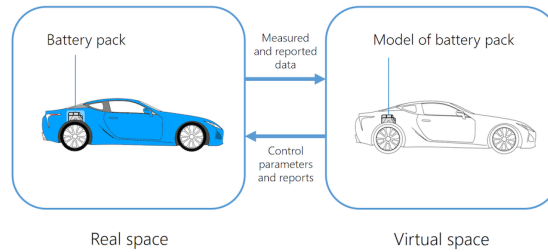


Figure 2.1.: The Digital Twin Concept exemplified on a Battery Pack in a Hybrid Car. [12]

It contains three main parts: [11]

- physical products in real space
- virtual products in virtual space
- the connections of the virtual and real space

In Figure 2.1, an example of a DT can be seen, the DT of a battery pack. One can see the different main parts, the real and the virtual space as well as the connection between them. Data and information is exchanged and ties the virtual and real products together.

2.2.2. Keyword Analysis for DT and CPS

To give a better overview about the development of publications related to the topic Digital Twin and Cyber-Physical System, a literature analysis was conducted. Information about the most important keywords and the number of papers related to these can be obtained by these graphs. These graphs are represented in this section, to give new insight into this area. To obtain the data, Elsevier's abstract and citation database Scopus was used. The number of publications in which the keyword was present in either title, abstract or the keyword section of the paper was determined. Even though not every paper can be captured in this way, this analysis serves to show the trend of the development and helps to predict the future development of the area.

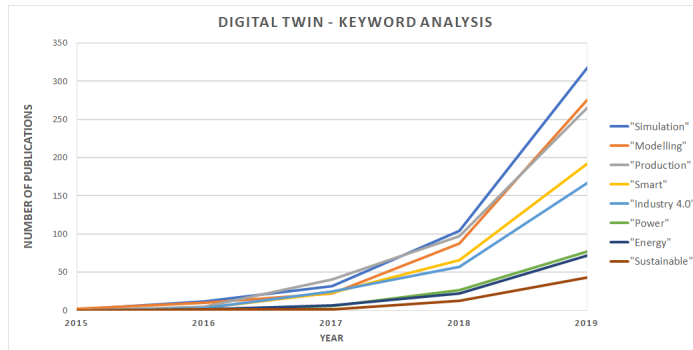


Figure 2.2.: Keyword Analysis to show the development in yearly Publications and which areas are important. The graph shows the yearly publications to "Digital Twin" with one of the shown words in either Title, Abstract or Keywords.

2.2.3. Development

2.2.3.1. Early Years: 2002 - 2010

The concept of the Digital Twin was first mentioned by Michael Grieves, in the year 2002. This happened at a presentation at the University of Michigan, it was not yet called Digital Twin, but conceptual ideal for product lifecycle management (PLM). Even though it had a different name, the elements of the Digital Twin which are mentioned above were all mentioned. Real space, virtual space and their connection were mentioned in the presentation, the idea of the DT was created. [11]

The concept was referred to as product lifecycle management (PLM), this meant that that the two systems would be linked together for the entire life-cycle of the product. This includes the following parts: [13]

- creation
- production
- operation
- disposal

2. Literature Study

2.2.3.2. Recent Years: 2010 - 2019

During the last decade, several changes could be noted. First, the DT was used in new areas, especially in astronautics and the aerospace field. NASA has used it several times, in their technology roadmaps [14] and in the proposals for sustainable space exploration [15]. Another field the DT was proposed to was to aircrafts, to fighter aircrafts and NASA vehicles [16].

The biggest change however can be seen in Figure 2.2. The number of publications changed significantly, a rise from 24 publication in 2016 to 934 publications in 2019 is shown. The increased interest in DT was due to its application in different industries like production design, the optimization of processes, prognosis and usage in the automotive and energy sector [17]. The development regarding the different aspects of DTs can be seen in Figure 2.2. It is shown which keywords are mentioned more frequently as others and how the development in the last 5 years looks like.

2.2.4. Digital Energy Twin

The term “Digital Energy Twin” is new to the scientific literature, it has not yet been used in a publication, as a Scopus keyword analysis showed. However, the terms “Digital Twin” and “Energy” have been used together and several approaches similar to the “Digital Energy Twin” described in this thesis have been made.

In 2018, Karanjkar et al present a case study for energy optimization in an automated industrial assembly line process [18]. This optimization was done by applying the digital twin concept to the assembly line, the results showed that an energy consumption reduction by a factor of 2.7 was possible without significantly affecting the line throughput.

2.3. Cyber Physical System

Cyber-physical systems (CPS) consist of mechanical components, software and modern information technology. They are a new generation of systems and contain capabilities which allow them to interact with humans. Via networks

like the internet, they are connected with each other and can be controlled and regulated. The exchange of data can take place in real time. Future research includes airplanes and space vehicles, hybrid cars, and autonomous driving. [19] Cyber-physical systems (CPS) are used for the integration of software components with physical processes [20]. In the literature, the relationships between DTs and CPS are described differently. Both are closely related with the other, but they differ in concept and core elements. Another difference are the fields of application, according to Lu et al. 2020 [21].

CPS enable the control and monitoring of complex systems and infrastructures, they provide services as real-time sensing, information feedback and dynamic control [22] Examples for CPS are:

- autonomous driving cars
- smart buildings
- industry 4.0
- smart grid

There are different perspectives to look at cyber-physical systems, what leads to different definitions in the scientific community. In the following, examples of representative definitions of CPS are given. CPSs are described as “physical and engineered systems, whose operations are monitored, coordinated, controlled, and integrated by a computing and communicating core” Rajkumar [23]. Another definition is “integration of computation with physical processes” by Lee [24], or “embedded systems together with their physical environment” by Marwedel [25]. All definitions have in common, that computing is deeply embedded into every physical component and that a real-time response is necessary. To conclude, CPS are complex, next-generation engineering systems that integrate a cyber part into the physical part. The cyber part is the embedded computing technology and the integration includes observation, communication, and control of the physical system. [17]

2.3.1. Development

The term CPS was coined in the USA, some years later the development was promoted by innovation programs of the European Union [26]. In 2006 the term CPS was used at the National Science Foundation (NSF) of the

United States [27]. Another step in the development happened in 2007 by the President's Council of Advisors on Science and Technology (PCAST). The organization recommended the investigation and development of CPS and promoted its importance in the scientific community [28].

In Europe, the European Union provided programs to increase the possibilities of research on CPS. The EU technology initiative ARTEMIS (Advanced Research and Technology for Embedded Intelligence Systems) have invested in the development of next-generation systems between European Nations. The vision of a world with smart and aware systems and machines which are connected and communicate with each other was promoted by this program. [29]. Another program (Horizon 2020) was launched by the European Commission in 2013 to tackle societal challenges by developing new strategies to deal with them. Horizon 2020 includes CPS and computing research and innovation. [30]

2.4. Comparison of DT and CPS

The distinction between Digital Twins and Cyber-Physical Systems is not trivial, they are frequently used in similar ways or to describe alike problems. Both are frequently mentioned in the context of internet of things (IoT), Industry 4.0, and production optimization. A comparison of the number of publications is shown in Figure 2.3. One can see that CPS is at a higher level and DT started only in 2015. The publications to DT however increased from only 24 in 2016 to almost 1000 in 2019. The subject areas to which the publications can be connected can be seen in Figure 2.4 and Figure 2.5.

Another difference can be found in the field of applications. While CPS aim at monitoring and controlling processes, DTs aim at analyzing/understanding real-time data of an object or system by means of its virtual representation and deriving conclusions and learning from the data. The control of processes and systems is part of CPS but not of DTs. According to this definition, DTs are the prerequisite for the development of CPS. [31] A way to visualize the differences between the two concepts is to analyze publications. An analysis of the publications using the data provided by Scopus was done and can be seen in Figure 2.3, Figure 2.4 and Figure 2.5.

2.4. Comparison of DT and CPS

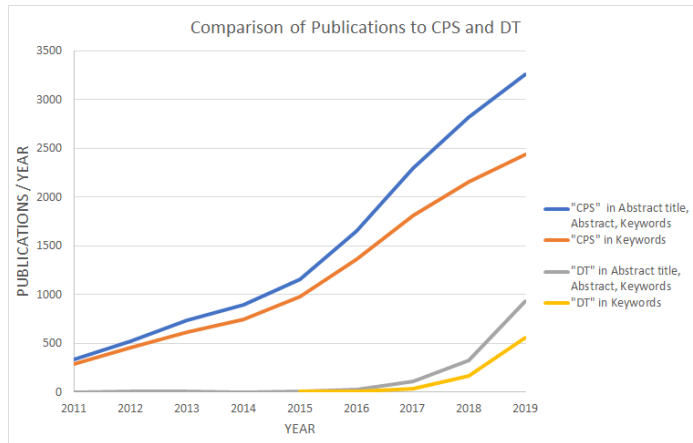


Figure 2.3.: Keyword Analysis to show the Development of DT and CPS.

In Figure 2.3 the publications to DT and CPS are visualized and compared to each other. One can see that CPS start at a higher level and even today there are more than three times as many publications published as to DTs. Until 2016 there were almost no publications on the topic DT, but in recent years the increment can be seen clearly.

In Figure 2.4 and Figure 2.5 the publications are organized with respect to their subject areas. There are many similarities, both have engineering, computer science and mathematics as the three biggest subject areas and engineering and computer science dominate more than half of the field. But there are also differences visible, the biggest field in CPS is computer science while in DT it is engineering. In CPS the three biggest subject areas cover over 3/4 of the publications, while the publications of DT are more diversified and natural sciences are more present.

2.4.1. Tools: Modeling and Simulation

The most important tool in the creation and editing of DT and CPS is modeling. This is a central component, DT and CPS would not exist without modeling. For the analysis and optimization of CPS, methods and tools are needed for both the cyber and the physical part.[31] Furthermore, recent studies have

2. Literature Study

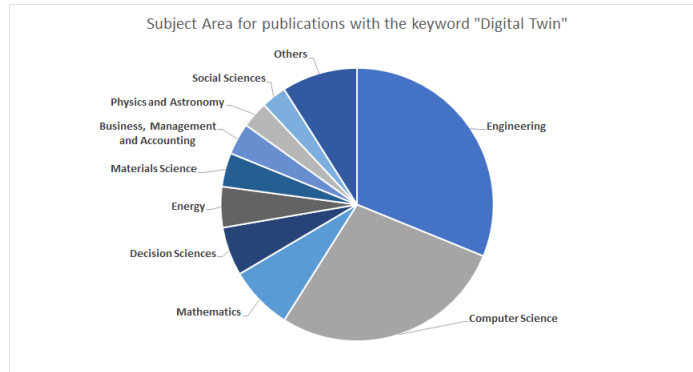


Figure 2.4.: The most important Subject Areas for Digital Twin. The number of Publications was analyzed.

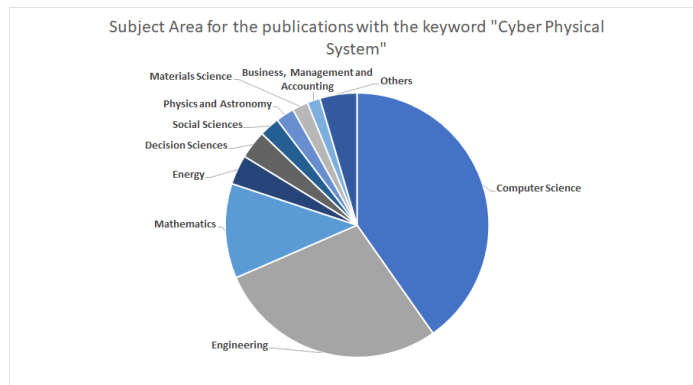


Figure 2.5.: The most important Subject Areas for Cyber Physical Systems. The number of Publications was analyzed.

shown that co-simulation is a promising approach for the modeling and simulation of complex systems. [32] In the following chapter, the principles of modeling, the different approaches, and their applications are explained in more detail.

2.5. Modeling Theory

2.5.1. Modeling Paradigms

A trend in modeling and optimization is the increased complexity of the models and the systems which are analyzed. This fact and that subsystems have to be considered together increases the requirements. These increase in complexity is a challenge to traditional techniques, new tools for modeling and simulation of complex systems are needed. The combination of data-driven models with first-principle models is a new approach. This Co-Simulation is a promising approach as recent studies have shown [32]. Subsystems are coupled and exchange data in discrete points which enables a new form of complexity. [31]

2.5.2. Types of Modeling

2.5.2.1. White Box Modeling

White-box models are specified by the fact that before the modeling process is started, the modeler already has deep knowledge about the system and physical insight to it. One can argue that it is not possible to have a white box model since we never have perfect physical insight into a system. If we take a simple example such as the heat flux through a wall, the wall will differ slightly from brick to brick, only an assumption can be made in the modeling process. [33]

2.5.2.2. Black Box Modeling

Black-box models are created from data, before the modeling process we have no or only limited knowledge about the system and only little physical insight. It is usually formed from a known basis of model terms, which is flexible enough to represent a broader range of behaviors.

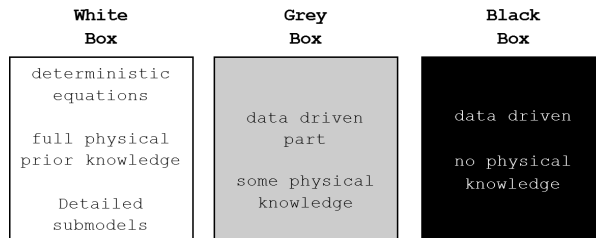


Figure 2.6.: Different types of Models are distinguished by the Amount of Prior Knowledge they Incorporate.

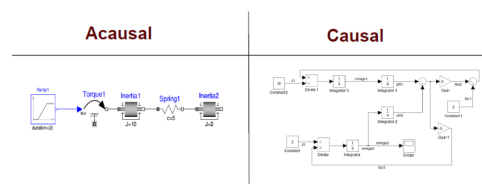


Figure 2.7.: Comparison of Acausal and Causal Modeling [31]

2.5.2.3. Grey Box Modeling

Grey-box models lie in between black and white-box models, they are obtained when less physical insight is available. There are two sub-classes: physical models and semi-physical models, this depends on the amount of knowledge we have about the system.

In Figure 2.6, a representation of the key elements of each model type can be seen.

2.5.3. Physical Modeling

Physical modeling is closely connected to the principle of white box modeling. In this field, a distinction can be made between causal and non-causal modeling, this is explained in Figure 2.7 .

Acausal refers to the functionality of the model, if the modeled system is directional or not. In this form of modeling, one uses ordinary differential equations (ODE) to describe the system. The equations are used in an explicit

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form and can be regarded as direct, which makes it understandable how one can derive the unknown parameters from the known ones[34]. In general, such a system has the form:

$$\dot{x} = f(x(t), u(t), p) \quad (2.1)$$

where x is the state variable, t is the time, u is the controlled variable and p are parameters.

In causal modeling on the other hand, differential-algebraic equations (DAE) in implicit form are used to describe the system.

$$F(\dot{x}, x(t), y(t), u(t), p) = 0 \quad (2.2)$$

where y is the algebraic variable. The equations must be used to solve the unknowns in view of the known quantities determined by a certain usage context. Solving DAEs is generally more difficult than solving explicit ODEs [34]. Results from Schweiger et al. 2020 [34] show that causal modeling paradigms are suitable for modeling complex systems, causal techniques are less suitable. Both can be used for simulation.

2.5.3.1. Modelica and Dymola

Modelica is an object-oriented modeling language for physical models. It was released in 1997 in the programming language standard 1.0. In April 2017, version 3.4 was released. In Modelica, a physical model is described with algebraic and ordinary differential equations. A Modelica translator is used to translate these equations into a mathematical model. The goal of Modelica is to model the dynamic behavior of technical systems consisting of components from different domains in a convenient way. The models are described by differential, algebraic, and discrete equations. [35]

There are free and commercial versions of Modelica simulation environments. Dymola is based on the open Modelica language, in Dymola hierarchical models composition is supported. Many libraries with models that can be modified for specific purposes exist. The reusability of the models - which is also an

important factor in the Digital Energy Twin - is a main advantage of Dymola. [36]

An example for a library is the Buildings library from the IBPSA Project 1, it is a "Modelica Framework for building and community energy system design and operation " [37]. It is formed by cooperation from different universities in Europe and the USA. Parts of this library were used in the Use-

2.5.3.2. Examples

A physical model is a smaller or larger physical copy of an object that is built in terms of logic and mathematical equations, examples are:

- model car
- model rocket
- simple model of a house
- model of a wind turbine

To summarize, processes that can be idealized and still give meaningful results can be described by physical modeling.

2.5.4. Data-driven Modeling and Machine Learning

Physical modeling requires a priori knowledge of a system and its parts. For the development of physical models one therefore needs experts which also limits the availability. Furthermore, it is often difficult to evaluate the performance and error of the models [38].

In data-driven modeling, large amounts of data can be used to automatically construct models for monitoring or fault detection. The difference to physical modeling is that we do not need any insight into the system or a priori knowledge. The learning happens by observing the system, this is a good alternative for complex systems or systems where we have no physical insight [39]. Of this huge field, the focus in this work lies on machine learning since these were the methods that were applied to the data. In the following chapter, an overview of this topic is given in more detail, the applied algorithms are explained in Chapter 3.3.

2.5.4.1. Training and Data

It is not trivial to obtain the data, that are needed for the training of a model. Many times, more time and effort is needed to obtain the data as for the creation and the training of the model. Depending on the size of the dataset, usually 70% - 85% of the data are used for training purposes and the remaining part for testing of the model.

2.5.4.2. Examples

Typical examples of data-driven models that also demonstrate the situation in where machine learning methods is useful and can produce meaningful results and predictions are:

- model to predict live cycle of a virus [40]
- model to predict protein interfaces [41]
- model of a complex building

Whenever a system is complex and the idealization leads to big errors, one may try to collect data and model the object without detailed knowledge about the system.

2.5.5. Co-Simulation

This field combines parts of physical and data-driven modeling. The systems under consideration become more complex and the efficiency has to increase. One approach to this problem is Co-Simulation [32]. There are two approaches to this problem and to efficiently simulate the interaction between subsystems:

- (i) the whole system can be modeled using a single tool, this is referred to as a monolithic simulation
- (ii) subsystems can be coupled in a so-called co-simulation.

There are several differences between these approaches, the second one has the advantage that it is possible to specialize each subsystem and implement more knowledge. Different simulators can be used to combine the subsystems and for their interaction [42]. The communication can slow down the simulation, the communication steps have to be chosen in an interval according to the simulation time. The number of applications of co-simulation has risen in many areas because of the factors mentioned above. [43]

Dynamical models produce traces, each trace is calculated by the simulation of the subsystem. The subsystems are connected through their traces by the simulators. Two things are needed to run a co-simulation [44].

- a co-simulation scenario
- an orchestrator algorithm

The function of these are to connect the subsystems and to produce the final result. The co-simulation scenario takes the role of the connector between the parts and couples the models together. Each model needs inputs and produces outputs, how these interact with each other is described by the co-simulation scenario. The results are generated by the orchestrator algorithm, all subsystems and the simulations are started with a starting value. This sets their input and produces an output, over the simulation time the development of the coordination happens over the orchestrator [32]. To differentiate the characteristics of the simulators and their interaction, one can distinguish two main approaches for co-simulation, namely *discrete-event* (DE) and *continuous-time* (CT) co-simulation. Both approaches can be used for the co-simulation of continuous, discrete, or hybrid coupled systems [44].

2.5.5.1. Discrete Event

Discrete event means, that the communication of the simulation units happens in events. These units are characterized by the two factors, the reactivity and transiency [44].

- reactivity: the DE Simulation unit has to process an event instantly
- transiency: events can cause other events to occur instantaneously

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To give an example of a DE system, one can consider a traffic light. The modes are: red, yellow, green or off. The traffic light is described by events, initially, it can be green and change to red after 60 seconds. But a police officer could also trigger a change in between from red to off. The system's output is an event, from one state to another.

2.5.5.2. Continuous Time

A Continuous-Time (CT) has a state that evolves continuously overtime, which means that ideally in CT co-simulation, the simulation units exchange their values continuously. The states of a CT simulation unit change continuously and its output may have to obey the physical laws of continuity [44].

2.5.5.3. Hybrid

The combination of CT and DE paradigms lead to hybrid co-simulation. An example for this combination can be found in many regulation units. In the use case, the CT system represents the temperature of the heat bath, the DE part is the controller that switches the heating systems like the boiler or the heating cartridge on or off.

2.5.5.4. Functional Mockup Interface

The Functional Mockup Interface (FMI) is used simulation from different languages or programs, it combines the subsystems between different languages. It is an industry standard that provides an exchange format for code and data. In the Use-case which is presented later, a FMI standard was used to combine Python and Modelica. It has proven to be the state of the art tool for combining different modeling approaches [45].

2.6. Electroplating Theory

2.6.1. Requirements and Basics

Definition: Electroplating is the electrochemical deposition of metals on a surface, in the process substrates are coated with some metallic deposits. Electroplating takes place in an electrolytic bath, a liquid with free moving ions. Current is conducted through the electrolytic bath, the object to be plated is usually located at the negative pole (cathode), the metal to be plated is located at the positive pole (anode). Electric current is used to obtain a metal deposited on the object, this happens by dissolving metal ions by reduction. The metal ions can be deposited from the solution, which leads to a change of concentration of the electrolyte, or the anode dissolves at the same time and the concentration stays constant.

A distinction is made between the electrodeposition of thin layers and the electrodeposition of thick layers. Pre-treatment of the substrate is necessary, usually in two steps, first the degreasing and second the removal of the oxide layer.

2.6.2. Processes and important Terms

2.6.2.1. Deposition of metal without external power source

The form of deposition does not use any external power source to supply the electrons which are needed for the reduction of the metal. These electrons are supplied by an inner current source, there are three categories:

1. ion exchange process
2. contact procedure
3. reduction process

The first procedure is used in one step for the galvanization process at AT&S and is described here briefly. It was however not used during the experiment. The ion exchange process consists mainly of the process of putting the to be coated part at a high temperature in the corresponding solution. The basis is the deposition of a noble metal present in solution in ion form on a base

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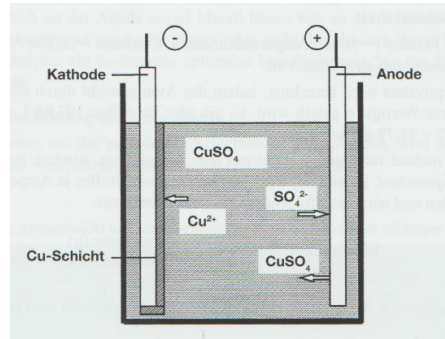


Figure 2.8.: Electroplating in a Copper Sulfate Solution with a soluble Copper Anode. [46]

metal.

In the process, the less noble metal is dissolved as an ion and thus provides the electrons necessary to discharge the ions of the more noble metal, which is then deposited in metallic form. The ion exchange stops immediately when the surface of the base metal is completely covered, so only very thin layers can be deposited. [46]

2.6.2.2. Deposition of metal with external power source

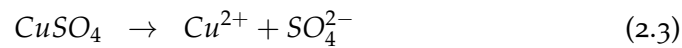
Metal deposition with an external power source is based on the process of electrolysis. Its settings determine the quantitative process, the qualitative process, and among other things the structure and properties of the resulting coatings. The control of these reactions makes it possible to create coatings of uniform thickness with the desired properties.

Electrolysis: When two metal strips are immersed in the solution of a metal salt and connected to the poles of a direct current (DC) source, a current flows through the solution.

The positive ions, the cations, migrate to the negative electrode, the negative ions, the anions, to the positive electrode (anode). The cations take up negative charge at the cathode, are reduced and deposited in metallic form, the reverse process occurs at the anode. The anions migrate with their excess electrons to the anode, release the excess and become neutral particles.

Reactions: Solutions of metal salts are dissociated. If electrolysis is carried out in a copper sulfate solution, the copper ion migrates to the cathode, where metallic copper is deposited. The sulfate ion migrates to the anode, is discharged there, and combines with a copper ion formed during the dissolution of the anode to form copper sulfate. The copper sulfate dissociates again and the process is repeated. Thus the concentration of the electrolyte remains constant.

Dissociation of copper sulfate:



Process at the cathode:



Process at the anode:



This reaction sequence applies if the anode consists of a soluble layered metal, otherwise the reaction mechanism is much more complicated.

2.6.2.3. Important Terms

Electrolyte:

Electrolytes are divided into basic and acid, depending on their pH value. They are further classified by the applied metal salt. The main content of the electrolyte is salts containing the coating metal to be deposited, components for controlling the electrolyte properties, and components for controlling the layer properties.

Faraday's Law

The quantitative relationships between electrochemical current and deposited mass in electrolysis were discovered by Michael Faraday, who formulated two laws. This allows the amount of metal deposited, the layer thickness, exposure times, etc. to be calculated. Faraday's 1st law states that the amount of material chemically converted by the electric current is directly proportional to the amount of current. Faraday's 2nd law states that the quantities of different substances deposited on the electrodes by the same amount of current are proportional to their chemical equivalent weights. The following applies: 1 Faraday deposits 1 gram equivalent of metal. The gram equivalent is calculated as follows: The atomic weight is divided by the valence of the metal relevant to electrolysis. In practice, an electrochemical equivalent is used. It indicates how many grams of a substance are deposited per ampere-hour and is calculated according to the following equation:

$$\text{electrochemical equivalent} = \frac{\text{atomicmass}(g)}{\text{valence} \cdot 26,8} \quad (2.6)$$

In Table 2.1 the electrochemical equivalent of some important metals can be found.

Current density

The ratio between the amount of current and the electrode surface is called current density. It indicates the amount of current per unit area. The cathodic current density is important for the quality of the coatings. There is an optimal current density range for each electrolyte.

Deposition rate

To deposit a coating with a certain layer thickness, the time required for this is calculated from the deposition conditions, these can be seen in Table 2.1. The corresponding formula is:

$$t = \frac{d \cdot s \cdot A \cdot 1000}{Ee \cdot i \cdot r} \quad (2.7)$$

In this equation, the variables have the following meaning:

- t = exposition time [hours]
- d = coating thickness [mm]
- s = density of the laminated metal [g/cm^3]
- A = area to be coated [dm^2]
- Ee = electrochemical equivalent [g/Ah]
- i = current [A]
- r = cathodic current yield [1]

In Table 2.1, density, atomic weight and electrochemical constants of some important coating metals are shown. These are the metals that were considered as anodes for the experimental setup. [46]

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Table 2.1.: Density, Atomic Weight and Electrochemical Constants for selected Coating Metals [46]

M ... Name of the metal
 S ... Symbol
 d ... Density at 20°C / g/cm³
 u ... atomic mass
 v ... valence
 Z ... electrochemical equivalent
 c ... current yield

R ... deposition rate at 1 A / dm³ and the specified current yield

M	S	D	u	v	Z	c / %	R / μ m / h
Copper	Cu	8,96	63,54	2	1,19	97-100	12,8 - 13,2
Iron	Fe	7,87	55,847	2	1,04	95-100	12,5 - 13,2
Silver	Ag	10,5	107,87	1	4,02	85 - 95	32,6 - 36,4
Zinc	Sn	7,29	118,69	2	2,21	70 - 95	21,3 - 28,9

3. Methodology

3.1. Development of the Use Case for a Thermohydraulic System

Machine learning methods, in particular neural networks, have become increasingly important in recent years. Fields of application are very diverse and range from artificial intelligence, autonomous driving to the prediction of photovoltaic modules. In the natural sciences, however, it is not yet very widespread, which is why development is primarily associated with the expertise of users and accumulated experience.

The method of data-driven modeling follows a step-by-step approach. The basis is data of the process or energy supply system to be modeled. The more data available, the sooner a model can be developed and trained to provide accurate and reliable information on the behavior of a process. The first step in the DET project was the data-model of the photovoltaic system. The basic approach of the method has been developed and successfully applied to a PV module. The next step is the application of data-driven modeling to a process bath at AT&S. The motivation of the next step in the development is to refine the method and the model in the mathematical environment of learning. It should be noted that at the end of this experiment the model does not map the actual process at AT&S. It is merely the first development step, but was designed in a way to have several points in common with a real heat bath from AT&S.

Definition

The following use-case demonstrates how physical models of different domains and data-driven models can be co-simulated. For this purpose, a sim-

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plified use case in the field of industrial energy supply was developed, this can be seen in Figure 3.3. A heat bath with a periodically varying heat demand is supplied from three sources, the boiler, a heating cartridge which is supplied with energy from the photovoltaic system (PV) and waste heat from different sources. The surplus part of the PV energy is fed into the grid. The photovoltaic power is calculated by a data-driven model in Python, the physical model is developed in the modeling language Modelica [47]. The co-simulation is based on the Functional Mock-up Interface (FMI) standard [48]. A recent study has shown that the FMI standard is considered the most promising standard for co-simulation[32]. The data model was exported from Python as a functional mock-up unit for co-simulation and imported into Dymola. [31]

3.1.1. System Engineering

The demand for a working model, a use-case model that demonstrates the principle of modeling on an example related to some process at AT&S was already discussed in the first meeting, the project kick-off. This model should fulfill several requirements:

- represent a production process from AT&S
- show the principle of physical modeling
- show the principle of data driven modeling
- be simple
- be easily adaptable
- simulation results should be created
- a energy intensive process step should be modeled

The development process started at kick-off meeting and was followed by several discussions within the TU Graz team and with the project partners, especially with the team from AEE Intec.

3.1.1.1. First step: Design of a working Example

It was decided to choose a heat bath for the physical modeling, in which important steps in the production of printed circuit boards take place and

3.1. Development of the Use Case for a Thermohydraulic System

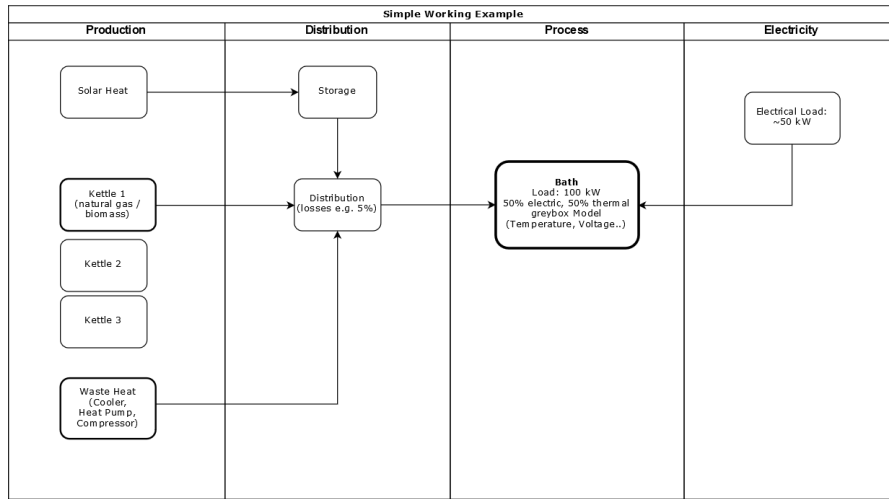


Figure 3.1.: Sketch for the Physical Model. The Bath is the central Process, with a Load of 100 kW, which is provided by three sources. These are the Kettle, Solar Heat and Waste Heat. There is an Electrical and a Thermal Part, Losses are considered.

which is also an energy-intensive process step. A first sketch of the parts which were modeled and their connection can be seen in Figure 3.1. In the kick-off meeting, a guided tour through all the process steps was given by AT&S, this knowledge and other facts from the company were used to create an example that was designed to resemble the process at the factory.

In Figure 3.1, a simple working example of a thermal bath can be seen. The diagram is divided into four parts which are described in the following paragraphs:

Production

The production part includes the different sources of heat, to supply the bath with the needed amount of energy to reach the wanted temperature. At the company, the heat is provided mostly by a kettle, which can run on natural gas or biomass. Another heat source is the waste heat of which plenty is available from sources like the heat pumps, the cooling system, and the compressors. This waste heat is not used so far and therefore it is interesting to look at the

3. Methodology

potential it has in the model. Finally, solar power was included in the working example. AT&S does have some capacity installed, so it is a reality-based approach.

Distribution

In this part, the distribution of the heat was considered. Since the demand of the bath strongly varies, a storage unit is necessary to supply big amounts of heat when needed and to store the produced heat when not needed. For the distribution, a loss of 5 % was supposed.

Process

This is the main part of the working example, the bath. An example would be the copper coating of the printed circuit boards, in these chemical processes a high temperature is necessary. It was decided to assume a load of 100 kW, which should be supplied to 50% by thermal power and to 50% by electrical power.

Electricity

The electrical part was represented by a heating cartridge. This heating cartridge is supplied by a PV system and is used to heat up the bath. One goal is to reduce the gas used in the kettle by increasing the share of PV energy used by the heating cartridge.

3.1.2. Implementation of the Model

3.1.2.1. Symbolic Representation

In Figure 3.2, a symbolic representation of the main parts can be seen. The weather input is used by the PV model to predict the output of the photovoltaic system, which can either use the power to heat the bath or feed it to the grid.

3.1. Development of the Use Case for a Thermohydraulic System

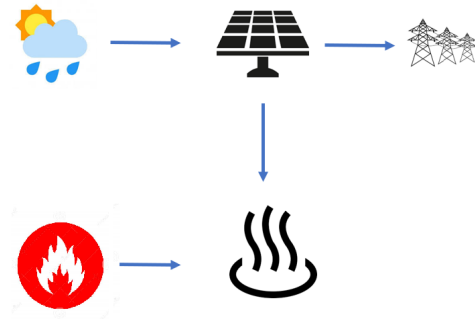


Figure 3.2.: A symbolic Representation of the Use-Case to show the main Components of the Model.

The bath has another heat input which consists of the kettle and the waste heat. By these two connections energy can flow to the bath and change its temperature.

3.1.2.2. Detailed Representation

The model consists of three main parts, which are described in more detail further down:

- thermohydraulic System
- electrical System
- datadriven model of the photovoltaic system

3.1.3. Description of the Components

Thermo-hydraulic System

The thermohydraulic system consists of different heat suppliers and heat dissipation and a volume, which represents the bath. The heat suppliers are connected to the bath and are controlled by PI-controllers. On the supplier side there are considered:

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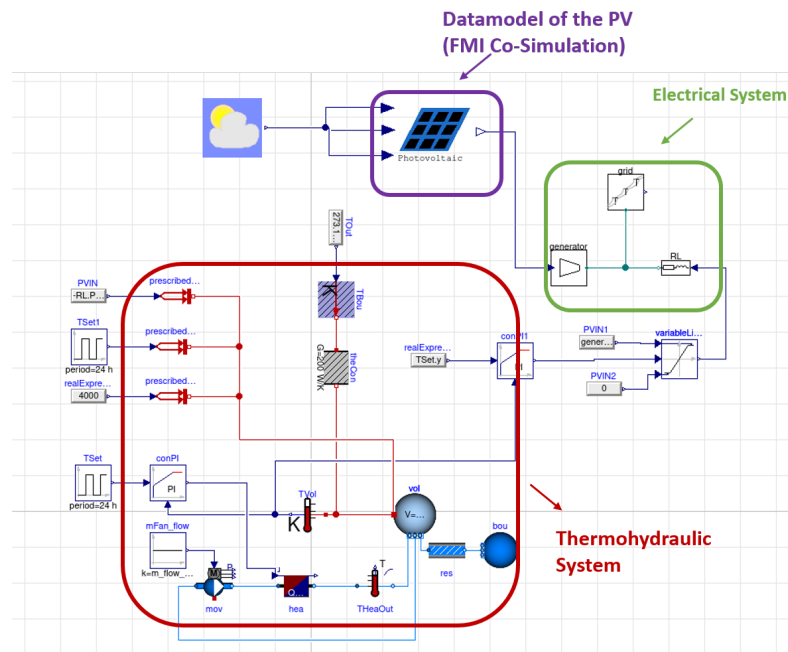


Figure 3.3.: The Use-Case in the Simulation Software Dymola. The System consists of three main Parts, the Thermohydraulic System, the Electrical System and the Datamodel of the Photovoltaic System.

3.1. Development of the Use Case for a Thermohydraulic System

- kettle
- waste heat
- heating cartridge

On the heat dissipation side there are considered the following parts:

- heat flow from the hot bath to the environment
- heat dissipation due to the inserted cold materials

The volume is left one of the blue circles, it is connected by the red lines to the heat suppliers and dissipaters.

The parameters which were used frequently for simulation examples can be seen in Table 3.1.

Table 3.1.: Parameter for the Use-Case with standard Values

- V ... volume of the bath
- P_k ... power of the kettle
- P_c ... power of the heating cartridge
- T_E ... temperature environment
- P_w ... used power of the waste heat processes
- τ ... periodicity of the temperature changes

V / l	1000
P_k / kW	15
P_c / kW	45
$T_E / ^\circ C$	20
P_w / kW	4
τ / h	24

Volume: The size of the volume can easily be modified, several simulations were run with a size of 1000 liters. The volume is connected to the heat fluxes, the temperature varies as is specified with $T_{desired}$. The temperature of the volume is measured and is used as an input to the PI-controller. The volume is connected to a flow resistance to decouple the pressure state from the boundary conditions.

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Electrical System

The electrical system takes the input from the PV system, a generator converts it to AC current. The power can now be used in two ways, either in the heating cartridge to heat up the volume, or the power can be sold to the grid. The first option is preferred, one wants to use the maximum of the generated electricity. If the desired temperature is reached, however, only a little power is needed to keep the temperature and some part of the generated power can be sold to the grid.

Data-driven model of the PV system

The model was created by a Co-Simulation between a data-driven model and a physical model. The data-driven model was created in Python, the physical model in Modelica. The data which was used for the training of the data is separated into two parts:

- (i) the meteorological data containing temperature, global radiation, air humidity
- (ii) the power of the PV system

A data model was designed to predict the energy production of the photovoltaic system. The model was based on real measured data provided by TU Graz, comprising 10,968 hourly measurements of the production of a 48 kWp PV system, as well as hourly averages of temperature, humidity and global radiation, collected between July 2018 and December 2019. In the model used for the use-case, an ensemble learning variant of decision tree induction was applied. This random forest regression can map the influence of the weather values on the production extremely accurately, without computationally intensive equations.

Regulation

The heat suppliers are regulated by PI-Controllers. The PI-controllers compare the actual temperature value with the desired value and controls the system

3.1. Development of the Use Case for a Thermohydraulic System

in a way that the desired value is reached, in this case the desired temperature of the bath. As desired value of the temperature, a period with a length of 24 hours, which changes between 40 °C and 60 °C was used. The system is regulated by two PI-controllers, one for the kettle and one for the heat cartridge. In the controllers, two temperatures are compared, the actual temperature of the volume and the desired temperature, which varies periodically with time. The controller regulates the kettle and the cartridge in way that the difference between these two temperatures becomes minimal.

Kettle

The Kettle is the main part of the system and can be seen in the lower part, to the left of the volume. A kettle from the buildings library, which is an open source library for dymola developed by the IBPSA Project 1, was used and adapted to fit the demands of this example.

In this system water flows between the volume and the kettle, where it gets heated up and flows back to the volume. By default a power of 15 kW was used for the kettle.

Waste Heat

An important factor is the waste heat, since it is available from several sources at the factory. The waste heat flows directly into the volume in this model, a default value of 4 kW was assumed in this case.

Heating Cartridge

The heating cartridge is also an existing part in the real baths. In this model it used the power generated by the photovoltaic system to heat the volume, if the actual temperature is lower than the desired temperature. The efficiency of the heat cartridge was assumed with 90 % and it is regulated by a PI-controller. The PV system has a power of 48 kWp, combined with the assumed efficiency of 90 % that leads to a maximal power of approximately 45 kW.

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Heat dissipation

This heat flow has a negative sign, which means heat flows out of the system (the bath) to the environment (the factory hall). It is a function of the temperature of the bath and of the environment. The temperature of environment was by default 20 °C. The consequence of these heat flows is, that even when the desired temperature is reached, some heating has to take place to keep the temperature at a steady level.

Another process that can not be neglected is the insertion of materials, which are generally at room temperature. This leads to a heat dissipation in the bath, this part was modelled with a periodicity over time, which should represent the reality at the factory. A set of printed circuit boards is put into the bath for a certain time, which draws heat from the bath in that time.

3.2. Electroplating Experiment

3.2.1. Experimental Set-Up and Conduction

In the electroplating experiment, a copper substrate was electroplated with copper. The electroplating was conducted in beaker glasses, the temperature was regulated by putting the beaker glass in a heated water bath. The parameters which were varied and measured can be seen in table 3.2. The range of the parameters duration and current density was selected according to the theory and formulas found in the book [46].

Safety:

Laboratory equipment as laboratory coat, nitrile gloves, and safety glasses were used in all the necessary situations. The work with the sulfuric acid was performed under a vent.

Experimental Set-Up:

The experimental set-up had some similarities with the experiment silver coulometer from the laboratory experimental physics 2. The idea to conduct this experiment was influenced by this laboratory exercise and there are similarities in the experimental set-up. A schematic overview of the experimental set-up can be seen in Figure 3.4. A cathode was put in an electrolyte, between two anodes inside a vessel. A laboratory power supply was used to provide the current and voltage, the outputs were connected to the copper plates. The vessel was put into a heated water bath, which was used to perform the experiment at different temperatures. The temperature was additionally measured with a thermometer. Since the accuracy of the laboratory power supply is low, a high precision multimeter was used to adjust the current, it was also used to measure the current three times during the experiment as well as the voltage.

Preparation of Cathode and Anodes:

Before performing the experiment, the cathode and the anodes had to be prepared accordingly. They were cleaned in several steps:

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Table 3.2.: Parameters that were varied during the Experiment

Parameter	Range	Uncertainty
Electroplating duration	10 - 90 min	1s
Temperature	20 - 60°C	+/- 2°
Current density	0,5 - 5 A/dm ²	< 5 %

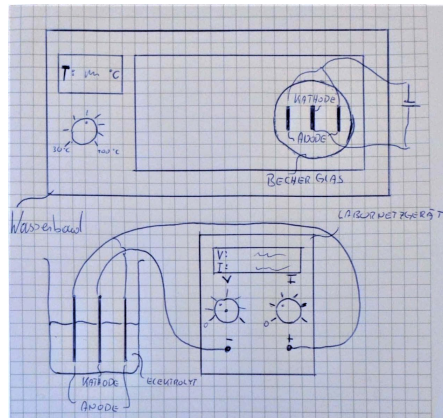


Figure 3.4.: A sketch of the Experimental Setup.

- mechanical cleaning with soap
- ultrasonic cleaning
- removal of oxide layer

Preparation of the Electrodes:

The first step was performed using perfume-free liquid soap and cleaning sponges. A hard mechanical cleaning was done, after this step, the copper plates were put into the ultrasonic bath for 15 minutes. The ultrasonic bath was heated to 40 °C and was filled with water and some liquid soap. After the ultrasonic bath, the copper piece was cleaned in water and put into the sulfuric acid for at least 10 minutes to remove any residuals and the oxide layer. This cleaning procedure was done for three pieces of copper for each experiment, two anodes and one cathode.

Once three pieces of copper were cleaned, they were marked with a permanent marker and on the cathode a strip of duct tape was put on the copper piece to get an area of about 30 cm^2 . The area was measured using a caliper, both sides have to be taken into account since plating happens on both sides. Before experimenting, the anodes and the cathode had to be weighted, in order to determine the weight difference after the experiment.

Preparation of the Electrolyte:

The electrolyte, slightly acid copper sulfate solution was used. The preparation steps were as follows: In a beaker glass, 132 g of the copper sulfate was mixed with 750 ml of distilled water. 10 ml of sulfuric acid were added to get the solution to a pH value of 4. The solution was put on the magnetic stirrer and stirred for 15 minutes until all the copper sulfate dissolved. The electrolyte was used for about 5 experiments, depending on the level of contamination it was changed sooner or later.

Preparation of the Set-Up:

Then the random value generator was used to create a data-set of duration, temperature, and current density. These values were used in the experiment later on. In the next step, 350 ml of electrolyte were put into a beaker glass, which was put into the heated water bath. In this beaker glass, a distance holder was put, in order to perform the experiment with the same distance between cathode and anodes. The electrolyte level had to be on the duct

3. Methodology

VersuchNr.						
SOLL		min.		°C		A/dm ²
						A
	Nummer	Masse Start [g]	Masse Ende [g]	Fläche Kathode [cm ²]		
Kathode						
Anode 1						
Anode 2						

Figure 3.5.: The Template which was used during the Experiment.

tape part of the cathode, so all the measured area was in the electrolyte. The electrodes were connected and the current was adjusted. A template was prepared to put the measured values in for each experiment. This helped to avoid any confusions and to reduce the risk of forgetting a measured value, this template can be seen in Figure 3.5 .

Measurements during the Experiment

During the experiment, the time was measured using software with several different stopwatches which can be labeled. The current was measured three times during the experiment, equally distributed over the time period. The voltage was measured one time. Current and voltage were measured using the multimeter since the accuracy was higher. The temperature was measured three times, also equally distributed over the time period.

Measurements after the Experiment

When the time was up, the laboratory power supply was turned off, the anodes and the cathode were rinsed off with water to remove the electrolyte and put on the side to dry. A hairdryer was used to ensure all the water was dried. Then the weight was measured again, of the cathode and the two anodes separately.

Objective

Non-goals: The real bath process of the production line at AT&S should not be mapped. The parameters relevant to the product are not fully mapped. These will only be addressed at the end of the methodology development. The project team is only at the beginning of the methodology development.

3.2. Electroplating Experiment

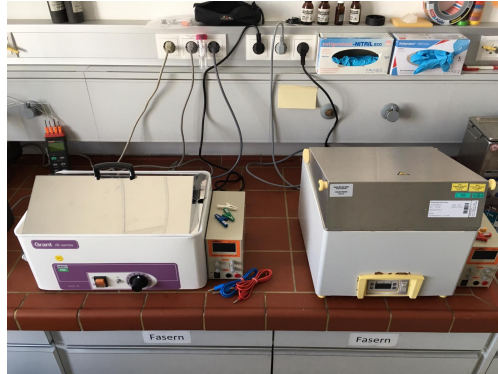


Figure 3.6.: Heat bath 1 and 2 with the corresponding Power Supplies.



Figure 3.7.: The heat bath 3 and 4 with the corresponding Power Supplies.



Figure 3.8.: The used Chemicals and the Copper Plates

3. Methodology

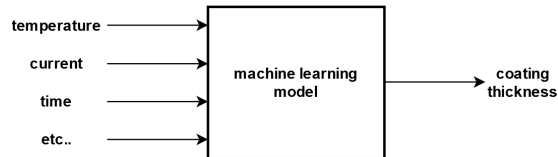


Figure 3.9.: Visualization of the Inputs and Outputs of the Model.

Objective: The primary objective is to apply data models to a new area and to investigate how well they are suited to this. Figure 3.9 shows the schematic structure, the input and output data. After learning, the model should be capable of predicting the layer thickness using the parameters temperature, duration, current, and concentration. For the DET, it is also important to predict the energy demand of a given electroplating process. One can change the input structure to predict the energy demand, this step was also tested.

Creation of Randomized Parameters

For better usability for the data model, a randomized set of the parameters is created. This decreases the risk of learning non existing patterns.

3.2.2. Table of Devices, Table of Chemicals

In this section, the used devices and chemicals are shown with detail in Table 3.3 and Table 3.4.

Table 3-3.: Equipment used for the Electroplating Experiment

abbreviation	device	producer	specification	uncertainty
HB	heated water bath 1 (60 °C)	Lauda	Aqualine AL 12	2 °C
HB	heated water bath 2 (40 °C)	Grant JB series	-	2 °C
HB	heated water bath 3 (25 °C)	-	-	2 °C
HB	heated water bath 4 (50 °C)	Harry Gestigkeit GmbH	W16, 1480202	2 °C
PS	laboratory power supply 1	Volttech	RNG 3003 (1)	5%
PS	laboratory power supply 2	Volttech	RNG 3003 (2)	5%
PS	laboratory power supply 3	GW DC Power Supply	GPR-3030 D	-
PS	laboratory power supply 4	ELV	PS 7030	-
MM	Multimeter	Keithley	179A TRMS Multimeter	-
TL	temperature logger	Voltcraft Datalogger	K 204, Inv. Nr: 060600503	-
PSc	precision scales	Acculab	Vicon	±0.05g
MS	Magnetic Stirrer	Carl Roth	R 1000	-
S	scales	Ikea	Drycken	-
-	hair dryer	-	-	-
UB	ultrasonic bath	Bandelin Sonorex	0146799	-
TE	thermal element	-	-	-
KPG	KPG stirrer	Janke&Kunkel	Inv.Nr: 0175973	-
S	Copper Substrate	-	-	-
C	Caliper	-	-	-
-	Beaker Glass	Carl Roth	volume: 1 l	-
-	Tweezer	-	-	-

Table 3.4.: Materials and Chemicals that were used for the Electroplating Experiment

abbreviation	material/chemical	producer	specification	toxicity
CS	copper sulfate	Carl Roth	Copper(III) sulphate pentahydrate	-
SA	sulfuric acid	Carl Roth	25 %	-
DW	distillated water	-	-	-
-	perfume free soap	-	-	-

3.2.2.1. Correlation with AT&S

The experiment conducted strongly differs from the actual electroplating processes at the production units of AT&S. The goal was not to create a copy, which would not be possible in this scope for several reasons, such as the complexity of the system and the protection of privacy data. Even though the experiment is different, it was conducted in a way to have similarities, it was electroplated with copper - which is also the most important step to make circuit boards conducting. If possible, the parameters were chosen to coincide with the process at the factory, such as the coating thickness, the duration, and the current. This was discussed with the staff of AT&S and during a workshop with the bath producer Atotech.

3.3. Data-models

3.3.1. Introduction

In the following section, the machine learning methods which were applied to the data-set of the PV system or on the data-set which was produced during the electroplating experiment are explained in more detail. A train-test-split was done, that means randomly a part of the data was chosen for training the model and another part for testing the model. To measure the quality of the model, the R^2 value was calculated, for the training data and - with a higher significance - also for the test data.

3.3.2. Basic Principle

Machine learning is the general term when computer learn from data, the data has to be provided in a certain way. There are many different ways the machine can learn:

- (i) supervised
- (ii) unsupervised
- (iii) reinforced

The data one feeds into a machine learning algorithm can consist of input-output pairs or just inputs. Supervised learning algorithms require input-output pairs, they need the output to learn. Unsupervised learning algorithms can learn from only the input data. Supervised learning works in general as follows: One feeds in an example input, then the associated output. This is repeated many times until eventually the algorithms picks up a pattern between the inputs and outputs. Once this is done, one can feed it a unseen input and it will predict the output. Using unsupervised learning algorithms, one feeds in an example input without the associated output, usually the output is not known for a certain input. This step is repeated many times, eventually the algorithm will recognize clusters in the input data and can organize it. Now one can feed it a unseen input and it will predict which cluster it belongs to [49]. Since we have input-output pairs in both examples, supervised learning algorithms were applied to the data sets.

3.3.3. Workflow

Data Acquisition: The most time consuming part for the PV system and the galvanization model was creation of the data sets. For the PV system, the data with the output of the PV unit was provided by TU Graz, it were almost 11.000 data points with 1 hour resolution. The weather information was provided by KFU Graz with an resolution of fifteen minutes. The data for the machine learning model of the galvanization experiment was created in the laboratory. The input parameters were temperature, duration, current density and voltage. The output is the mass difference of the cathode before and after the experiment.

3.3.4. Machine Learning: Terms and Algorithms

Overfitting and Underfitting: To describe these concepts, one has to look at the performance of the model on the testing and the training data and compare these two. If the model does not have the ability to predict well the labels on the data it was trained on, it has a *high bias*. The model **underfits**, which can have the following reasons:

- the information is not detailed enough
- the model is too simple to describe the data

To solve this problem, one can use data with a higher predicitive ability or change to a more complex model.

Overfitting is another problem, here the model performs very well on the training data, but not on the testing data. Overfitting is also called the problem of *high variance*. Reasons for overfitting are:

- the data consists of many features but a small number of examples
- the model is too complex to describe the data

To solve this problem, one can try a simpler model, if possible add more training data, regularize the model or reduce the dimensionality of examples in the data-set. Regularization is a widely used approach.

3. Methodology

Gradient descent is a numerical optimization algorithm which is frequently used for optimization. It is an iterative optimization algorithm, to find a local minimum one starts at a random point, computes the gradient of the function at this point and takes a step in the negative direction to reach a minimum at some point. Often we do not know for sure if we are at the global or a local minimum but in many cases one does not care and a local minimum is sufficient. [50]

3.3.4.1. Linear Regression

A frequently used regression learning algorithm is linear regression. A model is learned, that is a linear combination of features of the input. One wants to build a model $f_{\mathbf{w},b}(x)$ as a linear combination of features of example x :

$$f_{\mathbf{w},b}(x) = \mathbf{w}x + b \quad (3.1)$$

It is desired to fit the data points as good as possible with only a linear model. As a loss function, the squared error loss was used in this case. This is an arbitrary decision, one could also use the absolute value of the difference or the cube instead of a square. The loss function is defined by:

$$f_{loss} = \sum_{i=1}^N (f_{\mathbf{w},b}(x_i) - y_i)^2 \quad (3.2)$$

In the optimization procedure, the parameters \mathbf{w} and b of equation 3.1 are found that minimize the loss function, so the mean square error becomes minimal. [51]

3.3.4.2. Polynomial Regression

The polynomial regression works similar as the linear regression, but polynomials of higher orders are used to fit the data. This allows one to fit more complex patterns, linear regression is often too simple for real data. In this example, a hyper parameter fitting was used to figure out the degree of the

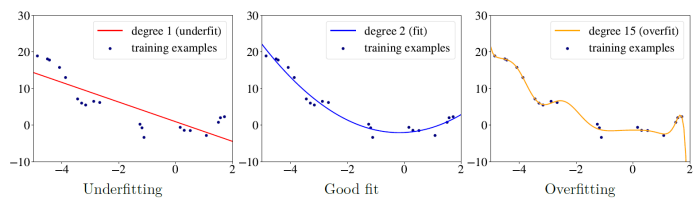


Figure 3.10.: Examples of Underfitting, good fitting and Overfitting on the same Data. [52]

polynomial which has the lowest error. This can be used to eliminate the problem of under fitting if the linear regression is too simple to describe the data properly.

In Figure 3.10 one can see the effect of overfitting to the data due to the use of a high degree polynomial. In this case a polynomial of degree 2 has a good fitting behavior. The overfitting curve does give very good results on the training data, but if one tests it with new data it will not return good results.

3.3.4.3. Decision Tree Regression

A decision tree has influence in a wide area of machine learning, covering *classification* and *regression*. It can be used to visualize decisions and decision making. A decision tree is drawn upside down, the root starts on top and it grows down with the branches. At a node of the branches, a specific feature is examined. A choice is made according to some criterion, if the value is below a chosen threshold the left branch is followed and otherwise the right branch. Once the leaf node is reached, a class is found for the example. In the background, one has to decide which features to choose and what threshold is used for splitting. Also one needs to define when to stop splitting and a criterion to measure the quality of a split. [53]

3.3.4.4. Random Forest Regression

Closely related to decision trees is random forest regression. The Random Forest Algorithm combines the output of several Decision Trees to generate

3. Methodology

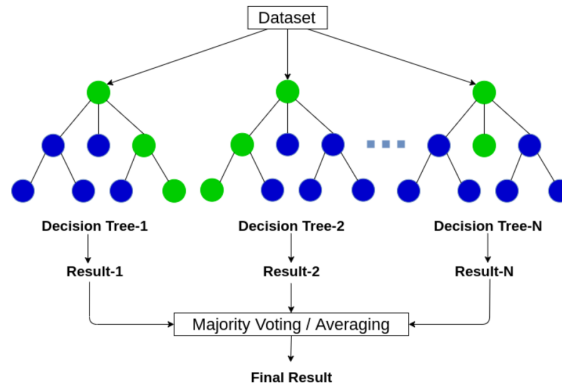


Figure 3.11.: The Random Forest Algorithm generates the Output by combining many randomly generated Decision Trees. [55]

the final output. It is an ensemble algorithm, meaning that models of the same nature are combined. Decision trees have an aspect that prevents them from being the perfect tool for predictive learning, namely inaccuracy [54]. Random forests combine the simplicity of decision trees with flexibility, this results in an improved accuracy.

3.3.4.5. Neural Network

An artificial neural network (ANN) or neural network (NN) consists of artificial neurons, which are arranged in layers. A NN can be understood as a function, where the most important parts are the neurons and the connections between them. Each neuron of a layer is connected to all neurons of the directly adjacent layer. So an NN takes information about its input layer and outputs the result of its calculation at the output layer. In between there are several hidden layers, where the main part of the information processing happens.

This structure can be seen in Figure 3.12. In this Figure, on the left one can see the input neurons. This is where information such as a recognizable image or text is entered. A representation of the information within the states of the individual input neurons (A, B and C) is selected. The input neurons are linked to the neurons of the next layer via weighted connections. The

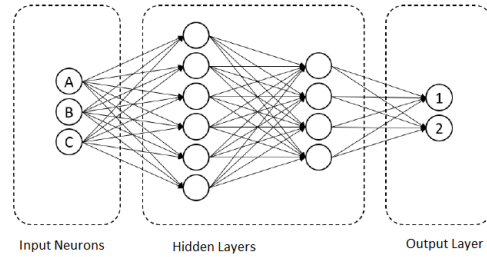


Figure 3.12.: The Structure of a Neural Network. It is constructed by different types of Layers.

signal of the input neurons is therefore passed on to the following neurons with different degrees of intensity and processed there. When the signals of all inputs of a neuron have been processed, the resulting signal is again forwarded in the same way as before. Finally, the result of the NN can be read at the output layer. Should this neuron light up and have a strong output signal, this can be interpreted in terms of its significance as a result. [56]

4. Results

4.1. Use-Case

4.1.1. PV prediction Model

In experiments on randomized training and test data in a ratio of 80 % to 20 %, the model achieved determination coefficients of $R^2(\text{train}) = 0.96$ on the training data and $R^2(\text{test}) = 0.87$ on the reference data. The model is therefore sufficiently generalizable. The methods for preparing the data and implementing the model are based on the framework developed by Schranz et al. 2020 [8]. The prediction was performed in milliseconds range, with only a minimum communication overhead.

The correlation between the generated output in kW of the PV system and the different weather parameters was analyzed and is shown in Figure 4.1. The correlation and therefore the influence for the data model is high for radiation, medium for temperature. The correlation between generated power and humidity is negative, that indicates an anticorrelation.

Table 4.1.: Results of the Regression Algorithms for the PV System

Method	$R^2(\text{training data})$	$R^2(\text{test data})$
Linear Regression	0.86	0.84
Polynomial Regression (Degree 3)	0.88	0.87
Decision Tree Regression	0.999	0.78
Random Forest Regression	0.98	0.87
Neural Network	0.88	0.87

4. Results

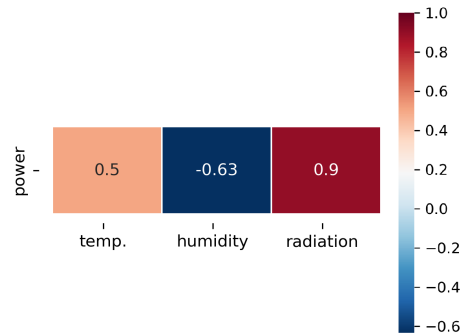


Figure 4.1.: The Correlation between the predicted Energy Output of the PV system and the different meteorological Parameters. The correlation with Radiation is high, with Temperature medium. With Humidity one even has Anticorrelation.

As can be seen in Table 4.1, Random Forest Regression, polynomial Regression and Neural Networks showed the best result on the test data. The Random Forest algorithm was used for the Co-Simulation in Modelica.

4.1.2. Simulation of the Heat Bath

In this section, selected simulation results that were created in the Modelica model which is described and can be seen in chapter 3.1.2 are shown. The simulation was done for a heat bath that changes its temperature in a periodic interval and has different heat flows in and out of the system. The model was created to be a simple example for a working model and to represent the heat bath at AT&S.

4.1.2.1. Temperature Behavior

Simulation of the bath with a periodically changing temperature is shown in Figure 4.2. The simulation was done for bath with different volume, which leads to different heat inertia which means the bath react differently to the change of the setpoint temperature.

4.1.2.2. Photovoltaic Usage

In Figure 4.3, the produced (black line), the consumed (yellow area) and the excess energy (blue area) from the PV system is shown. The consumed energy is used to heat up the bath or to keep the temperature constant, the excess energy is fed into the grid.

4.1.2.3. Overall Consumption

In Figure 4.4, the total consumption and the individual sources supplying the bath are shown. In the first few hours, the bath is heated up; the boiler and heating cartridge run at maximum capacity. Shortly after $t = 12\text{h}$, the desired temperature is reached, the boiler is shut down and the PV system covers the demand necessary to maintain the temperature. Excess energy is fed into the grid. The waste heat is used continuously, but only covers a small part in this simulation. One can see interesting details by comparing the above figures. The brown line for volume 2 in Figure 4.2 and the PV usage in Figure 4.3 are from the same simulation run, one can see that at $t = 12\text{h}$ the set point temperature is reached. This leads to reduced use of PV power due to the reduced amount of the heat bath. In Figure 4.4, one can see how the heating systems react to the different demands. During the process of heating up the bath, both the kettle and the heating cartridge run on full capacity. The heating cartridge uses all the power it can get from the PV system. After $t = 12\text{h}$, when the set-point temperature is reached, the kettle reduces its power to roughly 10%, the PV system to roughly 50%. One can see that the temperature is kept constant mostly by the PV system, which leads to a reduction of gas consumption in the kettle.

4. Results

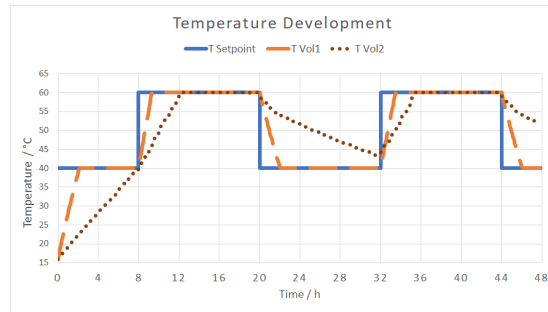


Figure 4.2.: The Setpoint Temperature (blue) and the course of the current Temperature of two Baths of different Volumes.

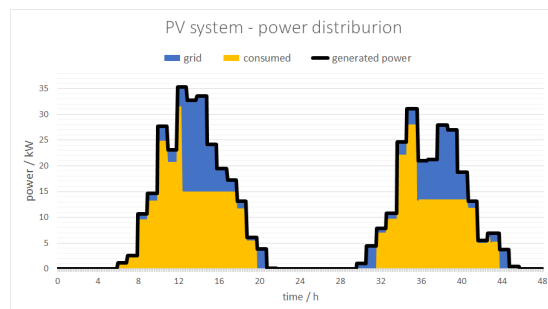


Figure 4.3.: The produced Energy of the PV system, the Self-Consumption of the heat cartridge and the feed-in into the Grid.

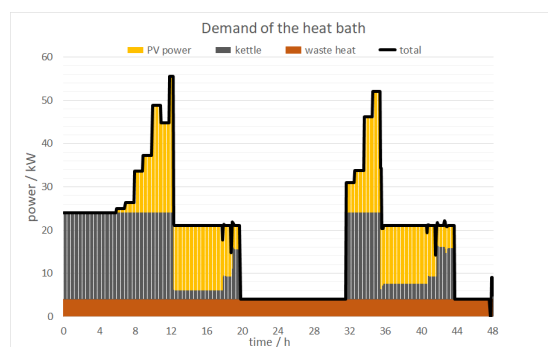


Figure 4.4.: Simulation Results of the various Sources used to heat the bath: Waste Heat, PV Energy of the Heating Cartridge, Boiler and the total Demand.

4.2. Electroplating

The results of the electroplating experiment and a visualization of the distribution with respect to the different parameters is shown.

4.2.1. Experiment Execution

The experiment was executed 202 times, subtracting the samples where errors were discovered later on the data set consists of 199 samples. The measured values can be found in the Appendix in Table A.1 and Table A.3. The distribution of the data in respect to the varied parameter can be seen in the following graphs: the distribution of the temperature in Figure 4.6, the distribution of the current density in Figure 4.5, and the distribution of the experiment duration in Figure 4.7. The data-set was used to create data-driven models using machine learning methods. The velocity of testing was increased during the testing phase, at the beginning, only one experiment was conducted at the time. After several days the one was able to parallelize the procedure and four setups were installed which could be operated at the same time. The temperature was varied from room temperature to 60 degrees in 10 degrees steps. This results were later used to generate data models by applying machine learning methods to these data sets.

4.2.2. Visualization of the Data

In the Figures 4.5, 4.6, and 4.7 the distribution of the conducted experiments with respect to the current density, the temperature and the duration are shown. One can see that the temperature distribution is uniformly distributed, for the current density and the duration more experiments were conducted in the lower range.

4. Results

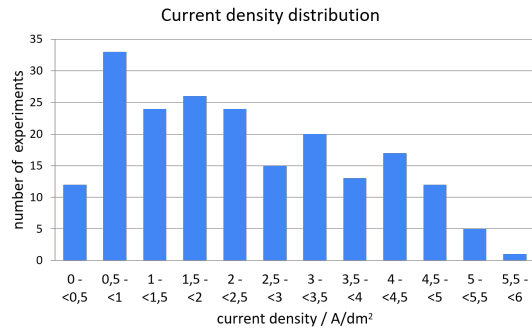


Figure 4.5.: The Distribution of the conducted Experiments with Respect to the Current Density.

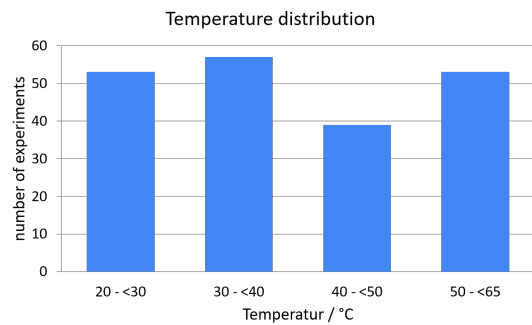


Figure 4.6.: The Distribution of the conducted Experiments with Respect to the Temperature.

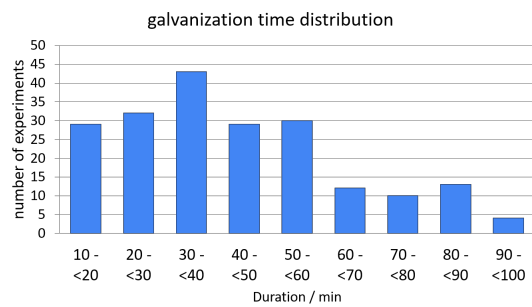


Figure 4.7.: The Distribution of the conducted Experiments with Respect to the Experiment Duration.

4.3. Data model Electroplating

4.3.1. Comparison of the Models

The results were analyzed by different machine learning algorithms. The accuracy was high, with R^2 values over 0,98.

The training of the model was done with 70% of the data, the testing with the remaining 30%. Several algorithms were used to calculate models that predict the amount of deposited material. A value to determine the quality of a model is the R^2 value. This quality measure has been calculated for various models and is shown in the table 4.2.

4.3.2. Coefficient of Determination (R^2)

The important number is the R^2 on the test data, since it tells how well the model performs on the unseen data. Here the best algorithms were polynomial regression and the neural networks. For both models, the parameters have to be tuned, for the polynomial regression the degree must not be too high, as one can see in table 4.2. At a high degree the R^2 value becomes even negative, this is because of overfitting, the model fits the training data perfect but can not work well on the test data. The Neural Network must not have too many layers or it will perform poorly.

One major goal of this analysis was to find out the effect of the different parameters on the velocity of deposition and therefore the amount of deposited material. This correlation between the deposited mass - the mass difference of the cathode before and after the experiment - and the other parameters that were varied. The result can be seen in Figure 4.8.

4.3.3. Correlation Analysis

4. Results

Table 4.2.: Results of the Regression Algorithms for the Electroplating Experiment

Method	R^2 (training data)	R^2 (test data)
Linear Regression	0.830	0.683
Polynomial Regression (Degree 2)	0.981	0.962
Decision Tree Regression	0.99	0.908
Random Forest Regression	0.992	0.943
Shallow Neural Network	0.973	0.946
Deep Neural Network	0.988	0.947

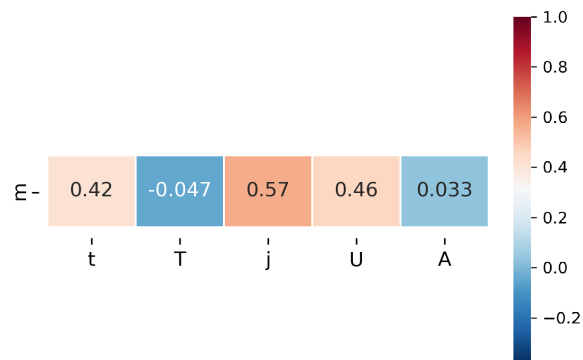


Figure 4.8.: The Correlation between the Deposited Mass on the Cathode and the different Parameters Exposition Time, Temperature, Current Density, Voltage and Area.

5. Discussion

5.1. Modeling of Energy System

One trend in model-based analysis and optimization of CPS is the increasing complexity of the systems under consideration, which is further intensified by the need for interoperability and increased efficiency requirements. Subsystems can no longer be considered separately and computer-based systems such as microprocessors, software, and communication networks (the cyber part of CPS) cannot be ignored when understanding system behavior. These developments pose new challenges to traditional modeling and simulation techniques: For the analysis and optimization of CPS, methods and tools are needed for both the cyber and the physical part. It is necessary to combine data-driven techniques with first-principle models. The concept consists of coupling two or more models in a co-simulation in which the data exchange between the subsystems is limited to discrete communication points. These different trends and possibilities push established methods and tools to their limits and even beyond. The results of the different algorithms for the PV model can be seen in Table 4.1, the simulation results results of the use-case in Figure 4.2, Figure 4.3, and Figure 4.4.

Improvements for the Use-Case

This model does not make the claim to simulate the case perfectly, the main focus of the model was to show that a Co-simulation works and that data-driven models and physical models can interchange data. Some improvement ideas are to include a battery for the photovoltaic system, add different waste heat sources with data taken from the factory, include a solar thermal system which is already installed at the factory. This model will be under further

5. Discussion

development in the project, the next steps will be to improve the kettle model, to include a load profile that corresponds to the actual load in the factory, and to include a battery system to store the excess power generated by the photovoltaic system.

5.2. Electroplating

The experiment was conducted 202 times, 199 of these experiments were usable. The result - the deposited mass on the cathode - was always in an expected range. To check the results a template was used that marks the values if they are out of a reasonable range. This was in 199 experiments not the case. The temperature and the current changed during the experiment, to minimize the error due to these changes they were measured three times and the mean value was calculated. The voltage changed with the position of the copper sheets since the resistance depends on the distance of electrolyte between them. To keep it constant a simple construction out of wood was used.

The results were meaningful when compared to the expected values which were calculated theoretically. The measured values are shown in the Appendix in Table A.1 and Table A.3. The distribution of the data in respect to the varied parameter can be seen in the following graphs: the distribution of the temperature in Figure 4.6, the distribution of the current density in Figure 4.5, and the distribution of the experiment duration in Figure 4.7

5.3. Data Model

The data-model used for the PV System depends mostly on the weather prediction since the output is strongly connected to the predicted radiation of the sun. The error will be much bigger if a weather forecast is used and not historic data since the weather forecast has an error on its own. The data-model that was created from the electroplating experiment was used to train different machine learning algorithms. Neural networks and polynomial regression showed the best results, the results can be seen in Table 4.2.

6. Conclusion and Outlook

6.1. Use Case

In the first part of the thesis, a Co-Simulation model was created. The thermohydraulic and electrical system was modeled in the physical modeling language Modelica. A data-driven model that used a random forest regression algorithm to predict the performance of a PV system based on given temperature, humidity and global radiation values was created in python. The data model is integrated into the physical model based on the FMI standard for co-simulation. The results show that the power predicted by the data model corresponds very accurately to the actual measured data. Furthermore, it is shown that the use of the boiler can be significantly reduced by connecting the PV system. Further development steps are upscaling of the model and integrating more parts to increase its complexity and to simulate the process at AT&S better. Research is needed in the following areas, among others: Automatic model generation, automatic model updates based on measured data or analyses to scale different models and modeling paradigms.

6.2. Electroplating Experiment and Datamodel

The experiment was conducted successfully, with the helpful tips of colleagues from the chemistry department the experiment was designed and set up at the department of physics. The experiment did not serve the purpose to create new insight into the galvanization process, but the creation of data sets and the application of machine learning algorithms like neural networks is a new topic to chemistry. The results showed that the machine learning tools were able to pick up the pattern underlying the data, almost all models had an accuracy of >95 %.

6. Conclusion and Outlook

This experiment showed that the application of machine learning methods to new parts of science has potential, a next step in the process could be an experiment that describes a more complex process. For such a machine learning model a bigger data set would be needed, this would be the next step for the integration in the Digital Energy Twin.

Appendices

A. Measurands of galvanization Experiment

APPENDIX

A.0.1. Measured Data during the Electroplating Experiment

A. Measurands of galvanization Experiment

Table A.1.: First part of the measured Data of the Electroplating Experiment.

Nr. ... number of experiment
m_C ... mass of cathode before the coating
m_{A1} ... mass of anode 1 before coating
m_{A2} ... mass of anode 2 before coating
m_C' ... mass of cathode after coating
m_{A1}' ... mass of anode 1 after coating
m_{A2}' ... mass of anode 2 after coating
t ... duration of the plating process

Nr.	<i>m_C</i> / g	<i>m_{A1}</i> / g	<i>m_{A2}</i> / g	<i>m_C'</i> / g	<i>m_{A1}'</i> / g	<i>m_{A2}'</i> / g	<i>t</i> / min
1	17,42	15,70	15,88	17,81	15,50	15,70	30,05
2	17,80	15,51	15,70	18,71	15,05	15,28	45
4	18,69	15,04	15,26	19,40	14,74	14,91	50
5	20,10	14,35	14,54	20,77	14,01	14,21	25
6	14,73	15,04	15,32	15,30	14,77	15,04	35,5
7	16,61	15,87	15,67	17,11	15,63	15,40	52
8	15,15	14,78	15,04	15,53	14,58	14,87	55
9	20,73	14,01	14,20	21,67	13,54	13,73	68
10	15,52	14,58	14,85	16,01	14,33	14,62	38
12	17,30	15,52	15,30	17,72	15,31	15,10	25
13	17,08	16,65	16,82	17,84	16,23	16,39	22
14	15,99	14,32	14,61	16,46	14,09	14,38	16,5
15	18,17	12,74	13,09	18,47	12,60	12,95	25
16	18,49	14,63	15,49	19,72	14,04	14,82	35
17	18,46	15,02	16,63	18,94	14,79	16,39	61
18	18,24	14,38	16,23	18,49	14,24	16,10	65
19	15,76	14,09	16,40	16,71	13,61	15,88	45
20	15,80	14,55	14,73	16,14	14,38	14,53	35
21	17,06	19,03	17,85	18,57	18,20	17,16	75
22	15,37	18,39	12,94	15,95	18,08	12,67	45
23	15,61	12,59	14,02	16,16	12,31	13,77	40
24	15,95	18,07	12,67	16,19	17,96	12,56	24
25	16,12	14,37	14,53	16,28	14,32	14,48	42
26	18,49	14,25	16,09	19,50	13,74	15,60	41

27	16,17	17,96	12,56	16,64	17,73	12,32	20
28	16,68	15,53	17,90	17,07	15,37	17,71	36
29	15,96	17,52	17,43	16,25	17,39	17,28	33
30	16,95	15,44	16,67	17,08	15,37	16,61	51
31	16,03	14,93	15,01	16,22	14,83	14,92	39
32	16,71	13,62	15,89	16,92	13,51	15,79	33
33	16,24	14,30	14,47	16,38	14,23	14,40	17
34	16,24	17,38	17,28	17,00	17,02	16,89	41
35	16,38	14,24	14,40	16,62	14,10	14,27	32
36	16,60	17,72	16,02	17,19	17,42	15,73	18
37	16,53	14,96	17,14	17,67	14,35	16,56	40
38	21,85	16,77	13,44	22,32	16,51	13,27	40
39	15,92	15,35	17,40	16,35	15,15	17,17	45
40	18,13	16,19	13,70	18,56	15,95	13,52	45
41	17,42	14,82	13,51	18,06	14,51	13,18	25
42	17,94	14,25	14,08	18,34	14,07	13,85	45
43	17,76	16,54	15,58	18,71	16,07	15,09	35
44	18,63	17,78	17,15	18,79	17,69	17,08	15
45	18,17	14,33	15,01	18,44	14,19	14,88	45
46	17,05	17,25	16,09	17,23	17,16	15,99	50
47	17,68	14,35	15,71	19,03	13,65	15,06	50
48	17,41	15,15	12,91	17,72	15,00	12,77	50
49	16,27	13,74	18,71	18,00	12,94	17,80	80
50	14,36	15,32	18,19	14,96	15,03	17,89	35
51	15,70	13,25	13,84	15,84	13,18	13,75	50
52	17,12	14,06	17,14	17,26	13,98	17,06	50
53	16,59	14,51	15,99	16,78	14,40	15,89	50
54	16,97	13,51	13,18	17,14	13,42	13,09	50
55	18,05	19,10	19,54	18,50	17,85	19,34	50
56	19,10	19,83	18,77	19,55	19,60	18,55	50
57	19,00	18,62	18,72	19,28	18,48	18,59	50
58	19,11	18,04	16,36	19,58	17,82	16,11	50
59	19,47	17,68	13,63	20,27	17,32	13,19	50
60	19,24	12,75	17,06	20,03	12,40	16,65	50

A. Measurands of galvanization Experiment

61	18,59	14,85	14,17	19,35	14,46	13,77	50
62	19,13	15,04	14,99	19,94	14,62	14,59	50
63	18,91	17,04	16,10	20,06	16,49	15,49	50
64	19,75	17,81	13,96	20,85	17,30	13,36	50
65	20,08	18,54	18,56	21,20	17,95	18,02	50
66	19,10	17,83	15,87	20,21	17,30	15,26	50
67	15,81	17,27	16,46	15,91	17,22	16,40	30
68	18,45	15,23	14,45	18,65	15,13	14,36	30
69	18,28	13,76	13,33	18,56	13,61	13,19	30
70	17,56	16,63	17,30	17,93	16,43	17,11	30
71	18,06	13,18	18,06	18,36	13,03	17,86	30
72	21,18	17,34	19,67	21,47	17,19	19,52	30
73	19,57	13,16	14,40	19,87	13,00	14,23	30
74	20,85	12,37	17,70	21,15	12,20	17,55	30
75	18,78	16,39	17,21	19,25	16,15	16,97	30
76	19,34	13,74	14,57	19,82	13,50	14,32	30
77	20,01	19,05	18,17	20,50	18,81	17,92	30
78	19,55	13,40	13,17	20,04	13,14	12,94	30
79	19,88	19,46	13,58	20,61	19,04	13,26	30
80	15,91	14,34	15,11	16,63	13,94	14,77	30
81	21,49	18,14	17,08	22,23	17,81	16,69	30
82	21,15	17,62	18,66	21,86	17,25	18,30	30
83	18,41	21,56	13,04	19,36	21,10	12,54	30
84	20,04	19,51	17,86	20,96	19,04	17,41	30
85	18,53	17,18	17,55	19,47	16,73	17,05	30
86	17,12	12,20	13,00	18,02	11,73	12,51	30
87	16,17	14,59	14,65	16,23	14,56	14,61	30
88	16,75	15,38	14,20	16,81	15,35	14,16	30
89	18,50	14,17	14,23	18,56	14,14	14,19	30
90	17,71	16,40	13,08	17,78	16,37	13,05	30
91	18,37	19,02	13,90	18,48	18,95	13,84	30
92	17,22	13,03	16,35	17,35	12,97	16,29	30
93	15,86	18,28	14,73	15,99	18,20	14,66	30
94	17,27	13,24	17,24	17,38	13,18	17,18	29,5

95	17,77	17,91	16,71	18,20	17,68	16,48	30
96	20,04	16,94	17,80	20,46	16,73	17,58	30
97	18,56	17,03	16,66	18,98	16,83	16,42	30
98	20,49	17,40	21,08	20,91	17,16	20,86	30
99	16,81	18,96	14,66	17,14	18,80	14,50	20
100	21,85	13,13	12,52	22,17	12,97	12,35	20
101	20,94	18,20	17,18	21,25	18,04	17,00	20
102	16,23	12,93	13,84	16,56	12,76	13,67	20
103	15,98	12,97	12,50	16,14	12,88	12,42	20
104	17,34	14,55	14,61	17,51	14,47	14,52	20
105	18,48	14,11	15,33	18,65	14,03	15,25	20
106	17,38	14,16	14,18	17,55	14,07	14,09	20
107	16,57	16,72	18,01	16,77	16,61	17,90	40
108	22,17	17,14	16,45	22,37	17,05	16,34	40
109	21,25	14,47	16,81	21,44	14,35	16,71	40
110	17,13	16,38	12,93	17,33	16,29	12,84	40
111	16,61	16,27	11,69	17,12	16,03	11,46	45
112	19,26	17,66	17,55	19,76	17,43	17,30	45
113	19,82	20,84	15,23	20,33	20,57	14,99	45
114	19,45	16,97	18,97	19,98	16,71	18,71	45
115	16,66	17,03	14,33	16,94	16,88	14,20	15
117	16,96	18,77	17,89	17,25	18,60	17,75	14,5
116	16,66	16,08	14,50	16,96	15,93	14,35	16
118	17,05	18,55	12,82	17,36	18,38	12,67	15
119	21,45	14,01	12,40	21,86	13,81	12,18	60
120	22,37	12,35	13,17	22,78	12,14	12,94	59
121	16,77	14,08	12,72	17,17	13,88	12,51	58
122	17,33	14,45	12,86	17,74	14,25	12,65	57
123	21,86	20,12	17,36	22,14	19,98	17,24	25
124	22,78	17,81	19,80	23,05	17,65	19,69	25
125	17,16	18,41	17,72	17,44	18,26	17,57	25
126	17,73	16,89	19,57	18,01	16,74	19,42	25
127	16,79	14,06	13,64	16,87	14,01	13,59	21
128	16,97	15,45	17,01	17,06	15,41	16,96	22

A. Measurands of galvanization Experiment

129	16,77	21,71	17,29	16,84	21,66	17,25	18,5
130	15,83	17,05	17,41	15,94	16,98	17,36	24,5
131	19,74	14,97	12,64	20,35	14,67	12,33	25,5
132	17,11	14,23	12,66	17,70	13,94	12,35	26
133	16,94	18,69	18,58	17,54	18,36	18,29	25,5
134	16,94	16,70	18,37	17,54	16,42	18,02	25
135	17,05	18,27	12,33	17,45	18,06	12,16	70
136	16,83	13,92	14,65	17,23	13,72	14,46	70
137	16,87	16,92	18,35	17,28	16,70	18,14	70
138	15,90	18,01	19,68	16,34	17,77	19,49	70
139	17,24	12,32	16,86	17,82	12,02	16,58	20
140	17,53	17,24	16,73	18,19	16,90	16,41	20
141	17,53	17,34	17,57	18,32	16,97	17,14	20
142	17,43	19,97	21,63	18,03	19,61	21,35	20
143	18,77	15,39	17,63	19,59	14,99	17,22	60
144	20,33	17,22	19,39	21,16	16,80	18,97	60
145	17,34	13,58	18,63	18,20	13,16	18,17	60
146	18,01	14,00	16,94	18,86	13,61	16,49	60
147	18,62	16,40	19,42	18,82	16,30	19,33	90
148	15,34	16,79	18,97	15,53	16,69	18,88	90
150	22,97	13,16	21,62	23,15	13,06	21,51	90
151	17,22	13,71	12,01	17,58	13,52	11,84	15
152	17,44	16,67	19,48	17,80	16,50	19,29	15
153	17,27	16,40	16,57	17,64	16,22	16,37	15
154	16,33	17,75	18,13	16,69	17,55	17,95	15
155	18,80	12,92	13,43	19,92	12,36	12,87	80
156	23,15	14,24	15,90	24,25	13,62	15,41	80
157	17,80	12,17	13,78	18,94	11,55	13,26	80
158	18,19	12,12	20,51	19,34	11,48	19,99	80
159	18,17	14,45	21,34	18,66	14,18	21,09	15
160	15,52	19,59	12,15	16,00	19,34	11,90	15
161	17,70	16,87	17,12	18,21	16,58	16,88	15
162	19,94	18,04	16,94	20,43	17,78	16,68	15
163	19,74	11,81	16,48	19,95	11,72	16,38	10

164	17,09	19,32	17,92	17,28	19,22	17,80	10
165	18,30	17,52	20,34	18,51	17,41	20,24	10
166	17,13	17,56	17,91	17,34	17,45	17,81	10
167	19,59	14,15	13,05	21,18	13,42	12,17	80
168	17,88	14,32	11,42	19,45	13,53	10,64	80
169	17,65	15,99	21,50	19,32	15,18	20,56	80
170	18,84	13,85	12,47	20,48	13,03	11,64	80
171	21,56	16,21	13,48	21,84	16,07	13,34	70
172	24,24	16,68	13,51	25,28	16,19	12,97	70
173	15,98	12,80	12,35	16,25	12,70	12,21	70
174	18,92	13,61	15,39	19,20	13,46	15,25	70
175	25,26	15,24	13,33	26,33	14,69	12,81	65
176	16,25	16,18	12,21	17,42	15,60	11,60	65
177	19,20	12,69	13,44	20,37	12,13	12,82	65
178	21,84	12,95	16,06	22,93	12,47	15,44	65
179	17,80	16,36	13,25	18,27	16,11	13,02	45
180	19,84	11,55	16,86	20,30	11,30	16,63	45
181	16,70	19,31	19,97	17,18	19,07	19,70	45
182	18,50	18,87	11,46	18,99	18,62	11,20	45
183	17,59	18,24	14,17	18,91	17,54	13,52	45
184	19,42	19,82	17,83	20,67	19,24	17,09	45
185	19,93	16,29	11,90	21,26	15,67	11,20	45
186	17,28	16,26	18,86	18,65	15,63	18,11	45
187	19,75	11,58	12,11	20,14	11,42	11,89	10
188	17,34	15,43	12,46	17,72	15,24	12,25	10
189	17,42	16,67	12,79	17,82	14,47	12,59	10
190	22,93	12,80	15,59	23,33	12,61	15,39	10
191	18,98	11,18	12,59	19,35	11,01	12,40	85
192	20,13	19,68	11,19	20,49	19,49	11,01	84
193	17,73	14,45	12,58	18,10	14,26	12,40	83
194	17,17	12,24	15,23	17,54	12,06	15,03	82
195	19,25	15,17	11,71	19,89	14,83	11,41	55
196	19,78	18,07	17,43	20,42	17,75	17,09	55
197	17,65	20,63	15,38	18,31	20,28	15,05	55

A. Measurands of galvanization Experiment

198	19,75	10,62	15,61	20,41	10,28	15,30	55
199	21,14	11,28	13,39	21,58	11,11	13,16	15
200	16,29	12,17	20,27	16,71	11,99	19,95	15
201	18,41	11,62	13,51	18,84	11,43	13,28	15
202	17,39	13,01	17,79	17,86	12,76	17,57	15

Table A.3.: Second part of the measured Data of the Electroplating Experiment.

Nr. ... number of experiment
 U ... voltage
 I ... current
 J ... current density
 A ... area of the cathode
 T ... temperature of the heatbath
 d₁ ... massdifference of the cathode
 d₂ ... massdifference of anode 1
 d₃ ... massdifference of anode 2

Nr.	U / V	I / A	J / A/dm ²	A/cm ²	T / °C	d ₁ / g	d ₂ / g	d ₃ / g
1	0,700	0,6480	2,012	32,20	39,0	0,39	-0,20	-0,18
2	1,200	0,9833	3,054	32,20	39,0	0,91	-0,46	-0,42
4	0,600	0,6567	2,549	25,76	60,0	0,71	-0,30	-0,35
5	1,500	1,3253	4,116	32,20	39,0	0,67	-0,34	-0,33
6	0,700	0,8023	2,492	32,20	25,5	0,57	-0,27	-0,28
7	0,600	0,4850	1,883	25,76	39,0	0,50	-0,24	-0,27
8	0,250	0,3303	1,026	32,20	60,2	0,38	-0,20	-0,17
9	1,100	0,6867	2,133	32,20	22,0	0,94	-0,47	-0,47
10	0,600	0,6187	1,921	32,20	59,0	0,49	-0,25	-0,23
12	1,100	0,7933	3,080	25,76	23,5	0,42	-0,21	-0,20
13	1,800	1,7113	5,315	32,20	39,0	0,76	-0,42	-0,43
14	1,200	1,3893	4,315	32,20	59,0	0,47	-0,23	-0,23
15	0,800	0,5870	1,877	31,28	21,7	0,30	-0,14	-0,14
16	0,300	1,7187	5,189	33,12	39,1	1,23	-0,59	-0,67
17	0,300	0,3770	1,301	28,98	60,2	0,48	-0,23	-0,24
18	0,350	0,1953	0,700	27,90	24,3	0,25	-0,14	-0,13
19	1,100	1,0467	3,291	31,81	39,5	0,95	-0,48	-0,52
20	0,300	0,4937	1,477	33,43	58,3	0,34	-0,17	-0,20
21	1,300	0,9837	3,308	29,73	25,0	1,51	-0,83	-0,69
22	0,600	0,6470	2,099	30,82	38,8	0,58	-0,31	-0,27
23	0,500	0,6480	2,058	31,48	59,7	0,55	-0,28	-0,25
24	0,400	0,4130	1,317	31,35	39,2	0,24	-0,11	-0,11
25	0,100	0,1493	0,452	33,05	58,7	0,16	-0,05	-0,05

A. Measurands of galvanization Experiment

26	1,800	1,1917	4,201	28,37	25,1	1,01	-0,51	-0,49
27	1,100	1,1217	3,578	31,35	38,5	0,47	-0,23	-0,24
28	0,419	0,4990	1,736	28,74	59,5	0,39	-0,16	-0,19
29		0,4150	1,382	30,03	39,2	0,29	-0,13	-0,15
30	0,207	0,1215	0,389	31,25	24,1	0,13	-0,07	-0,06
31	0,234	0,2570	0,791	32,48	59,2	0,19	-0,10	-0,09
32	0,368	0,3030	0,938	32,31	39,0	0,21	-0,11	-0,10
33	0,670	0,4325	1,469	29,44	24,8	0,14	-0,07	-0,07
34	1,014	0,8930	2,974	30,03	39,4	0,76	-0,36	-0,39
35	0,582	0,3763	1,278	29,44	26,1	0,24	-0,14	-0,13
36	2,171	1,5290	4,622	33,08	26,4	0,59	-0,30	-0,29
37	1,398	1,3987	4,319	32,38	28,2	1,14	-0,61	-0,58
38	0,352	0,2853	0,866	32,96	38,0	0,47	-0,26	-0,17
39	0,420	0,4293	1,419	30,26	58,4	0,43	-0,20	-0,23
40	0,383	0,4390	1,313	33,44	44,8	0,43	-0,24	-0,18
41	1,411	1,2420	4,072	30,50	39,7	0,64	-0,31	-0,33
42	0,388	0,4497	1,515	29,68	59,0	0,40	-0,18	-0,23
43	1,800	1,3093	4,350	30,10	28,0	0,95	-0,47	-0,49
44	0,445	0,4767	1,494	31,90	44,8	0,16	-0,09	-0,07
45	0,254	0,3013	0,901	33,43	60,3	0,27	-0,14	-0,13
46	0,180	0,1657	0,547	30,28	45,7	0,18	-0,09	-0,10
47	1,026	1,1573	3,562	32,49	60,6	1,35	-0,70	-0,65
48	0,360	0,3227	1,040	31,03	38,2	0,31	-0,15	-0,14
49	0,717	1,3497	4,249	31,76	44,4	1,73	-0,80	-0,91
50	0,833	0,8153	2,642	30,87	38,8	0,60	-0,29	-0,30
51	0,213	0,1577	0,522	30,22	25,2	0,14	-0,07	-0,09
52	0,174	0,1460	0,496	29,43	38,7	0,14	-0,08	-0,08
53	0,153	0,1610	0,505	31,91	48,3	0,19	-0,11	-0,10
54	0,154	0,1867	0,565	33,06	58,9	0,17	-0,09	-0,09
55	0,630	0,4470	1,465	30,50	24,9	0,45	-1,25	-0,20
56	0,533	0,4460	1,472	30,31	37,0	0,45	-0,23	-0,22
57	0,380	0,4507	1,461	30,84	48,3	0,28	-0,14	-0,13
58	0,325	0,4447	1,462	30,42	58,1	0,47	-0,22	-0,25
59	1,020	0,7710	2,473	31,18	26,6	0,80	-0,36	-0,44

60	0,835	0,7543	2,439	30,93	38,8	0,79	-0,35	-0,41
61	0,582	0,7343	2,428	30,25	61,1	0,76	-0,39	-0,40
62	0,656	0,7767	2,476	31,36	49,8	0,81	-0,42	-0,40
63	1,322	1,1007	3,493	31,51	27,8	1,15	-0,55	-0,61
64	1,170	1,0740	3,358	31,98	38,4	1,10	-0,51	-0,60
65	0,817	1,0583	3,472	30,48	60,3	1,12	-0,59	-0,54
66	0,839	1,0523	3,499	30,07	49,5	1,11	-0,53	-0,61
67	0,261	0,1560	0,531	29,39	26,4	0,10	-0,05	-0,06
68	0,410	0,3027	1,032	29,33	38,6	0,20	-0,10	-0,09
69	0,464	0,4540	1,571	28,90	39,4	0,28	-0,15	-0,14
70	0,705	0,5990	2,057	29,12	49,2	0,37	-0,20	-0,19
71	0,755	0,5060	1,616	31,30	26,3	0,30	-0,15	-0,20
72	0,667	0,4923	1,572	31,33	38,5	0,29	-0,15	-0,15
73	0,549	0,4977	1,633	30,47	59,4	0,30	-0,16	-0,17
74	0,666	0,4957	1,594	31,09	49,3	0,30	-0,17	-0,15
75	1,172	0,7857	2,392	32,84	25,8	0,47	-0,24	-0,24
76	0,913	0,8010	2,623	30,53	38,5	0,48	-0,24	-0,25
77	0,740	0,7700	2,562	30,06	59,4	0,49	-0,24	-0,25
78	0,813	0,7980	2,673	29,86	49,3	0,49	-0,26	-0,23
79	1,494	1,1893	3,889	30,59	27,3	0,73	-0,42	-0,32
80	1,541	1,1859	4,007	29,60	38,6	0,72	-0,40	-0,34
81	1,065	1,1913	3,813	31,25	58,5	0,74	-0,33	-0,39
82	0,118	1,1155	3,544	31,47	33,4	0,71	-0,37	-0,36
83	1,259	1,0410	3,093	33,66	49,2	0,95	-0,46	-0,50
84	1,934	1,4883	4,703	31,65	29,6	0,92	-0,47	-0,45
85	1,637	1,4977	4,523	33,12	38,8	0,94	-0,45	-0,50
86	1,457	1,4833	4,459	33,26	58,5	0,90	-0,47	-0,49
87	0,174	0,1057	0,327	32,29	28,9	0,06	-0,03	-0,04
88	0,148	0,1083	0,334	32,41	38,3	0,06	-0,03	-0,04
89	0,125	0,1243	0,398	31,26	59,5	0,06	-0,03	-0,04
90	0,131	0,1087	0,346	31,39	48,9	0,07	-0,03	-0,03
91	0,365	0,2010	0,630	31,89	23,7	0,11	-0,07	-0,06
92	0,291	0,2100	0,690	30,44	38,6	0,13	-0,06	-0,06
93	0,240	0,2063	0,667	30,93	59,7	0,13	-0,08	-0,07

A. Measurands of galvanization Experiment

94	0,236	0,2043	0,676	30,22	50,0	0,11	-0,06	-0,06
95	1,048	0,7013	2,285	30,69	24,2	0,43	-0,23	-0,23
96	0,833	0,6973	2,321	30,05	38,5	0,42	-0,21	-0,22
97	0,710	0,7000	2,304	30,39	59,4	0,42	-0,20	-0,24
98	0,742	0,7047	2,303	30,60	49,4	0,42	-0,24	-0,22
99	1,165	0,8190	2,647	30,94	25,7	0,33	-0,16	-0,16
100	0,877	0,7910	2,549	31,03	38,5	0,32	-0,16	-0,17
101	0,713	0,7917	2,552	31,02	58,2	0,31	-0,16	-0,18
102	0,822	0,8160	2,552	31,97	50,1	0,33	-0,17	-0,17
103	0,632	0,2947	0,963	30,59	25,6	0,16	-0,09	-0,08
104	0,493	0,3987	1,306	30,51	37,4	0,17	-0,08	-0,09
105	0,360	0,4063	1,309	31,03	59,5	0,17	-0,08	-0,08
106	0,434	0,4040	1,368	29,53	50,0	0,17	-0,09	-0,09
107	0,436	0,2537	0,789	32,16	25,7	0,20	-0,11	-0,11
108	0,342	0,2517	0,804	31,32	37,8	0,20	-0,09	-0,11
109	0,235	0,2547	0,815	31,25	59,6	0,19	-0,12	-0,10
110	0,282	0,2510	0,802	31,28	49,9	0,20	-0,09	-0,09
111	0,903	0,5507	1,833	30,05	23,4	0,51	-0,24	-0,23
112	0,651	0,5473	1,694	32,31	38,0	0,50	-0,23	-0,25
113	0,477	0,5500	1,810	30,39	59,6	0,51	-0,27	-0,24
114	0,597	0,5543	1,704	32,52	49,9	0,53	-0,26	-0,26
115	1,437	0,9830	3,323	29,58	23,8	0,28	-0,15	-0,13
117	1,103	0,9915	3,372	29,40	60,4	0,29	-0,17	-0,14
116	0,897	0,9725	2,978	32,66	38,0	0,30	-0,15	-0,15
118	0,940	0,9955	3,355	29,67	47,8	0,31	-0,17	-0,15
119	0,555	0,3520	1,045	33,67	24,6	0,41	-0,20	-0,22
120	0,472	0,3493	1,113	31,39	39,1	0,41	-0,21	-0,23
121	0,337	0,3473	1,083	32,09	59,1	0,40	-0,20	-0,21
122	0,379	0,3533	1,125	31,40	49,2	0,41	-0,20	-0,21
123	0,818	0,5557	1,607	34,58	24,7	0,28	-0,14	-0,12
124	0,635	0,5497	1,775	30,96	37,8	0,27	-0,16	-0,11
125	0,477	0,5510	1,699	32,43	58,5	0,28	-0,15	-0,15
126	0,573	0,5557	1,628	34,13	49,5	0,28	-0,15	-0,15
127	0,289	0,2063	0,694	29,75	37,7	0,08	-0,05	-0,05

128	0,355	0,2040	0,668	30,53	25,7	0,09	-0,04	-0,05
129	0,187	0,2060	0,684	30,10	64,9	0,07	-0,05	-0,04
130	0,250	0,2063	0,695	29,67	49,2	0,11	-0,07	-0,05
131	1,524	1,1530	3,492	33,02	26,5	0,61	-0,30	-0,31
132	1,375	1,1390	3,679	30,96	38,5	0,59	-0,29	-0,31
133	0,987	1,1563	3,788	30,53	58,0	0,60	-0,33	-0,29
134	1,165	1,1520	3,527	32,66	48,6	0,60	-0,28	-0,35
135	0,375	0,2433	0,795	30,61	26,5	0,40	-0,21	-0,17
136	0,368	0,2470	0,821	30,08	34,7	0,40	-0,20	-0,19
137	0,260	0,2553	0,930	27,44	53,6	0,41	-0,22	-0,21
138	0,294	0,3307	1,118	29,57	44,0	0,44	-0,24	-0,19
139	1,872	1,4290	4,816	29,67	27,7	0,58	-0,30	-0,28
140	1,844	1,5800	4,830	32,71	34,4	0,66	-0,34	-0,32
141	1,264	1,7603	5,799	30,36	54,4	0,79	-0,37	-0,43
142	1,315	1,3694	4,180	32,76	44,6	0,60	-0,36	-0,28
143	0,904	0,6843	2,250	30,41	27,5	0,82	-0,40	-0,41
144	0,890	0,6897	2,128	32,41	34,0	0,83	-0,42	-0,42
145	0,595	0,6957	2,311	30,10	55,2	0,86	-0,42	-0,46
146	0,655	0,6923	2,170	31,90	45,1	0,85	-0,39	-0,45
147	0,204	0,1053	0,348	30,31	25,0	0,20	-0,10	-0,09
148	0,169	0,1040	0,344	30,20	24,1	0,19	-0,10	-0,09
150	0,154	0,1043	0,347	30,10	46,0	0,18	-0,10	-0,11
151	1,560	1,1950	3,934	30,38	27,2	0,36	-0,19	-0,17
152	1,548	1,1817	3,817	30,96	31,9	0,36	-0,17	-0,19
153	0,953	1,1867	4,311	27,52	55,5	0,37	-0,18	-0,20
154	1,073	1,1827	3,944	29,99	46,2	0,36	-0,20	-0,18
155	0,951	0,6950	2,282	30,46	27,2	1,12	-0,56	-0,56
156	0,801	0,6880	2,293	30,01	34,0	1,10	-0,62	-0,49
157	0,601	0,6897	2,315	29,79	54,7	1,14	-0,62	-0,52
158	0,595	0,6977	2,111	33,05	43,2	1,15	-0,64	-0,52
159	1,965	1,5860	5,209	30,45	27,7	0,49	-0,27	-0,25
160	1,737	1,5687	4,993	31,42	35,2	0,48	-0,25	-0,25
161	1,216	1,5870	5,231	30,34	54,8	0,51	-0,29	-0,24
162	1,317	1,5870	4,729	33,56	44,6	0,49	-0,26	-0,26

A. Measurands of galvanization Experiment

163	1,200	0,9835	3,282	29,97	27,3	0,21	-0,09	-0,10
164	1,240	0,9875	3,182	31,03	34,3	0,19	-0,10	-0,12
165	0,820	0,9855	3,347	29,45	54,8	0,21	-0,11	-0,10
166	0,900	0,9920	3,151	31,49	45,1	0,21	-0,11	-0,10
167	1,300	0,9880	3,224	30,64	27,1	1,59	-0,73	-0,88
168	1,100	0,9823	3,238	30,34	33,1	1,57	-0,79	-0,78
169	0,791	0,9900	3,588	27,59	54,7	1,67	-0,81	-0,94
170	0,867	0,9927	3,049	32,56	43,2	1,64	-0,82	-0,83
171	0,320	0,2020	0,667	30,28	26,8	0,28	-0,14	-0,14
172	0,828	0,7273	2,394	30,39	33,9	1,04	-0,49	-0,54
173	0,195	0,2037	0,670	30,40	55,0	0,27	-0,10	-0,14
174	0,232	0,2043	0,680	30,05	44,2	0,28	-0,15	-0,14
175	1,090	0,8140	2,649	30,73	25,8	1,07	-0,55	-0,52
176	0,890	0,8693	2,842	30,59	34,6	1,17	-0,58	-0,61
177	0,628	0,8450	2,790	30,29	53,4	1,17	-0,56	-0,62
178	0,771	0,8230	2,686	30,64	44,6	1,09	-0,48	-0,62
179	0,750	0,5260	1,709	30,78	27,0	0,47	-0,25	-0,23
180	0,622	0,5193	1,695	30,63	34,0	0,46	-0,25	-0,23
181	0,396	0,5157	1,721	29,96	55,3	0,48	-0,24	-0,27
182	0,560	0,5310	1,791	29,64	43,7	0,49	-0,25	-0,26
183	2,013	1,4600	4,820	30,29	28,6	1,32	-0,70	-0,65
184	1,421	1,3730	4,444	30,89	34,5	1,25	-0,58	-0,74
185	1,051	1,5065	5,040	29,89	54,9	1,33	-0,62	-0,70
186	1,260	1,3460	4,465	30,15	44,5	1,37	-0,63	-0,75
187	1,590	1,2690	4,226	30,03	30,5	0,39	-0,16	-0,22
188	1,581	1,2775	4,186	30,52	34,8	0,38	-0,19	-0,21
189	0,960	1,2625	4,066	31,05	55,0	0,40	-2,20	-0,20
190	1,080	1,2630	4,135	30,54	42,5	0,40	-0,19	-0,20
191	0,380	0,2257	0,759	29,71	25,9	0,37	-0,17	-0,19
192	0,356	0,2513	0,829	30,32	33,2	0,36	-0,19	-0,18
193	0,200	0,2237	0,722	30,99	54,4	0,37	-0,19	-0,18
194	0,244	0,2283	0,762	29,98	44,8	0,37	-0,18	-0,20
195	0,840	0,5775	1,911	30,22	27,9	0,64	-0,34	-0,30
196	0,694	0,5615	1,901	29,53	34,0	0,64	-0,32	-0,34

197	0,464	0,5695	1,916	29,72	55,0	0,66	-0,35	-0,33
198	0,537	0,5805	1,751	33,15	44,5	0,66	-0,34	-0,31
199	1,780	1,4375	4,728	30,40	28,9	0,44	-0,17	-0,23
200	1,657	1,3765	4,605	29,89	24,8	0,42	-0,18	-0,32
201	1,105	1,3825	4,637	29,81	54,9	0,43	-0,19	-0,23
202	1,200	1,4170	4,360	32,50	43,9	0,47	-0,25	-0,22

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