MASTER THESIS

Device optimization using machine learning with hybrid heat pumps

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ABSTRACT

With the switch to electric energy from renewable sources and the desire to stop using natural gas for heating the electricity gets loaded more. This can lead to congestion and overloading of the grid. Methods currently already exist to prevent overloading of the grid by changing the power consumption of appliances in the household. To optimally plan the energy usage of the heating system models are needed for the specific heating system. In this work a literature survey is done on existing models and machine learning techniques to improve the models. Simulations are performed to determine what model benefits most of improvement and what data need to be collected during the experiments. Experiments are performed with a heat pump to make models under ideal and non-ideal conditions. The model created in non-ideal conditions deviates up to a maximum 0f 1.6% during the steady state operation compared to the model created in ideal conditions.

Contents

1 INTRODUCTION

To reduce greenhouse emissions the use of renewable energy sources is more and more favoured over the use of fossil fuels. This renewable energy is often supplied in the form of electricity generated by, for instance, solar panels and wind turbines. The production of this energy comes without emissions of greenhouse gases [23], but, since it relies on weather conditions, it is difficult to predict the output and the output cannot be controlled. This makes matching supply and demand and therefore optimal use of this renewable energy difficult.

In the Netherlands most houses are heated using a natural gas boiler [1]. In recent years a shift is seen to the use of heat pumps, this shift is caused by the desire to no longer use natural gas for heating [21]. These heat pumps transfer heat energy from outside to inside with a pump using electricity. This means that energy from renewable sources can be used to heat houses. The downside of this is that heat pumps consume significant amounts of electrical energy, which can lead to overload conditions, or congestion, in the electricity grid. This overloading of the grid is currently already a problem [2]. In order to prevent overloading of the electrical grid a solution is needed while still maintaining comfortable temperatures in the buildings.

A possible solution is the use of a hybrid heat pump setup. This setup uses both a heat pump and a natural gas boiler to heat the residential building. The benefit of this hybrid setup is that the comfort levels in the residential building can still be guaranteed by using gas even if the load on the electrical grid is high or becomes high. Another benefit is that it can also heat houses that cannot be sufficiently retrofitted with adequate insulation to be solely heated by a heat pump. In such a case the natural gas boiler can be used to supply the heat, especially during cold periods, for the building as it has a higher thermal output power than most heat pumps.

The generation capacity of renewable energy is uncontrollable, but its output can be predicted. Since heat pumps consume a lot of energy the energy generation of the renewable sources and the energy consumption need to be balanced. With the smart grid applications can be made to balance the energy supply and demand [11]. The smart grid can give consumers incentives to change their behaviour and use this to balance supply and demand in the grid, in contrast to the classical electrical grid where the consumer is just a passive user of the energy. One of the possible applications to implement an energy management system is dEF-PI (distributed Energy Flexibility Platform & Interface) [26]. It uses a standardized interface, the Energy Flexibility Interface (EFI) [30], to make creating energy management services that can control appliances easier. In order to allow useful control of the hybrid heating system models are needed that predict its behaviour. Models are needed for control algorithms to avoid grid overload and optimize renewable energy source usage while maintaining comfortable temperature levels in the buildings. Since every heating system is unique, for instance each heat pump has different characteristics and isolation varies from building to building, a unique model is needed for every heating system. Manually making a model for every situation is infeasible, therefore a solution that adapts itself to the unique properties of a system is required. These models can be created using machine learning or by automatically fitting parameters to existing models of such systems. The challenge with self learning system is determining what data and how much data is needed to create a model of the system with sufficient accuracy.

1.1 Research questions

The challenges of making unique models for individual systems lead to the following research question:
How can a model of the behaviour of hybrid heating systems in residential building be made more accurate using machine learning?
To answer the main research question the following sub-questions will have to be answered:

- What models exist for the components of the hybrid heating system?
- What machine learning techniques exist to improve the accuracy of such a model?
- What are the data requirements to sufficiently learn such a model using machine learning techniques?
- How can such an enhanced model be used in the energy usage planning or for controlling the hybrid heating system?

1.2 Outline

In Chapter 2 a literature study on existing models, machine learning techniques and the concept of smart grid is presented. Using the models found in Chapter 2 a model is made of the hybrid heating system in Chapter 3. This model is used to identify parts of the system model that can be improved using machine learning. With the identified parts of the model a simulation study is performed in Chapter 4. In this simulation study it is determined what data needs to be gathered during lab experiments. Based on the requirements of Chapter 4 the experimental setup and execution tools are described in Chapter 5. This chapter also discusses the execution of the experiments performed with the heat pump. The results from the experiments are presented and discussed in Chapter 6. Finally in Chapter 7 the research questions will be answered and identified future work will be discussed.

2 LITERATURE REVIEW

In this chapter existing literature will be discussed. Models for the different parts of the hybrid heating system will be discussed as well as the smart grid and machine learning techniques that can potentially improve the models of the hybrid heating system.

2.1 Hybrid heat pump system

A hybrid heating system is a system that combines multiple heat sources for space heating. In this work a hybrid heating system for residential buildings is considered. This type of system uses a heat pump and natural gas boiler to provide heat by using electricity or natural gas respectively.
The benefit of a hybrid heating system is that it can use both electricity and natural gas for heating. For instance it can use electricity when the price is low and the electricity grid has sufficient capacity. The natural gas boiler can be used to supplement the heat pump when the heat demand exceeds the capabilities of the heat pump or to reduce the electricity consumption of the consumer during periods of congestion in the electrical grid.

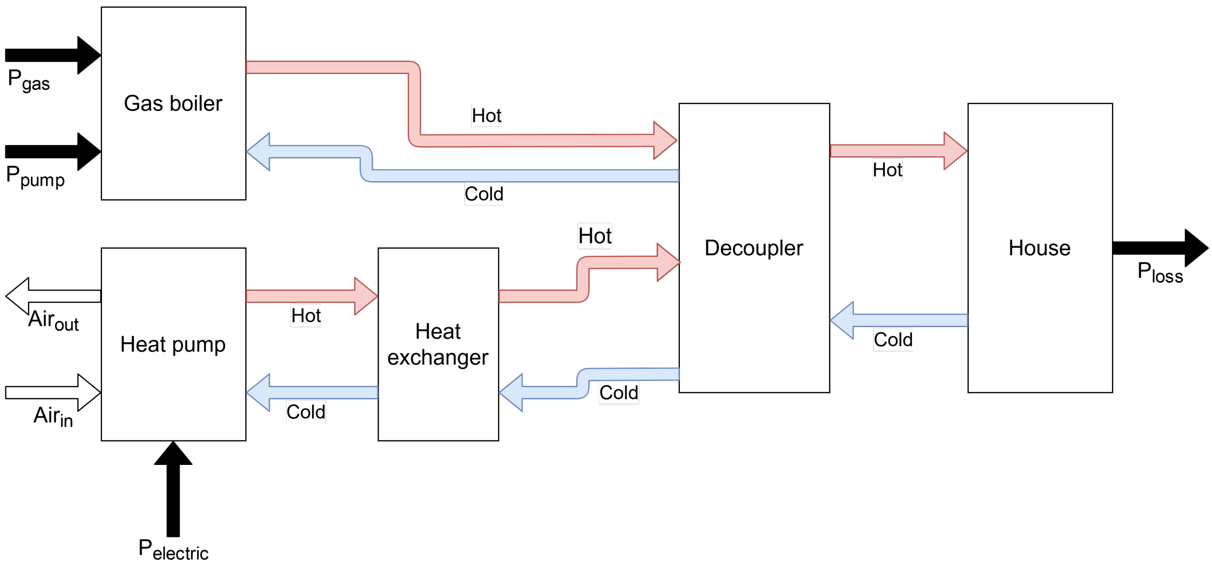

Figure 2.1: Overview of possible hybrid heating system setup

In figure 2.1 an overview of a typical hybrid heating system is shown. The figure shows how heat is exchanged between the different components in the system and where energy is added to and lost from the system. A literature survey is presented in the following subsections to describe existing models for the different parts of the hybrid heating system.

2.1.1 Heat pump

A heat pump is a device that uses mechanical work to move heat energy from a cold location to a warmer one [24]. In most cases this work is done by an electric pump. Since the process moves heat from a cold location to a hotter one, it is able to transfer more heat energy than the energy used for the work that is performed. The ratio of performed work and gained heat energy is called Coefficient of Performance (COP).
For the modelling of the heat pump the achieved COP is of interest, since this factor determines how much electrical energy is needed to supply a certain amount of heat energy. In [3] an overview is presented of different ways to model the performance of heat pumps. It identifies the following three different classes of models:

1. Calculation methods, these methods consider the Seasonal Coefficient Of Performance or the building specific seasonal performance factor. These models are based on a fixed COP for a given season.

2. Dynamic system simulation, these methods can calculate the COP based on current conditions like the temperature of the outside air.

3. Heat pump design models. These model the refrigerant cycle of the heat pump, they are the most accurate but need specialized knowledge about the physical process in the heat pump.

One type of a dynamic model is the performance map, these map the COP of the heat pump to the boundary conditions. Usually the outside temperature and the return temperature of the heating system are considered for this. In [18] a performance map is created by fitting data from heat pump to a model using linear regression.
The calculation methods achieve a maximum deviation of 4.7% on the seasonal performance factor over a season [3]. The heat pump design model is able to achieve inaccuracies smaller than 5% for the heat capacity and power consumption. The performance maps from [18] have a maximum error of 10.7% for the heating capacity and 10% for the power consumption. If the model is fitted for an individual heat pump the maximum error for the heat capacity can be reduced to 1.6% and the maximum error for the power consumption to 5.9%. The performance maps from [18] are deemed the best option to model the heat pump. This generalized model does have a higher error than the heat pump design models, but it can potentially be fitted to the individual heat pump and is able to achieve similar errors in that case at a reduced complexity.

2.1.2 Heat exchanger

A heat exchanger separates two parts of the heating system. This is done to reduce the amount of glycol needed, since now only the outdoor part of the circuit needs to use glycol to prevent freezing, while the indoor part of the heating circuit can use regular water.

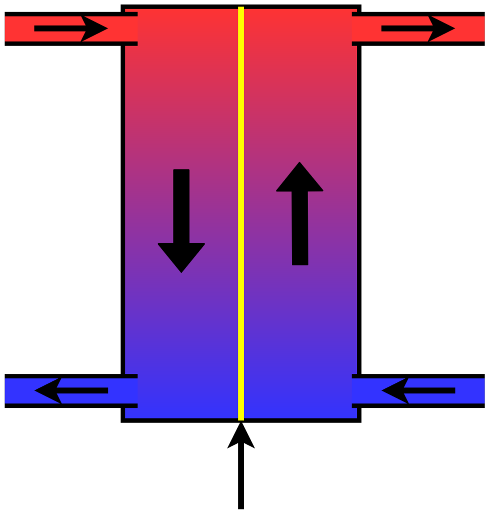

Figure 2.2: Counter flow heat exchanger of recuperator type.

The heat exchanger in the hybrid heating system is assumed to be a recuperator using counter flow of the fluid. In a recuperator the heat exchange is done directly between the fluids with a physical barrier between the fluids [8]. A schematical overview of a counter flow heat exchanger of the recuperator type is shown in figure 2.2.
In [8] multiple methods for sizing and performance analysis of heat exchangers are discussed. The log-mean temperature difference (LMTD) method uses the log-mean temperature difference together with properties like area and the overall heat transfer coefficient of the heat exchanger to calculate the energy transfer. Since the temperature difference is calculated, the input and output temperatures need to be known, therefore making it suitable for calculating the size of the heat exchanger. However, this method is not suitable to calculate the output temperatures of the heat exchanger when these parameters are already known.
The effectiveness-number of transfer units (ϵ-NTU) method, also described in [8], assumes that the size and the overall heat transfer coefficient of the heat exchanger are known, as well as the flow rate and inlet temperatures of both sides. Using these values the heat exchanger effectiveness is calculated which can be used to calculate the total heat transfer rate which can than be used to calculate the outlet temperatures of the heat exchanger.
In [9] the counter-flow plate heat exchanger is modelled using an idealized double pipe heat exchanger, this was done since modelling all the internals of the plate heat exchanger is hard to perform, especially since obtaining details of the exact internal construction is difficult. This method lumps the construction parameters of the heat exchanger in four parameters. Two parameters lump the length and cross section of the substitute pipe heat exchanger, while the other two parameters describe the heat transfer capabilities. These parameters are determined by performing tuning on measurement data from the heat exchanger to be modelled.
For modelling the hybrid heating system the ϵ-NTU method is the best choice. The LMTD method is not suited since it is not able to calculate the output temperatures. The method from [9] show to have a good accuracy with a maximum deviation of 0.3°C of the output temperature in performed test presented in [9]. The downside is that the parameters need to be determined using a fit on measurement data. However, such a fit could work well within the context of a self-learning system.

2.1.3 Gas boiler

The gas boiler uses natural gas to output heat. The heat from the gas boiler is used for both the heating of the building and for the domestic hot water supply.

For modelling the gas boiler the efficiency is interesting in order to keep track of the total energy consumption of the hybrid heating system. The gas boiler is assumed to be of the condensing type. It condenses flue gases, which are the combustion products, which increases the efficiency [22].
Commonly available natural gas boiler have a maximum thermal output power in the range of 20 to 35 kW. These boilers can also run at a output lower than their rated maximum capacity. This is to prevent continuous on/off switching of the natural gas boiler. When not running at full power they can output about 30% of the rated maximum power at a minimum.

2.1.4 Decoupler

The decoupler in the system is used to combine the heat outputs from both the heat pump and the gas boiler and use it for heating the building. It can either be a manifold connecting the heating circuits of the heat pump and the gas boiler together, or it can be a thermal storage buffer that is heated by both the heat pump and gas boiler. The thermal storage can be used to generate and store heat energy for later use, it can for instance be beneficial to store heat at a time when the generation of heat is cheap, for example with a surplus of PV generation.
The thermal storage can be modelled by modelling different levels in the thermal storage [19]. Each level has its own temperature and it is assumed that the flow of water in the tank does not mix the water in the different levels. In theory this means that 100% of the available capacity of the thermal storage can be used.
The thermal storage can also be modelled with only two layers and a charging coil as shown in [29]. Here the thermal storage is divided in the hot layer and the mixed layer which consists of the return supply of water with a lower temperature. This model can predict the total energy consumption of charging the heat buffer with an error smaller than 1%.

2.1.5 House

The heating system is used to heat or keep the temperature within the house at a comfortable level. The demanded heat output for heating the building is determined by characteristics of the building together with the indoor temperature and outdoor conditions.
In [29] a model for a single zone building is presented. It models the floor and the indoor zone of the house using resistances and capacitances. Hereby it takes several parameters of the house together and is therefore a lumped parameter model. This way the heat transfer from the heating system to the floor, from the floor to the internal zone and from the internal zone to outside is modelled. It also includes the heat energy from solar irradiation and occupants in the form of gain in the thermal zone. In figure 2.3 the electric equivalent of the single zone building model is shown.

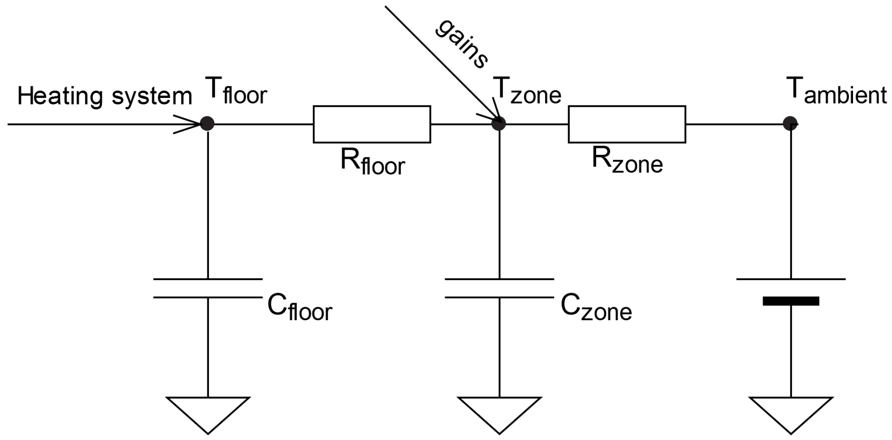

Figure 2.3: Model of single zone house with 2 resistances and 2 capacitances.

In [12] a more elaborate model with lumped parameters is constructed. It for instance models the wall and windows separately. It also suggests a possible model with four zones which leads to a model that is also able to model the heat transfers between the different zones in the building in case the temperatures in these zones are not the same.
The main difference between the models is that the multi-zone model of [12] is able to calculate the heat transfer between different zones (usually rooms) in a building. This comes at increased computational complexity and more parameters need to be estimated. The single zone model from [29] is computationally less complex and only four parameters need to be estimated. It also provides values for typical building scenarios like a detached house.

2.2 Smart grid

2.2.1 Concept

The current electrical grid is built around the system where electricity is generated centrally. It is built to transport electricity from centralized generation locations to the consumer of the electricity [11]. The end user is a passive participant in the current grid, who has limited knowledge about its electricity use and does not change its behaviour based on the current load on the grid. In a smart grid information and communication technologies are used to achieve a safe, efficient and sustainable grid. Among other goals the goals of the smart grid are to allow the usage of sustainable energy sources and optimizing the energy flow in the system to reduce losses. One of the ways to achieve this goal is by having active participation of the customer on the grid. This is useful since the consumer is not longer only a consumer of energy, but can also be a producer of electrical energy.
With the consumer no longer being a passive user of the energy possibilities arise to make better use of the available energy. In the context of the hybrid heating system this can be done by controlling the energy usage of heat pumps. The heat pump uses a lot of power (in the order of 2-4kW) and therefore has a large impact on the energy usage. By optimizing the control of the heat pumps the usage of energy can be made more efficient and overloading of the grid can be prevented.
A technique for controlling appliances on the smart grid is demand response [6]. With demand response the goal is to change the electric usage of the consumer using changes in prices or other incentives. By changing the electrical energy usage of the consumer unwanted situations, for example overloading of the grid, can be prevented. This can for instance be done by increasing the price during high load on the grid to lower demand. By changing the price of energy a

new equilibrium in supply and demand will be created. An example of an implementation of a demand response technology is PowerMatcher [17]. Each device does a bid for its willingness to consume or produce energy. This bid describes its entire supply/demand relationship. With this the auction agent can determine the market equilibrium for every bidding round without iterations. This equilibrium sets the price and generation/consumption at a point in time.
The energy consumption of the consumer can also be controlled with profile steering. With profile steering the production or consumption of the consumer or group of consumers is shaped in some way, for instance a flat profile [10]. This shaping is achieved by scheduling controllable appliances. The consumption of some appliances can only be shifted in time, its program will start at a certain time and will then be fixed, while other appliances can change their output and their power consumption. This flexibility of changing the shape of the power consumption has its limits, the flexibility constraints. These constraints can for instance be an appliance that needs to finish a task at a certain time or ensuring that the temperature in a building is always comfortable. To obtain the profile of the consumer the profiles of the different appliances within the house need to be summed together. This profile is compared to the desired profile and the deviation is calculated. For each appliance a candidate planning is evaluated to reduce its distance from the desired profile. The schedule of the appliance with the biggest improvement is selected. This process is repeated iteratively and is stopped when the progress is no longer sufficient. This method of scheduling can be done all level from the grid hierarchy.

2.2.2 DEMKit

Decentralized Energy Management Toolkit (DEMKit) is a simulation and demonstration framework for future multi-energy control systems [13]. It provides tools to analyze optimization algorithms in discrete time simulations. For the simulations it uses device components, grid components and optimization components, this way it offers flexibility to test different optimization strategies or perform hardware-in-the-loop simulations where a device component is substituted for a connection to a real device. In DEMKit a simulation with profile steering can be done, it uses its available models together with load profiles e.g. from the Artificial Load Profile generator (ALPG) [14].

2.2.3 dEF-PI

The distributed Energy Flexibility Platform & Interface (dEF-PI) is developed by Flexiblepower Alliance Network (FAN) with the goal to create an interoperable platform that can connect to a variety of applications and support multiple demand side management approaches [26]. It provides a runtime environment to quickly design and implement services dealing with energy management. Build tools are available to generate the skeleton of the application by providing a description of the interfaces. This way only the logical part of the energy management service needs to be implemented. The aim with the interoperable platform is to make switching between different services for energy management easier since the platform makes sure no switch of hardware is needed.
An important part of dEF-PI is the Energy Flexibility Interface (EFI) developed by TNO [30]. The EFI is a generic interface that can be used by device manufacturers to describe the flexibility of a smart device and which can be used by developers to describe how to use the flexibility offered by the smart device. The purpose of the generic interface created with EFI is to solve the interoperability problem between the many different smart devices. Many devices implement their own API and algorithms for energy flexibility, EFI aims to solve this problem by providing a standardized interface to describe energy flexibility using abstraction. This way the flexibility of the devices can be described in its essential form without device specific complexity. For describing the devices there are four different categories in EFI, these categories can be found in table 2.1

Flexibility category	Description	Examples
Inflexible	Devices that cannot be controlled. In some cases, like renewable energy, output can be predicted. In some cases control in the form of curtailment	PV generation, wind energy, domestic loads(e.g. TV)
Shiftable	Devices that can be controlled by shifting the operation in time. The profile of the energy usage cannot be changed. Shifting in time maybe limited to deadlines.	Smart washing machine, smart dishwasher
Storage	Devices that provide flexibility by storing energy. Energy can be stored to be used at a later time. Storing and releasing the energy can be constrained by load and minimum and maximum fill levels.	Battery, heat buffer
Adjustable	Devices where the output or energy consumption can be changed at will.	Gas boiler, heat pump, dimmable lighting

Table 2.1: Energy flexibility categories in EFI

These categories are used to describe different devices. The inflexible category can for instance be used to describe PV panels, the output of these panels cannot be controlled, but a prediction can be made of the generation and curtailment can be done if necessary. With the adjustable class a heat pump for example can be described. In this description transition times between on and off, and between starts can be described as well as the relation between energy and heat consumption.

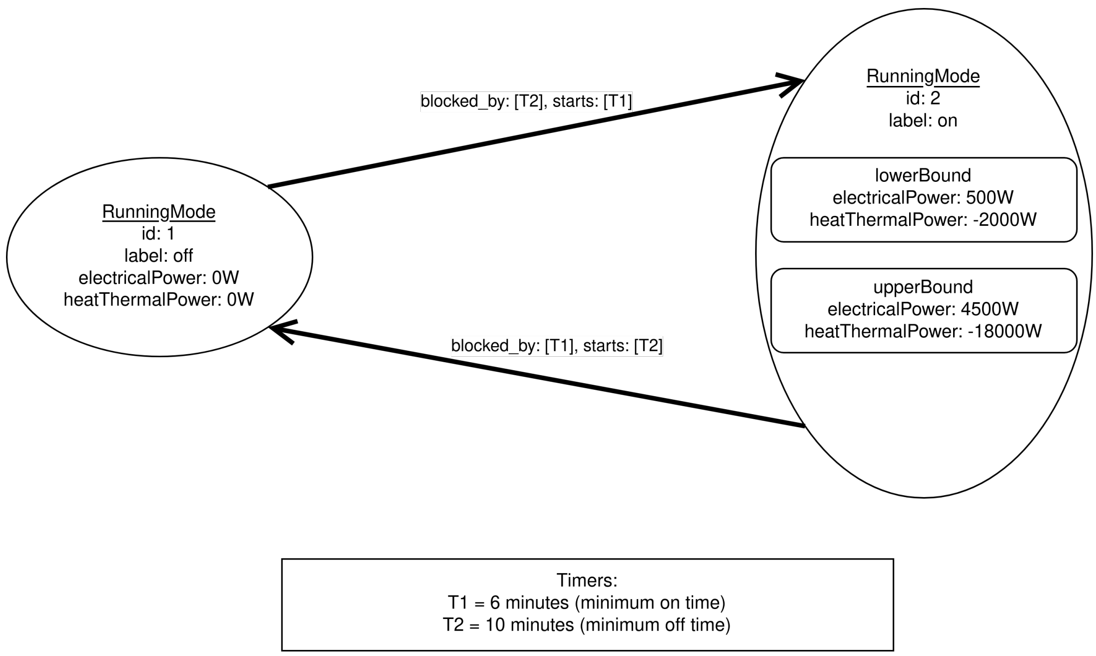

Figure 2.4: Example diagram of EFI description

In Figure 2.4 a diagram of an example EFI description in shown. It shows two different running modes, on and off, and the possible transitions between the running modes. The transitions between the running modes are guarded by requirements that need to be met, in this case for instance that the device has be turned off at least 10 minutes before it can be turned on again. In the "on" running mode a lower bound and upper bound is given, these set the operational range of the device. This range describes in this case the amount of electric energy consumed and the amount of heat energy generated.

2.3 Machine Learning

The models discussed in Section 2.1 are white box and grey box models. In a white box model all low level behaviour is simulated. This leads to realistic behaviour at the cost of complex and computationally expensive models and the need of many parameters that need to be found for the specific system. However, most of the models in the previous section are grey box models, they still use available knowledge of the physical processes but use simplifications and are only valid in certain regions of operation. For example the single zone building model in Section 3.6 assumes that the temperature is the same within a zone and lumps all the thermal storages of the zone in a single parameter.
Another approach to modelling is the black box approach. This approach does not break down the system into its underlying mechanisms and uses a description that is not based on the physics of the system. An often used method for black box modelling is machine learning.
Machine learning creates a model based on the relations of the input and output variables without knowledge of the system at hand. This means that the behaviour of a system can be modelled without understanding its physics, the downside is that for this a lot of data is needed to achieve accurate results [5]. Machine learning algorithms can be categorised in multiple classes [4]:

1. Supervised learning. These algorithms use input vectors together with their corresponding output vectors for learning the behaviour. It can learn to output discrete categories which is called classification, or it can output continuous variables in which case it is called regression

2. Unsupervised learning uses training data that does not have the corresponding outputs vectors. It is used to discovers clusters in data.

3. Reinforcement learning tries to find the correct actions to take. It is not presented with the desired action but rather uses a reward to find suitable actions using trial and error.

For modelling parts of the hybrid heating system the supervised learning category seems suitable. It could for instance in theory learn to model the COP of the heat pump based on the outdoor temperature and water output temperature.

2.3.1 Hybrid modelling

As discussed in the previous section one of the downsides of machine learning is that it needs a lot of data to achieve accurate results. Another problem is that machine learning is only accurate when it is interpolating [5], this means that the dataset for training must span all possible operation states.
When not enough real world measurement data is available bootstrapping can be used to pre train the model as described in [5]. With bootstrapping the machine learning model is first trained with synthetic data. This data comes from a synthetic model. This way a lot of data can be generated to initially train the model and it can be made sure that the generated dataset has data points for all possible inputs, such that this initial model can already be used from the start. During operation the original dataset can be updated with actual measurement data from the system. This data can either be added to the dataset or can be used to replace the synthetically generated data points in the dataset. With the new data in the dataset the machine learning model can be trained again which will improve the accuracy of the predictions.

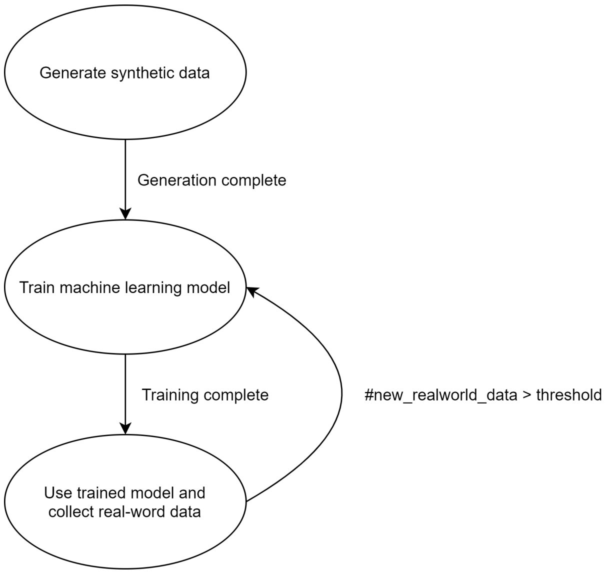

Figure 2.5: Operation flow of bootstrapping method

The flow of generating a synthetic dataset, training the machine learning model and updating the dataset over time to retrain the machine learning model is shown in Figure 2.5.
A method to increase the accuracy with respect to a grey-box model is a hybrid model where both a grey-box model and a machine learning model are combined [16]. The machine learning part of this model is trained using the inputs used for the grey-box model and the error created by to the grey box model to the actual value of the system. This training can be performed when more data is collected and can therefore increase the accuracy of the hybrid model over time.

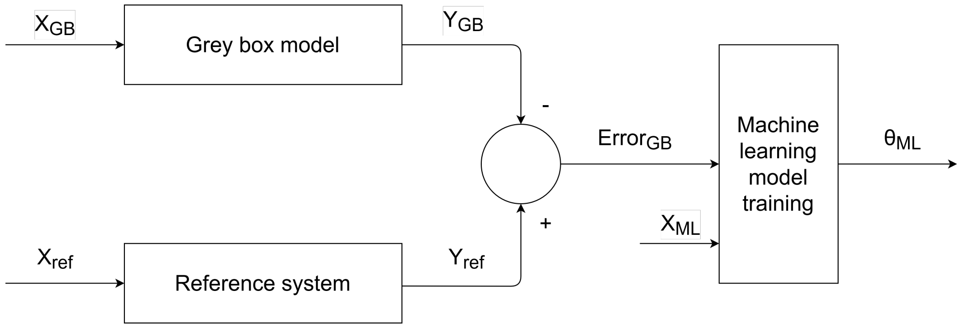

Figure 2.6: Training of the hybrid model

In Figure 2.6 the training procedure of the hybrid model is shown. X_{GB}, X_{ref} and X_{ML} are the inputs for the grey box model, reference model and machine learning model respectively. Y_{GB} and Y_{ref} are the outputs of the grey box model and the reference system. The reference system is the system to be modelled. The difference between the the output of the grey box model and reference system is calculated and used as an input for the machine learning training. Hence, the machine learning model is trained to predict the error of the grey box model. The result are the parameters θ_{ML} for the machine learning model.

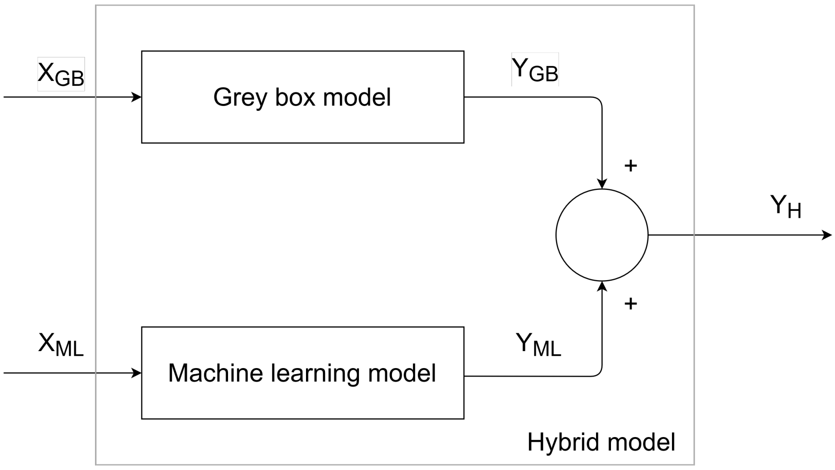

Figure 2.7: Operation of the hybrid model

Figure 2.7 shows the hybrid model in operation. As the machine learning model is trained to predict the error of the grey box model adding the outputs of the grey box model and machine learning model results in a system where this error is compensated for.
In [16] the hybrid modelling approach is tested with a building model. It is shown that the relative root mean square error (RMSE) for the day-ahead temperature prediction is reduced by 20% to 40% compared to the grey box model depending on the training period length. The RMSE reduces when a longer training period is used. The hybrid model outperformed the pure machine learning model in all cases. For the day-ahead energy prediction the average error is between 3% and 7% for the hybrid method where the pure machine learning approach achieves an error of 10% and 33%, here the results are again better with more training data. The grey box model has a stable prediction error of 8%. This shows that combining machine learning and grey box modelling can achieve better results than these methods can separately.

2.4 Conclusion

Models for the different components of the hybrid heating system are found. These models can be used to simulate and predict the behaviour of the different parts in the heating system. The models found in literature use white box and grey box modelling approaches. White box models model all the underlying behaviour, while grey box models use simplifications to make modelling and computation easier. Methods to combine and improve these models with machine learning are discussed. Existing models can be used to bootstrap a machine learning model by providing initial, synthetic training data. Another method is to use machine learning to correct the error of a grey box model. Combining existing model with machine learning has the potential to improve the final resulting model.

3 MODEL

In this chapter a model of the hybrid heating system is discussed. This model uses the models found in the literature study in Chapter 2. This model is used to identify the part of the system that benefits most from improvement with machine learning.

3.1 System

A model is created to simulate the behaviour of the hybrid heating system. This model is used to study the interaction between the different components and to see what influence changing conditions like different outdoor temperatures have on the total system. This way, the model can also be used to research the requirements of the self-learning system.
The model of the system is set up in a modular way, which allows for swapping the different parts of the model with different implementations. For the energy transfer the temperature and the flow rate of the water between the components is used. This choice was mostly made since the performance of the heat exchanger depends partly on the flow rates of the hot and cold sides.

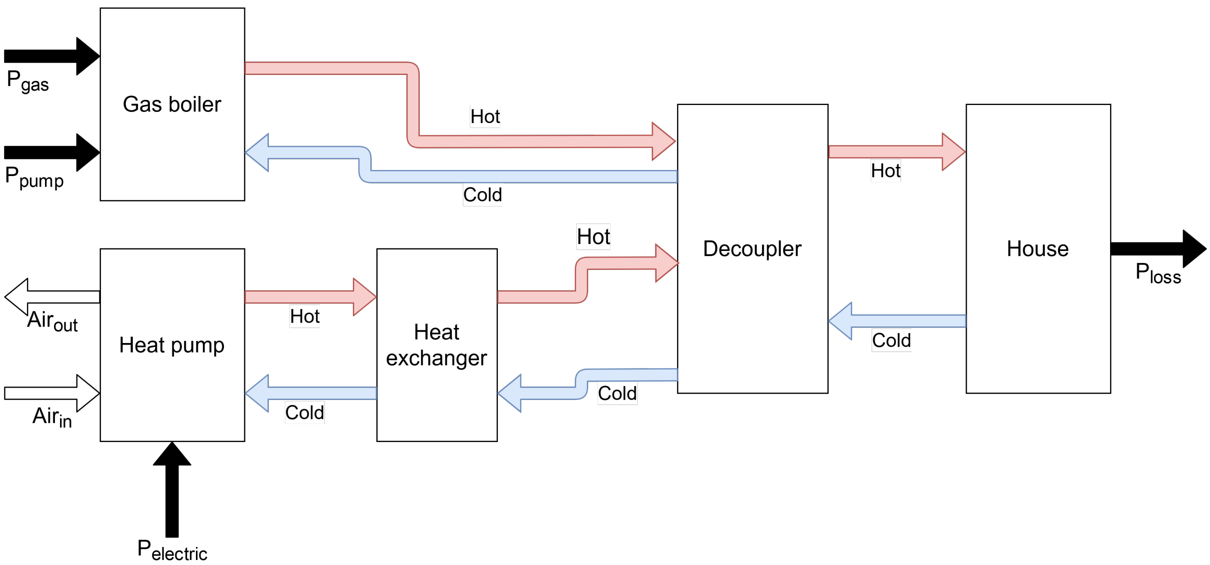

Figure 3.1: Overview of modelled hybrid heating system

The different modules of the model are based on the overview in figure 3.1, in this figure the interaction of the components in the models is the flow of water.
The symbols used in the equations for the model are listed in Table 3.1.

Symbol	Description	Unit
$\dot{m}$	mass flow rate	kg/s
A	Area	m^2
C	Heat capacity rate	J/K/s
$C*$	Heat capacity ratio	dimensionless
C_p	Specific heat capacity	J/K/kg
COP	Coefficient of performance	dimensionless
P	Power	W
$\dot{Q}$	Heat transfer	W
U	Heat transfer coefficient	W/(m^2 K)

Table 3.1: Symbols used in the model

3.2 Heat pump

The implemented model of the heat pump is based on [18]. The performance map is chosen since it is a sensible method to model the COP based on the current outdoor conditions without modelling the complete refrigerant cycle of the heat pump. The heat pump takes the outlet of the hot side of the heat exchanger. It uses the temperature of this water together with the temperature of the outside air and the outlet temperature of the hot side of the heat exchanger at the previous time step to calculate the COP using Equation 3.1. The COP is used to calculate the heat output power. The output power can be controlled, provided that the maximum heat output of the heat pump is able to deliver the required heat energy.

$$COP = COP_{rat} * f_{cop,t}(T_{in,wb}, T_{out}) * f_{cap,m}(\dot{m}/\dot{m_{rat}}) \tag{3.1}$$

$$f_{cop,t}(T_{in,wb}, T_{out}) = a + b * T_{out} + c * {T_{out}}^2 + d * T_{in,wb} + e * {T_{in,wb}}^2 * f * T_{in,wb} * T_{out} \tag{3.2}$$

$$f_{cap,m}(\dot{m}/\dot{m_{rat}}) = X + Y * (\dot{m}/\dot{m_{rat}}) \tag{3.3}$$

$$\dot{Q} = COP * P_{electric} \tag{3.4}$$

$$T_{outlet} = T_{inlet} + \frac{\dot{Q}}{\dot{m} * C_p} \tag{3.5}$$

$\dot{m}/\dot{m_{rat}}$ is the mass flow ratio, COP_{rat} is the rated COP of the heat pump and a-f, X and Y are fitted parameters. $f_{cap,m}$ is assumed to be 1 when $\dot{m} = \dot{m_{rat}}$.
The heat pump is only connected to the heat exchanger, T_{in} comes from the heat exchanger and the output T_{outlet} is also connected to the heat exchanger. T_{out} is the temperature of the outdoor air.

3.3 Heat exchanger

The ϵ-NTU method from [8] is used to model the heat exchanger. This method is chosen since it can be used to calculate the energy transfer in the heat exchanger and use this heat transfer to calculate the output temperatures. It also has the benefit that the required parameters U and A, the overall heat transfer coefficient and area of the heat exchanger respectively, can be estimated from the physical properties of the heat exchanger.
The following steps are performed to calculate the output temperatures of the heat exchanger:

1. Calculate the capacity rate ratio (Equation 3.6)
2. Calculate the number of transfer units (NTU) (Equation 3.9)
3. Determine the effectiveness (Equation 3.10)
4. Calculate the total heat transfer rate (Equation 3.11)
5. Calculate the outlet temperatures (Equation 3.12 and 3.13)

$$C^* = \frac{C_{min}}{C_{max}} \tag{3.6}$$

$$C_h = \dot{m}C_{ph} \tag{3.7}$$

$$C_c = \dot{m}C_{pc} \tag{3.8}$$

Where C_{max} and C_{min} are respectively the larger and smaller value of C_h and C_c which are the heat capacity rates of the warm and cold fluids.

$$NTU = \frac{UA}{C_{min}} \tag{3.9}$$

$$\epsilon = \frac{1 - exp[-NTU(1 - C^*)]}{1 - C^* exp[-NTU(1 - C^*)]} \tag{3.10}$$

The equation for effectiveness ϵ is taken from [15].

$$\dot{Q} = \epsilon * C_{min} * (T_{hot,in} - T_{cold,in}) \tag{3.11}$$

$$T_{cold,out} = T_{cold,in} + \frac{\dot{Q}}{\dot{m}_c * C_{pc}} \tag{3.12}$$

$$T_{hot,out} = T_{hot,in} - \frac{\dot{Q}}{\dot{m}_h * C_{ph}} \tag{3.13}$$

$T_{hot,in}$ is the water heated by the heat pump and $T_{hot,out}$ is the return water to the heat pump. $T_{cold,in}$ comes from the decoupler and $T_{cold,out}$ is the heated water going back to the decoupler.

3.4 Gas boiler

The fitted model from [7] resulted in an increasing efficiency with increasing inlet temperature, this is opposite from the expectation for efficiency of a condensing gas boiler and also does not match the by the authors presented efficiency plot. Since no suitable model was found the natural gas boiler was implemented as an adjustable source of heat energy. Heat energy can be requested from the natural gas boiler up to its upper limit. Since there is no underlying model with the efficiency of the gas burning no insight is created in the amount of natural gas used to supply the demanded heat.

$$T_{out} = T_{in} + \frac{\dot{Q}}{\dot{m} * c_p} \tag{3.14}$$

$\dot{Q}$ is the thermal energy added by the natural gas boiler. Both T_{in} and T_{out} are connected to decoupler. The implemented model does have a limit on the thermal output power and the outlet temperature. This limit is in place since real world natural gas boiler do not have unlimited thermal output power and do limit the output temperature.

3.5 Decoupler

The decoupler is modelled as a simple manifold. It takes the the outlet of both the heat pump and gas boiler and combines it by adding the flows and taking the weighted average temperature. Another implementation of the decoupler has been made based on the thermal storage model from [29]. The model takes the output of the heat pump and gas boiler as the source for the charging process of the heat buffer.
The two different models allow to study the behaviour when with and without the possibility to store the thermal energy.

3.6 House

The output of the hot water from the decoupler is used to heat the house. The model is based on the 2 resistances 2 capacitances model of [29], shown in Figure 2.3. The main difference is that the implemented model also allows for heat to be directly added to the zone by means of a radiator. The model calculates for every time step the room temperature, floor temperature, transfer of heat from floor to room, transfer of heat from room to outside, heat energy added to the floor and the heat energy added to the room by the radiator. At initialization the room and floor resistances and capacitances are set, as well as the resistance of the radiator(s) to the room. This model was chosen since there are parameters for different types of houses available in prior work.

$$heatingGain = (T_{fluid} - T_{floor}) * \dot{m}_{fluid} * C_{p,fluid} \tag{3.15}$$

$$E_{toroom} = \frac{T_{floor} - T_{room}}{R_{floor}} \tag{3.16}$$

$$E_{tooutside} = \frac{T_{outside} - T_{room}}{R_{room}} \tag{3.17}$$

$$T_{floor} = T_{floor} + \frac{heatingGain - E_toroom}{C_{floor}} \tag{3.18}$$

$$gains = gains_{outside} + gains_{radiator} \tag{3.19}$$

$$T_{room} = T_{room} + \frac{E_{toroom} + E_{tooutside} + gains}{C_{room}} \tag{3.20}$$

3.7 Discussion

With the simulation the interaction between the different parts of the models is studied.
For the heat pump the following coefficients from [18] are used:

$$a = 1.268 \tag{3.21}$$
$$b = 2.214 * 10^{-2} \tag{3.22}$$
$$c = -3.4135 * 10^{-6} \tag{3.23}$$
$$d = -1.2573 * 10^{-2} \tag{3.24}$$
$$e = 4.632268 * 10^{-5} \tag{3.25}$$
$$f = -1.46332 * 10^{-4} \tag{3.26}$$

It is assumed to the air flow rate of the heat pump is always at is maximum.
For the heat exchanger to heat transfer coefficient is set to 2000 W/(m^2 K)[27] and the area to 0.5m^2. For the decoupler in the simulation an open manifold is used which just mixes the outputs from the gas boiler and the heat pump. The maximum output of the natural gas boiler is set to 20kW.
For the house the following parameters are used, they are based on the values of the detached house from [29].

$$C_{floor} = 5100 * 3600 \tag{3.27}$$
$$R_{floor} = 0.0016 \tag{3.28}$$
$$C_{room} = 21100 * 3600 \tag{3.29}$$
$$R_{room} = 0.0064 \tag{3.30}$$

All the zones and the heating water at the different components are all 20°C at the start of the simulation. The outdoor temperature is set to 0 °C.
The heat exchanger reaches about 100% energy transfer during operation regardless of the exact parameters of the heat exchanger.

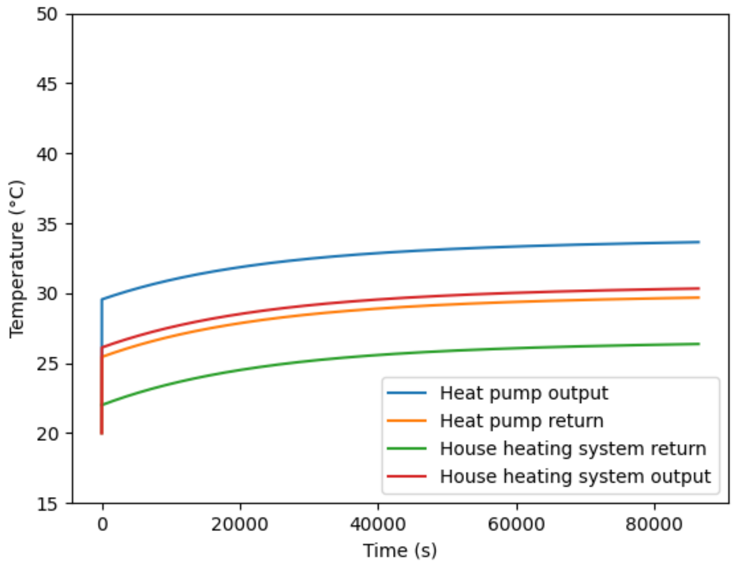

Figure 3.2: Temperatures at heat exchanger connections.

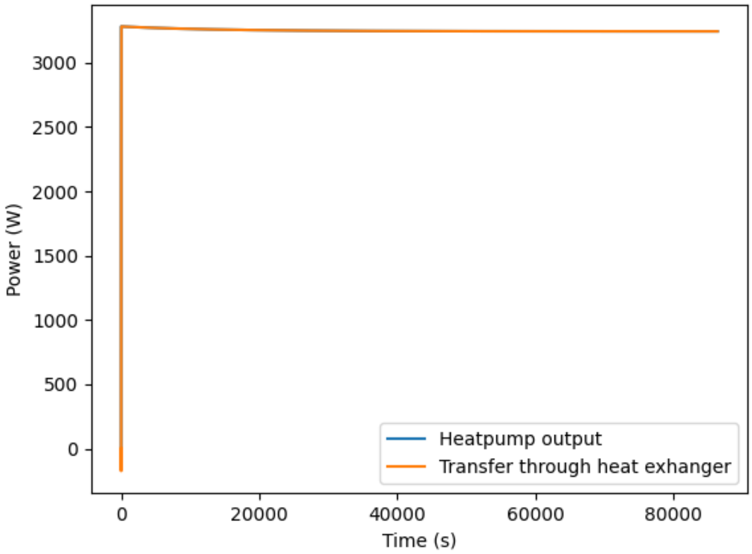

Figure 3.3: Power transfer through heat exchanger

In Figure 3.2 and 3.3 the temperatures and transfer power of a heat exchanger modelled with the ϵ-NTU method from [8] are shown. It shows that the temperatures at the side of the heating system do not reach the temperatures as outputted by the heat pump, but it does show that the thermal power of the heat pump is fully transferred to the heating system.
The power consumption of the heat pump does depend on the heat demand of the house. However, for the model of the house there are already parameters to model different types of houses to predict their heat demand.

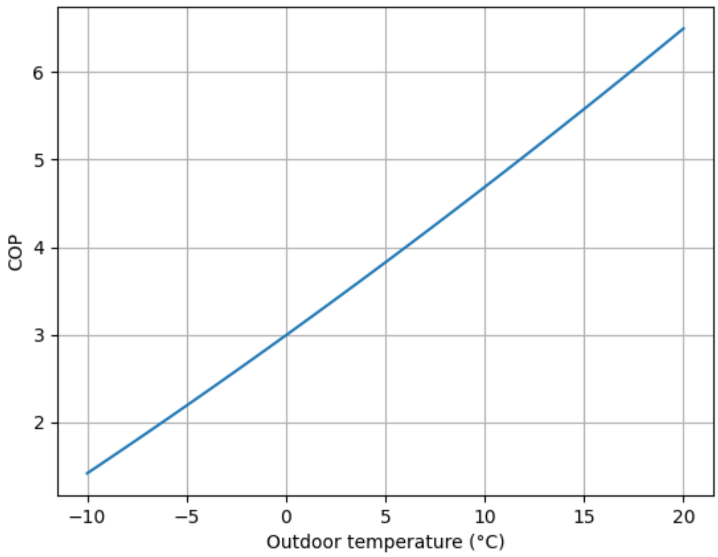

Figure 3.4: COP of heat pump against outdoor temperature

In Figure 3.4 the relation between the outdoor temperature and the COP at a fixed return temperature of 40°C is plotted. This shows that the COP depends on the temperature at the cold side of the compressor of the heat pump. Since a heat pump usually has a fixed maximum

electrical power consumption a lower COP also limits the maximum thermal output power.
To model the behaviour of the heat pump in different conditions a self-learning system is proposed to model the behaviour of the specific heat pump in the system by collecting data and and using this data to train a custom model for the particular heat pump.

3.8 Conclusion

A model of the hybrid heating system is made using models from the literature study. The behaviour of the model of the system and the individual model is studied to determine where improvements can be made. Since the heat pump is the largest electricity consumer of the hybrid heating setup, and controlling the electricity consumption is of interest, the model of the heat pump is the most promising to adapt to the individual system by using machine learning.

4 SIMULATION STUDY

In this chapter simulations are performed to determine the parameters for the experiments. The simulations are used to determine what data needs to be collected, what parameters need to be changed, how the parameters need to be changed and how many samples need to be collected.

4.1 Simulation study

For the planning of the energy consumption in a household accurate models of electricity consumers and producers are important. Since the heat pump in the hybrid heating system is the part in this system that consumes the most electricity it is the most promising part to increase the accuracy of its model. It is shown in Section 3.2 that the thermal output power of the heat pump depends on the return temperature of the heating water and the outdoor/ brine supply temperature. Therefore, to predict the electricity usage and heat supply of the heat pump a model is needed to predict the COP. By estimating the COP, the heat energy supply of the heat pump can be calculated, Subsequently, this COP can be used for the optimal planning of the operation of the heat pump, i.e. determine when and for how long the heat pump needs to run. In the literature review it is found that the COP of the heat pump depends on the conditions it is operating in. The most important factors for the COP of the system are the return temperature of the heating system, and the temperature of the cold side of the heat pump (the outside air or the brine supply). Since the behaviour of the system mostly depends on the return temperature and cold side temperature the machine learning system needs to learn the relation between these conditions and the resulting COP. Therefore, the goal of the machine learning system is to predict the COP of the heat pump based on the current and expected conditions of the system. The current implementation in DEMKit [13] does not consider the operating conditions of the system and assumes a constant COP for the heat pump.
The machine learning system should be able to learn the behaviour of the system under normal operating conditions, this means that it should be able to learn the behaviour of the system without performing measurements in artificial conditions. Learning the behaviour of the heat pump in changing conditions should increase the accuracy of the model. In the case of the available test setup at the TNO HESI facility, which consists of a heat pump with a brine source, the operational range for this specific heat pump is 8-30°C for the brine supply and 20-50°C for the return temperature of the heating water. It is assumed that the temperature of the return water does not become colder than 20°C room temperature and always transfers some heat to cool down from its 50°C supply temperature.
Given the dependence of the COP on the return temperature and the temperature of the cold side supply, these two parameters need to be varied during the measurements to learn the response of the system to these changes. In order to get a properly working model with machine learning the parameters need to be varied over the whole operational range, or at least the desired range in the which the model should achieve the desired accuracy. For fitting variables on a predetermined formula in theory less points can be used with less spread, but more points with more spread will lead to a more accurate representation. Machine learning with for example a neural network tries to fit the data as close as possible with no knowledge of the underlying process and therefore usually only works accurately enough when it is interpolating as mentioned

in Section 2.3.1. For machine learning to properly fit the model it needs many measurements points throughout the operational range. To fit a curve to the provided data at least as many measurement points as variables in the function need to be provided. In the case of the COP formula from [18] it uses six variables; this means that for this formula at least six distinct different points are needed to curve fit the data to this formula.
To define and test a measurement protocol for lab experiments, simulations have been performed. The goal of these simulations is to find a suitable method to learn the behaviour of the heat pump as a baseline. These simulations do use artificial conditions to cover the operational range of the heat pump. By performing simulations assumptions can be tested and verified in a known environment. For the simulations the heat pump model from [18], Equation 3.1 is used. The flow is set to 0.2l/s, the electric power consumption of the heat pump is set to a continuous 3000W. During the simulations different parameters for the return temperature and the cold side supply temperature were used, no other components of the hybrid heating system are simulated to generate these values. In the cases noise was added to measurements random noise with a standard Normal distribution with a seed was used, the seed ensures the random noise added is the same during the different runs, the sigma of the normal distribution was set to 0.12. When noise is added, the resulting output is rounded to the nearest 0.05 increment; this matches the output resolution of the available sensors in the test setup. It also only outputs every fifth sample of the simulation. The following variables are logged during the simulation: demand (fixed to always on), cold side supply temperature, return temperature, output temperature for heating system, flow of heating system, electric power consumption and COP of the model used to generate data.
For the simulations the focus was placed on learning the behaviour using curve fitting on the formula for COP from [18]. This choice was made since it was shown that this formula can model the behaviour with reasonable accuracy and it should, in theory, be able to do this with less data than for example a neural network.

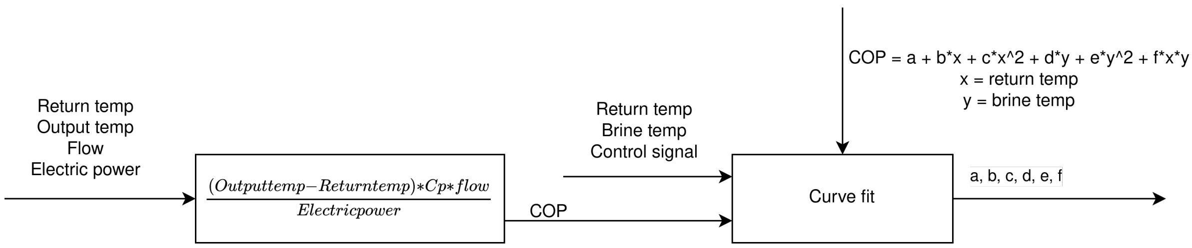

Figure 4.1: Curve fitting to model.

In Figure 4.1 the learning phase of the model is shown. First the gathered data is processed to calculate the COP, where C_p is the specific heat capacity of the water in the heating system. C_p is assumed to not change with temperature and is set to a fixed value of $4180 J/K/kg$, which is the specific heat capacity of water of around 40°C [28]. This COP together with the return temperature and brine temperature, and Equation 3.1 is input to the curve fitting algorithm. The result is the set of parameters required to describe the behaviour of the heat pump.

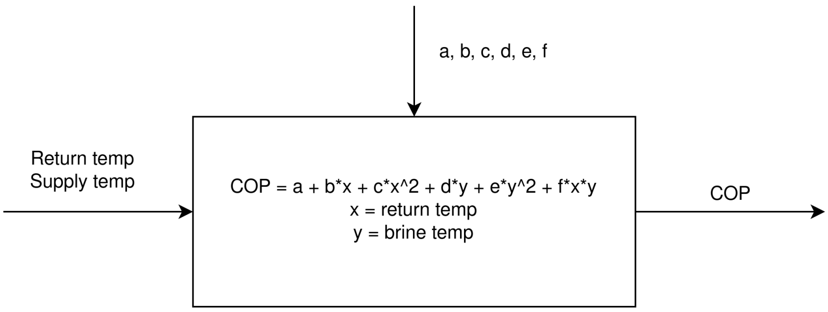

Figure 4.2: Operational mode of curve fitted model

In Figure 4.2 the usage phase of the model is shown. The previously determined set of parameters is used to predict the COP given the return and supply temperature.
A simulation was performed with six regions of operation, since, according to theory, that should be enough to accurately fit the behaviour of the heat pump. At each region of operation 500 samples were taken. The parameters from Table 4.1 are used.

Return temperature	35	35	35	45	45	45
Brine temperature	8	13	18	18	13	8

Table 4.1: Regions of operation for simulation with 6 regions.

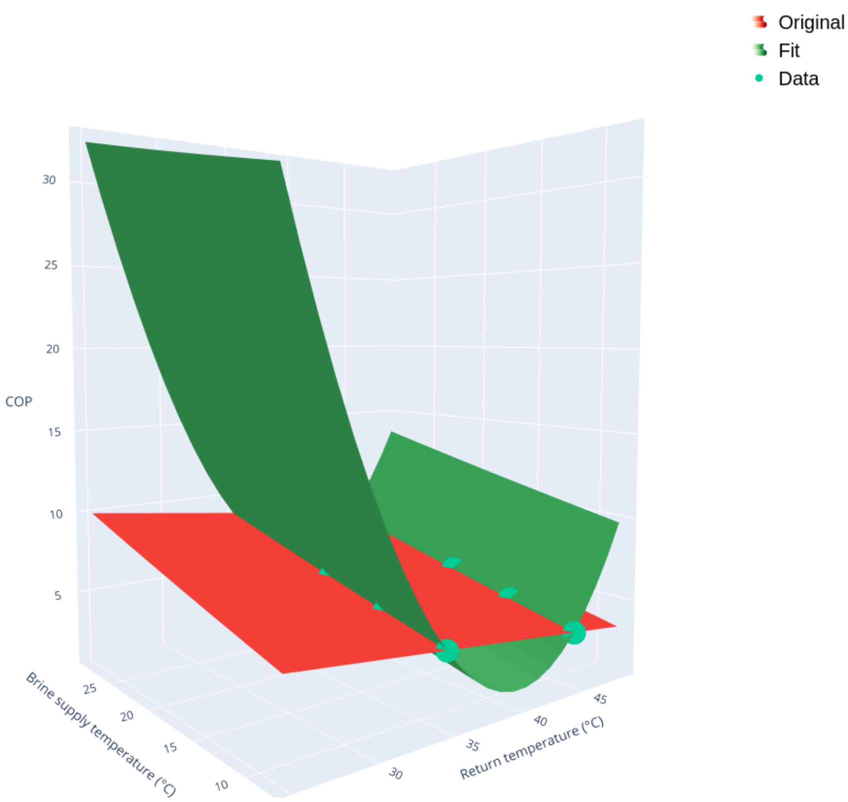

Figure 4.3: Plot of original model and curve fitted model with 6 data points and no noise.

In Figure 4.3 it can be seen that the fit is not as desired. It fits nicely on the data points, but deviates by up to a factor 3 outside the given data points.
With nine regions of operation there should be enough data to fit the 2nd order component of both the brine supply temperature and return temperature. It also ensures there is enough data to determine the combined contribution of the supply and return temperature. For the fit with 9 regions of operation the parameters from Table 4.2 are used.

Return temperature	35	35	35	40	40	40	45	45	45
Brine temperature	8	13	18	18	13	8	8	13	18

Table 4.2: Regions of operation for simulation with 9 regions

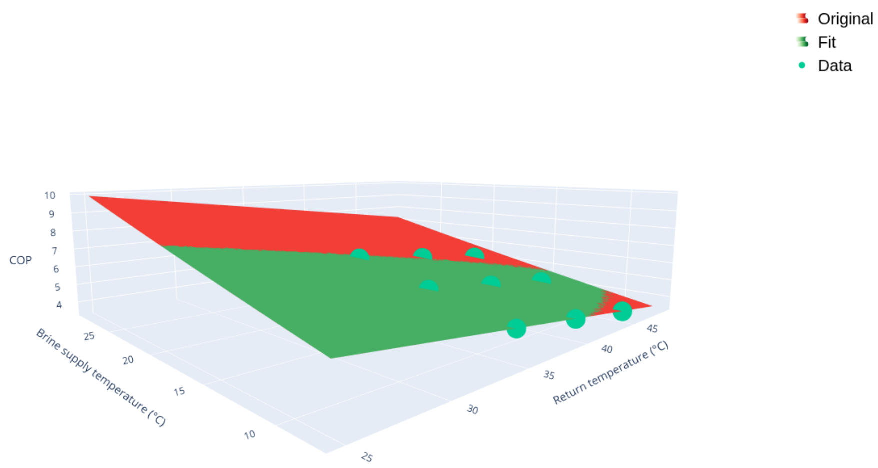

Figure 4.4: Plot of original model and curve fitted model with 9 data points and no noise.

In Figure 4.4 it is observed that the fit now matches the original better. Without noise the highest achieved error in the operating range is $6.77 * 10^{-3}$, the relative error is 0.094% at most.

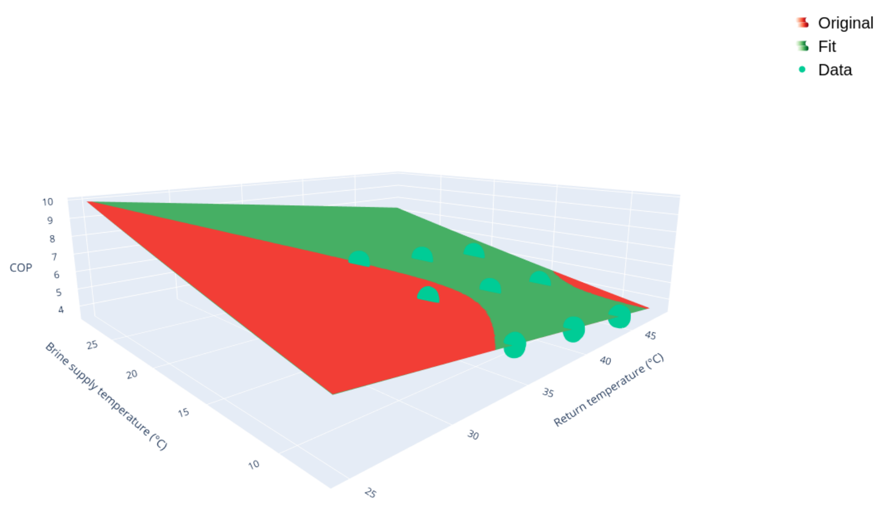

Figure 4.5: Plot of original model and curve fitted model with 9 data points and noise.

With noise and a rolling average over the return temperature, supply temperature, output temperature and the flow of 12 samples, which is 1 minute of data from the simulation, a maximum error of $1.02 * 10^{-1}$ is achieved. Doubling the number of samples reduces this error to $5.00 * 10^{-2}$, the resulting fit is shown in Figure 4.5.

4.2 Conclusion

With the simulations a suitable method is determined to model the behaviour of the heat pump. It is shown that measurements in at least 9 different regions of operation with a rolling average leads to a suitable model of the heat pump.

5 EXPERIMENTS

Experiments are performed to collect real world data of a heat pump to create models. The experiments are performed in two different ways. An experiment under ideal conditions is done to collect data for a baseline model. A second experiment is done in non-ideal conditions in order to create models with data from more realistic data.

5.1 Experiment setup

The heat pump setup at the TNO HESI facility is used to perform the experiments. The HESI, Hybrid Energy System Integration, facility is a facility of TNO to test energy solutions. It has the capability to test different heating configurations, whether it is electric, natural gas or a combination. A heating and cooling grid are present to supply warm or cold water to the test setups. The setup consists of an EcoGeo Basic B1 3-12kW heat pump which uses a ground source and is equipped with sensors to measure the performance of the heat pump. In Figure 5.1 an overview of the measurement setup is shown. It shows how the different parts of the setup are connected together, where the different sensors are placed and how the setup is connected to the cooling and heating grid in the HESI facility. The heating and cooling grid supplies warm and cold water of about 40°C and 15°C respectively to perform experiments involving (hybrid) heating systems.

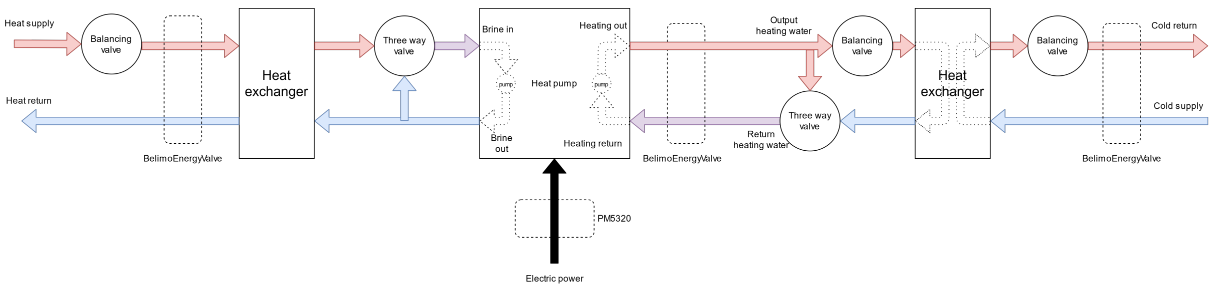

Figure 5.1: Overview of setup at TNO HESI.

In Figure 5.2 the actual measurement setup at the TNO HESI facility is shown. The heat pump is placed on a cart to allow usage in different test setups. All parts of the test setup where water flows between are connected with hoses that have an internal diameter of 19mm to allow easy change of the measurement setup. In table 5.1 the used equipment is listed. The Belimo Energy Valves measure the flow and the supply and return temperatures. The PM5320 measures the electricity consumption of the heat pump. Using the three way valves the supply temperature of the brine and the return temperature of the heating water can be controlled. The heat pump itself is able to measure the brine temperatures, the temperatures of the heating system and power usage among other things. The setup is connected to the cooling and heating circuits that are present in the HESI facility.

Figure 5.2: Experiment setup at TNO HESI facility.

Part of setup	Part model
Balancing valve	STAD PN 25 (DN20)
Heat exchanger	Alfa Laval CBH16-17H
Three way valve (heating system)	Belimo H514B
Three way valve actuator (heating system)	Belimo NV24A-SR-TPC
Three way valve controller (heating system)	WuT Web-IO Analog-In/Out PoE 57662
Temperature sensor (heating system feedback)	ANTF2
Three way valve (brine system)	Belimo H532B
Three way valve actuator (brine system)	Belimo LV24A-SR-TPC
Three way valve controller (brine system)	Siemens RLE 162
Heat pump	EcoGeo Basic B1 3-12kW
Electricity meter	Schneider PM5320
Flow and temperature meter	Belimo Energy Valve
Connection hoses	GEYSER 2A STEAM HOSE (OD 33mm)

Table 5.1: Equipment used in the experiment setup.

5.2 Experiment implementation

5.2.1 Software

The software for the experiment is written using the dEF-PI framework [26] in Java. The goal of dEF-Pi is to create a platform for easily implementing services dealing with energy demand. The main part of dEF-Pi is the orchestrator, it is responsible for the deployment and management of services and exposes an API which is used by the web-based user interface. Services are created as stubs with the code generation provided by dEF-Pi, this makes sure the services can communicate with the orchestrator. With the dEF-PI orchestrator the experiment software can be started and controlled using a graphical user interface.

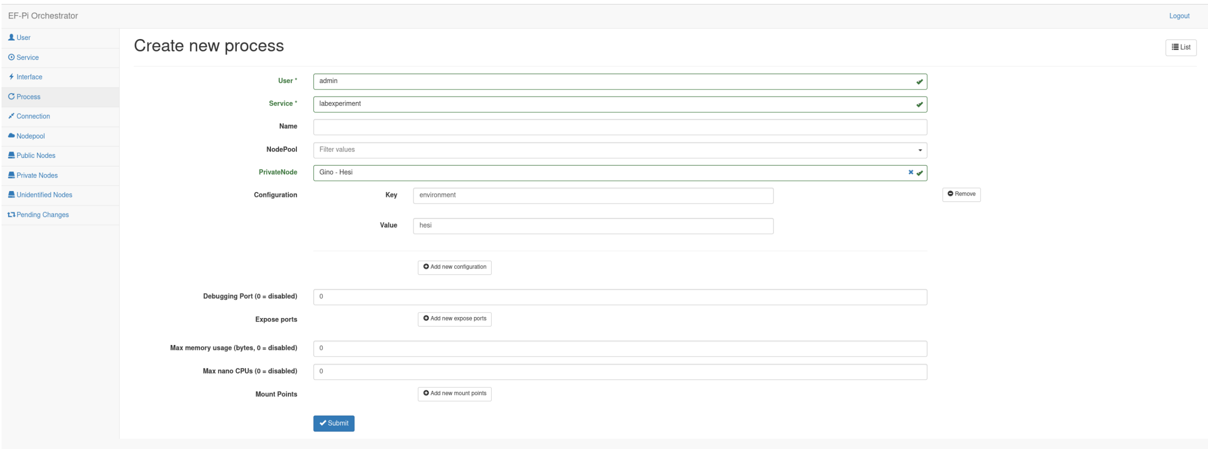

Figure 5.3: Interface of dEF-PI to configure services.

For the service implemented for this experiment the values for the return temperature, parameters for the PID-controller, the measurement period and the state of the heat pump can be set in the graphical user interface as shown in Figure 5.3. The software logs the output from the Belimo Energy Valves, PM5320 energy meter, heat pump and three way valve controller every 5 seconds to a TimescaleDB server. The measured values and their sources are listed in Table 5.2. The values from the three way valve driver that are collected are listed in Table 5.3.

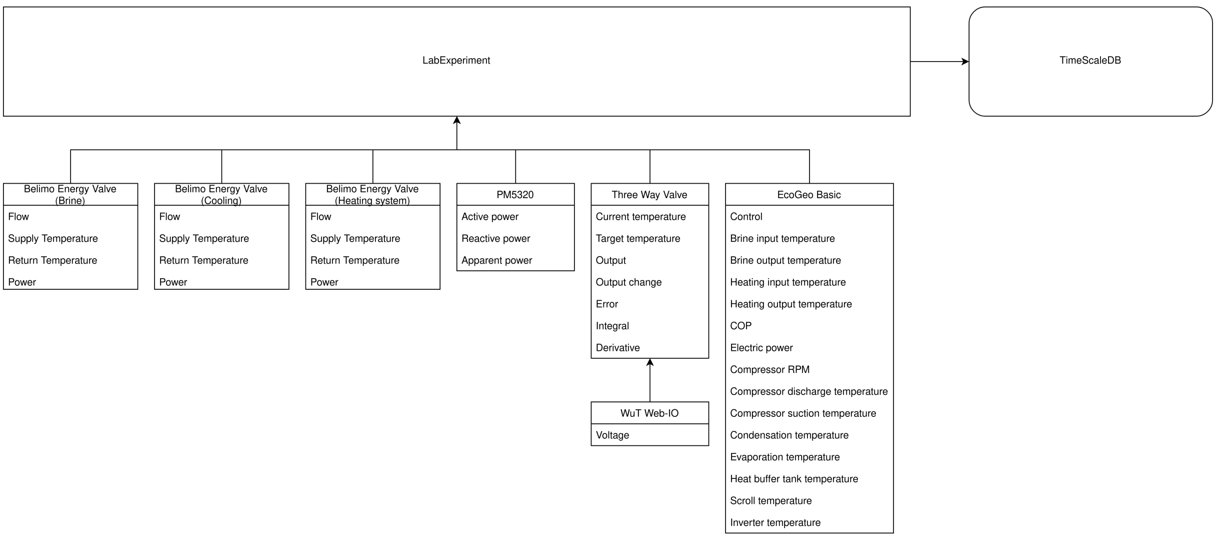

Figure 5.4: Overview of collected data.

Parameter	Source
Supply temperature brine at heat pump	Heat pump
Return temperature brine at heat pump	Heat pump
Supply temperature brine from heat network	Belimo Energy Valve
Return temperature brine to heat network	Belimo Energy Valve
Brine flow of the heat network	Belimo Energy Valve
Absorbed power from brine	Belimo Energy Valve
Supply temperature from cooling network	Belimo Energy Valve
Return temperature to cooling network	Belimo Energy Valve
Flow of cooling network	Belimo Energy Valve
Added power to cooling water	Belimo Energy Valve
Return temperature heating water	Heat pump & Belimo Energy Valve
Supply temperature heating water	Heat pump & Belimo Energy Valve
Flow of heating water	Belimo Energy Valve
Added power to heating water	Belimo Energy Valve
Active power	Heat pump & PM5320
Reactive power	PM5320
Apparent power	PM5320
CoP	Heat pump
Compressor RPM	Heat pump
Compressor discharge temperature	Heat pump
Compressor suction temperature	Heat pump
Condensation temperature	Heat pump
Evaporation temperature	Heat pump
Heat buffer tank temperature	Heat pump
Scroll temperature	Heat pump
Inverter temperature	

Table 5.2: Collected values and their sources.

Return temperature heating water
Target return temperature heating water
Control output
Change in control signal
Error
Integral
Derivative

Table 5.3: Collected values from the three way valve driver.

Most drivers have been implemented by TNO for their own experiments using (parts of) the setup. The driver for the WuT Web-IO Analog-In/Out PoE 57662 and the three way valve controller that uses the Web-IO module driver have been written for this experiment specifically. The driver for the Web-IO module exposes an interface to read and set the voltages of its two inputs/outputs. For controlling the three way valve one channel is connected to a temperature sensor and the other channel is used to output a voltage to control the position of the three way valve.

5.2.2 Temperature sensor return temperature heating water

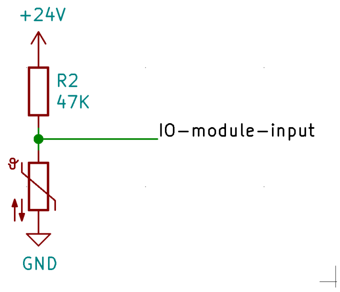

Figure 5.5: Schematic of voltage divider with NTC.

The circuit of the NTC temperature sensor is shown in Figure 5.5. It is a voltage divider with a known resistance and a known supply voltage, this way the resistance of the NTC can be calculated.

$$R_{NTC} = \frac{R_2 * V_{measured}}{V_{supply} - V_{measured}} \tag{5.1}$$

$$R_2 = 47000\Omega \tag{5.2}$$

$$V_{supply} = 24V \tag{5.3}$$

The resistance of the NTC is calculated with Equation 5.1. This resistance is used with the thermistor equation to calculate the temperature measured by the NTC.

$$T = \frac{B}{\log \frac{R_{NTC}}{R_0 * \exp \frac{-B}{T_0}}} \tag{5.4}$$

In Equation 5.4 the thermistor equation is rewritten to output a temperature when the resistance of the NTC is known. The result T is the temperature in Kelvin, T_0 is the base temperature in Kelvin, R_0 is the base resistance of the NTC and B is the parameter of the NTC. From the datasheet of the NTC [20] T_0 and R_0 are taken from the resistance characteristics table, while B is estimated using the provided resistance value at 0 and 100°C. With the estimated value of B the calculated temperature in the range from 20°C to 50°C deviates at most 0.24% compared to the provided resistance table from the datasheet.

$$R_0 = 47000\Omega \tag{5.5}$$

$$T_0 = 298.15K \tag{5.6}$$

$$B = 3941.51 \tag{5.7}$$

5.2.3 PID-controller return temperature heating water

The three way valve controller is a driver on top of the I/O-module driver, the controller used is a PID-controller that changes the output based on the measured error. The control loop is executed at a rate of 1Hz.

$$e(t) = x_{set}(t) - x(t) \tag{5.8}$$

$$i(t) = i(t-1) + e(t) \tag{5.9}$$

$$d(t) = e(t) - e(t-1) \tag{5.10}$$

$$u(t) = (K_p * e(t) + K_i * i(t) + K_d * d(t)) \tag{5.11}$$
$$y(t) = y(t-1) - u(t) \tag{5.12}$$

$$K_p = 0.02 \tag{5.13}$$
$$K_i = 0 \tag{5.14}$$
$$K_d = 0.5 \tag{5.15}$$

Equation 5.8 to 5.15 describe the PID-controller. Where $x_{set}(t)$ is the setpoint in °C at time t, $x(t)$ is the temperature in °C at time t, $u(t)$ is the change in controller output at time t and $y(t)$ is the resulting output at time t. $u(t)$ is limited to an amplitude of 0.07, this is the maximum speed at which the actuator for the three way valve can actually move, given the execution rate of 1Hz. This makes sure the output is always close to the actual position of the three way valve, this is done since no feedback from the actuator is used to determine the current position of the three way valve.

5.2.4 Controller brine supply temperature

To control the the brine supply temperature the Siemens RLE162 is used. This is a dedicated PI-controller for controlling the temperature of water. The setpoint of the brine is set using a physical slider on the device.

5.2.5 Heat pump

The heat pump used is a modulating heat pump, therefore the compressor does not need to run at its maximum operating capacity all the time. The modulation of the compressor however cannot be set by the user and can only be done by the heat pump based on the return temperature of the water and the setpoint of the heating water. During the experiments the setpoint of the heating water was set to the maximum of 59°C to make sure the heat pump would alway operate at its maximum capacity.

5.2.6 Data filtering

Only data is used where the compressor was reported running by the heat pump and the electricity consumption was more than 4000W, this electricity consumption or higher is reached in all the steady state cases during the measurements. In the cases where the non-ideal conditions were simulated the minimum power consumption for data to be selected was 500W, this ensures the internal pumps and the compressor of the heat pump are all running.
For the simulation in ideal conditions only steady state data is used. This is done because it is observed that before reaching steady state, for example when the compressor is still ramping up, different COP values are observed compared to the steady state situation. To remove the non steady state data the following steps are performed:

- Smooth input data using a rolling average
- Calculate Δ over δ samples (Equation 5.16)
- Discard data if Δ above threshold

Next to only removing the non steady state data a moving average can also be applied. For this moving average it is made sure that data from different operating regions does not influence each other, this is implemented with the following steps:

- Smooth input data using a rolling average
- Calculate Δ over δ samples (Equation 5.16)

- Discard data if Δ above threshold
- Take raw input data in split in separate continuous parts
- Apply moving average to separate parts of data

$$\Delta = |X[t + \frac{\delta}{2}] - X[t - \frac{\delta}{2}]| \tag{5.16}$$

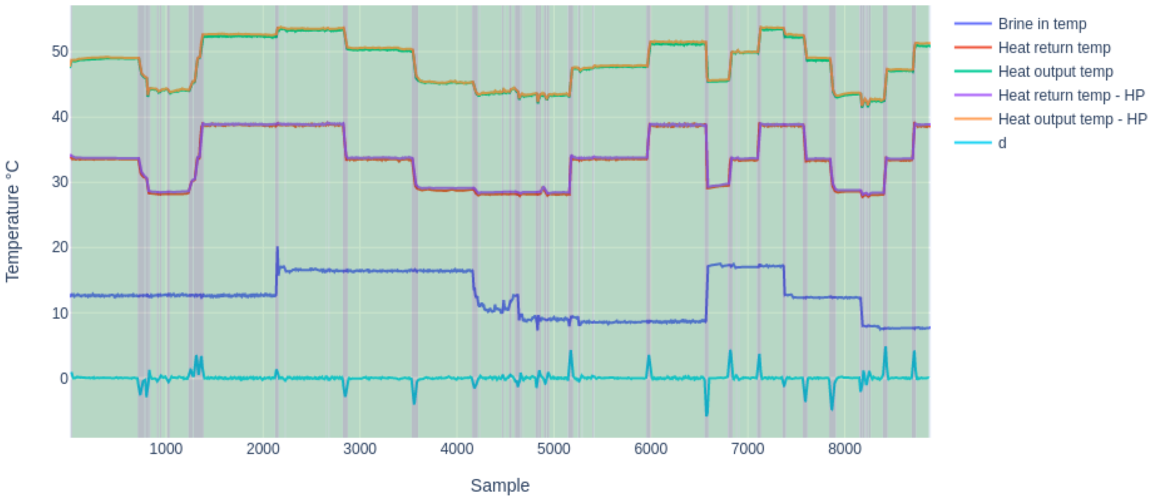

Figure 5.6: Splitting and filtering of measurements

In Figure 5.6 an example is shown of the filter removing non steady-state data. The grey areas are parts where the resulting Δ (d in the plot) is larger than the selected threshold and will be removed. In the case that a moving average is applied it is applied to each green area separately, this way no data of different parts of the operation influences the moving average of other operating conditions.

5.3 Return temperature controller test

A subset of the measuring setup is responsible for controlling the return temperature of the heating system water to the heat pump. This part of the system was tested separately to ensure it is able to control the return temperature of the heating water. The test setup for controlling the return temperature is show in Figure 5.7, the physical implementation of this test setup is shown in Figure 5.8.

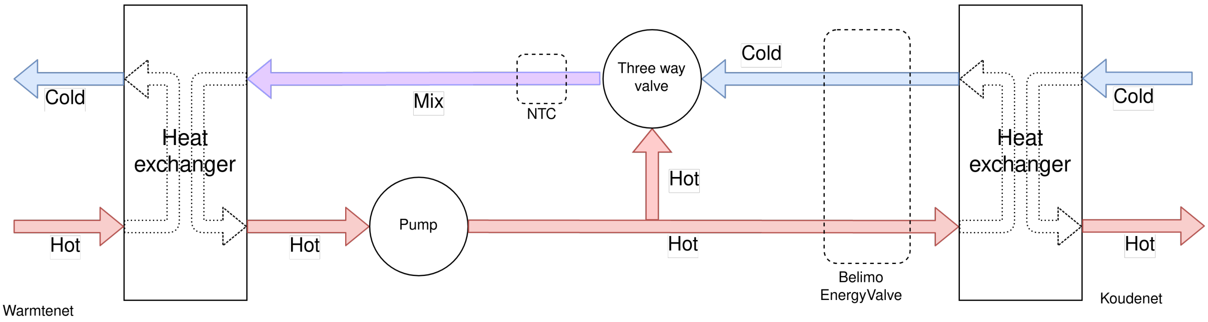

Figure 5.7: Test setup of return temperature control

Figure 5.8: Test setup of return temperature controller at HESI facility.

A controller was implemented to control the position of the three way valve to control the return temperature. With tuning of the parameters the maximum overshoot that is achieved by the controller is 0.4°C.

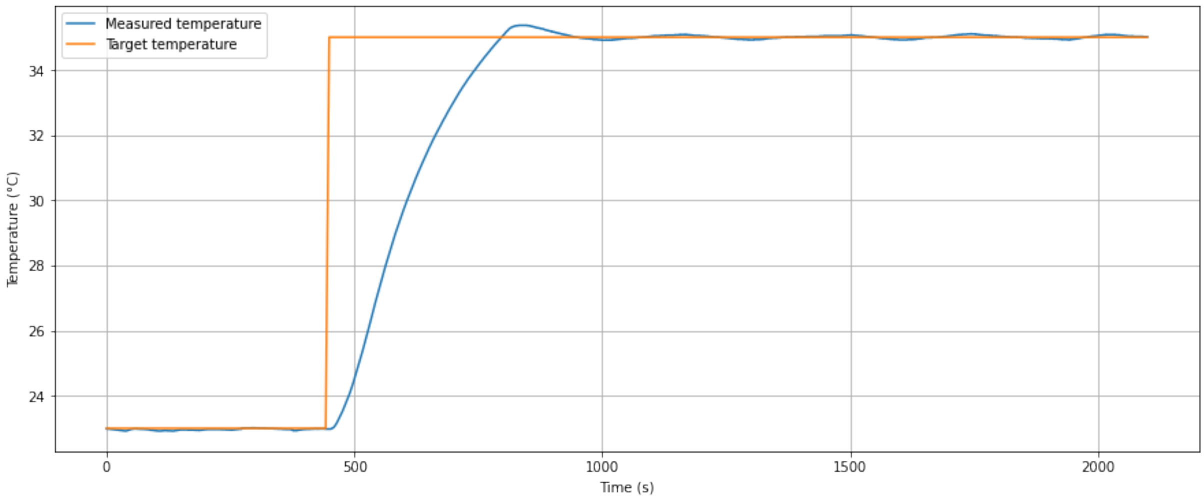

Figure 5.9: Step response of return temperature controller

In Figure 5.9 the response of the controller to a changing setpoint is shown. The slow behaviour of the controller is mostly determined by the slow speed of the motor driving the three way valve. The valve actuator takes 150 s to fully move the three way valve from one extreme to the other [25].

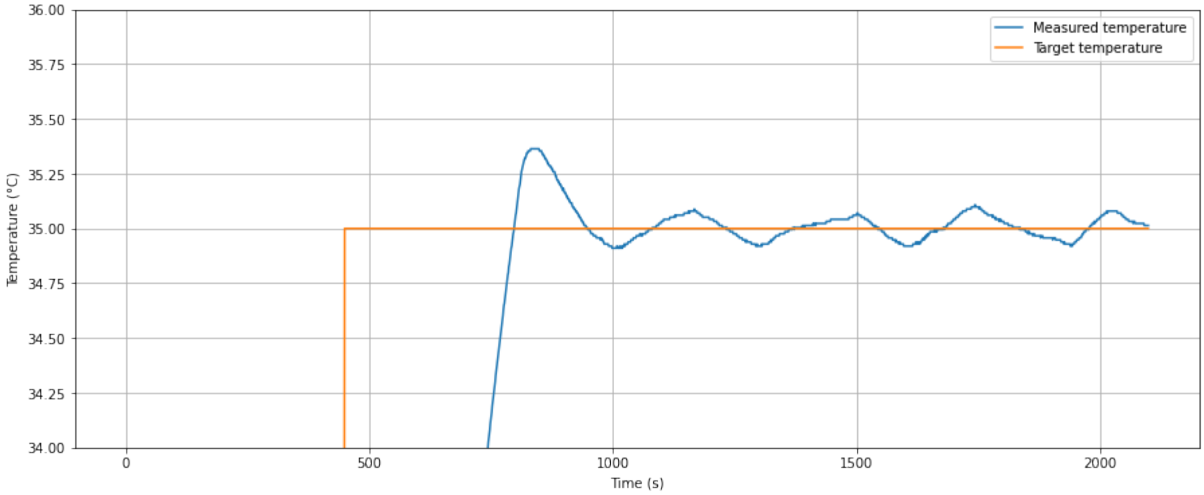

Figure 5.10: Steady state behaviour of return temperature controller

In Figure 5.10 the behaviour of the controller around the setpoint is shown. It shows that the controller does oscillate around the setpoint with an amplitude of about 0.15°C. Part of the oscillation is caused by the behaviour of the three way valve actuator, when making small changes it does not always react and only starts moving when the change becomes large enough. For example when the error is small the actuator does not move, due to the persisting error the output keeps changing and at some threshold the actuator moves to the output value.

5.4 Execution

5.4.1 Ideal conditions

For the experiment in ideal conditions measurements will be done when the heat pump is operating in a steady state. Measurements with different operating parameters will be done to collect data to create a baseline model of the heat pump.
For the measurements the following steps are performed:

1. Set brine supply temperature to desired value using the PI-controller
2. Set return temperature to desired value
3. Start data collection
4. Instruct heat pump to turn on, verify it is running
5. Wait for brine supply temperature and return temperature to stabilize around their set-point
6. Wait for output temperature to stabilize
7. Collect data, for acceptable fit at least 200 samples are needed
8. Return to step one for measurement with new parameters

The first two steps set the desired parameters for the measurement, these are the parameters that will be varied between the runs. Data collection should be running as soon as the heat pump is started, this is done to also collect data about the starting behaviour of the heat pump. For the main measurements it is important that the heating system reaches a stable state. Once the stable state is reached at least 200 samples need to be collected, as discussed in Chapter 4. The experiment is performed with lower return temperatures than initially were chosen. This is done because it was observed that at a return temperature of 45°C the output would become hotter than 55°C leading to the heat pump modulating and decreasing its output. The lower values were chosen to make sure the heat pump would operate at maximum power at each tested region of operation.

Return temperature	30	30	30	35	35	35	40	40	40
Brine temperature	8	13	18	8	13	18	8	13	18

Table 5.4: Regions of operations for lab experiment in ideal conditions

5.4.2 Non-ideal conditions

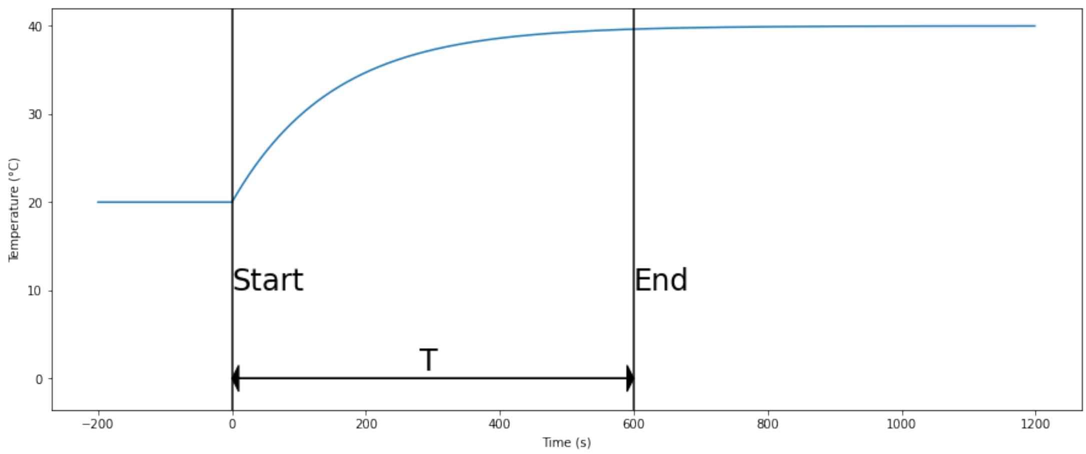

Figure 5.11: Radiator heating behaviour modelled with RC-response

Next to the experiment with the ideal controlled conditions a second experiment is performed. In this experiment the brine supply temperature is set fixed for an experiment run but the return temperature of the heating water is varied. The return temperature of the heating water follow an RC-curve to model the behaviour of the heating system of a house warming up. The heating behaviour is shown in Figure 5.11, it starts at 20°C and heats up to 40°C. The time T it takes to heat up the system is varied between 10, 15 and 20 minutes. The heating curve is generated with Equation 5.17, where the $T_{set,t}$ is used as setpoint $x_{set}(t)$ for the three way valve controller and τ is set to $\frac{T}{4}$, this way after the selected period 98.2% of the final value is reached.

$$T_{set,t} = T_{start} + (T_{target} - T_{start}) * (1 - e^{-\frac{t}{\tau}}) \tag{5.17}$$

For the second experiment the following steps are performed:

1. Set brine supply temperature to desired value using the PI-controller
2. Set return temperature target and heat up time to desired value
3. Start data collection
4. Instruct heat pump to turn on, verify it is running
5. Wait for brine supply temperature and return temperature to stabilize around their set-point
6. Wait for output temperature to stabilize
7. Collect data, for acceptable fit at least 200 samples are needed
8. Instruct heat pump to turn off
9. Lower return temperature and run heating circuit pump to cool down heating water
10. Return to step one for measurement with new parameters

5.4.3 COP calculation

Since the COP is an important measure of the performance of the heat pump it will be calculated from the collected data. The COP is calculated with the following equation:

$$COP = \frac{(T_{heating,output} - T_{heating,return}) * C_{p,water} * \dot{m}_{water}}{\dot{Q}_{electric}} \tag{5.18}$$

Where $C_{p,water}$ is $4180 J/K/kg$, which is the same value used in Chapter 4.

$T_{heating,output}$	Belimo Energy Valve
$T_{heating,return}$	Belimo Energy Valve
$\dot{m}_{water}$	Belimo Energy Valve
$\dot{Q}_{electric}$	Schneider PM5320

Table 5.5: Source of values for external COP calculation

$T_{heating,output}$	Heat pump
$T_{heating,return}$	Heat pump
$\dot{m}_{water}$	Belimo Energy Valve
$\dot{Q}_{electric}$	Heat pump

Table 5.6: Source of values for hybrid COP calculation

The COP is obtained from the data in three different ways:

1. Heat pump: COP value reported by the heat pump
2. External: using Equation 5.18 and the values with the sources as described in Table 5.5
3. Hybrid: using Equation 5.18 and the values with the sources as described in Table 5.6

No calculation using the data from only the heat pump can be done since the flow of the heating water is not reported by the heat pump.

5.5 Summary

Experiments are performed with a heat pump setup at the TNO HESI facility. For this experiment software has been written to collect and store data and to control the return temperature of the water. Two different experiments are performed, one in optimal conditions where the heat pump and its water system operate in steady state and another experiment in non-ideal conditions where the water of the heating system heats up over a period of time.

6 RESULTS

In this section the results from the experiments are discussed. First some general observations about the behaviour of the heat pump and the testing set up are are discussed, followed by the results from the ideal and non-ideal condition experiments.

6.1 General observations

It is observed that when starting the heat pump it takes some time for the compressor RPM and the electricity consumption to stabilize. In Figure 6.1 the starting behaviour of the heat pump is shown. It takes about 8 minutes for the heat pump to reach a stable operating state. It is also observed that the power consumption measured by the external energy meter is higher than what the heat pump reports.

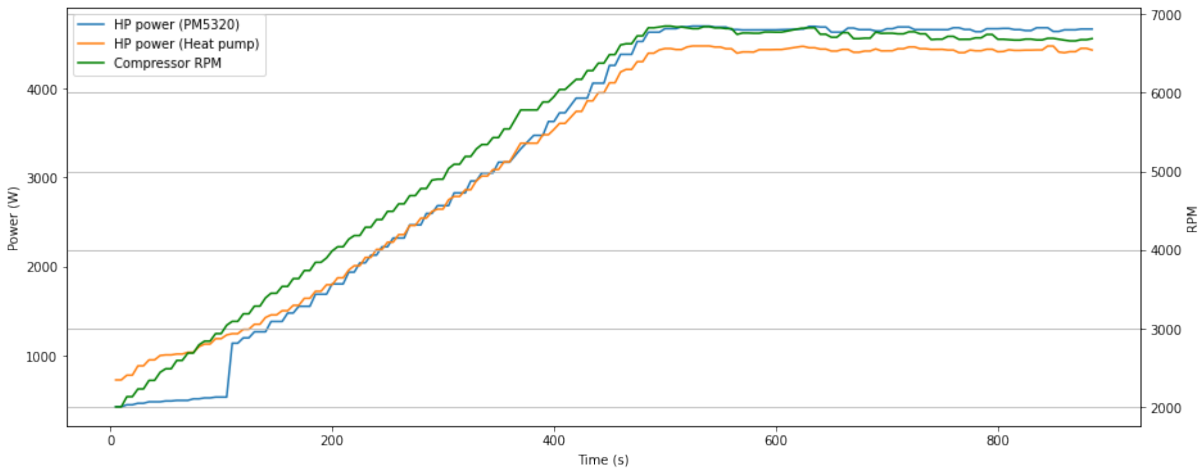

Figure 6.1: Start behaviour of used heat pump

In Figure 6.2 the energy consumption as reported by the external meter and the heat pump are compared in different cases where the compressor of the heat pump is not running. It can be seen that the energy consumption of the pumps for the brine and heating circuit is not reported by the heat pump. When both the heating circuit pump and the brine pump are running at their maximum capacity, which is observed to happen during operation, they consume on average 207W of power. For demand side management on the electrical grid the total power consumption of the heat pump is of interest. Therefore the COP is assumed to include the total electric energy used by the heat pump.

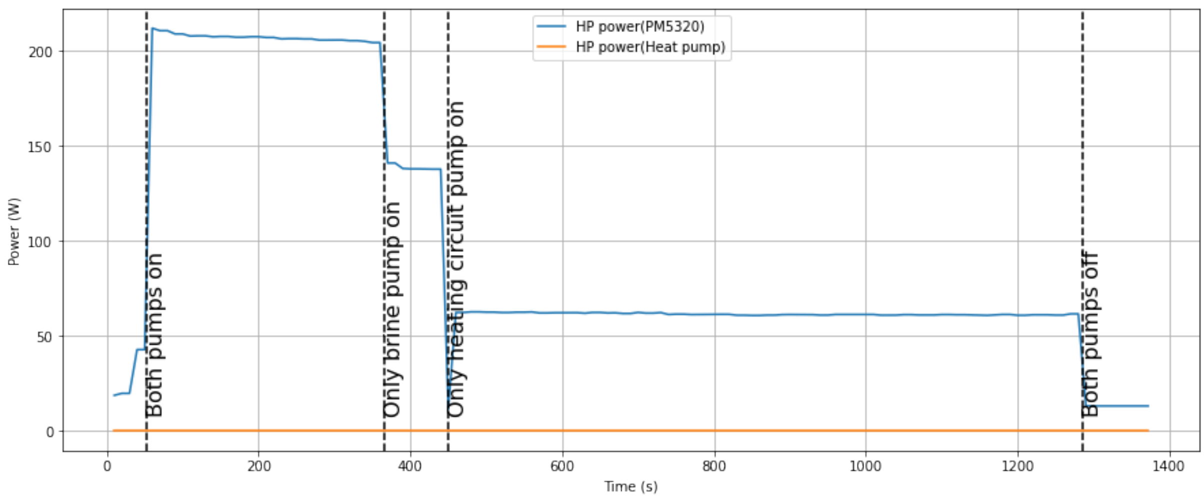

Figure 6.2: Comparison of power consumption reported by external meter and heat pump

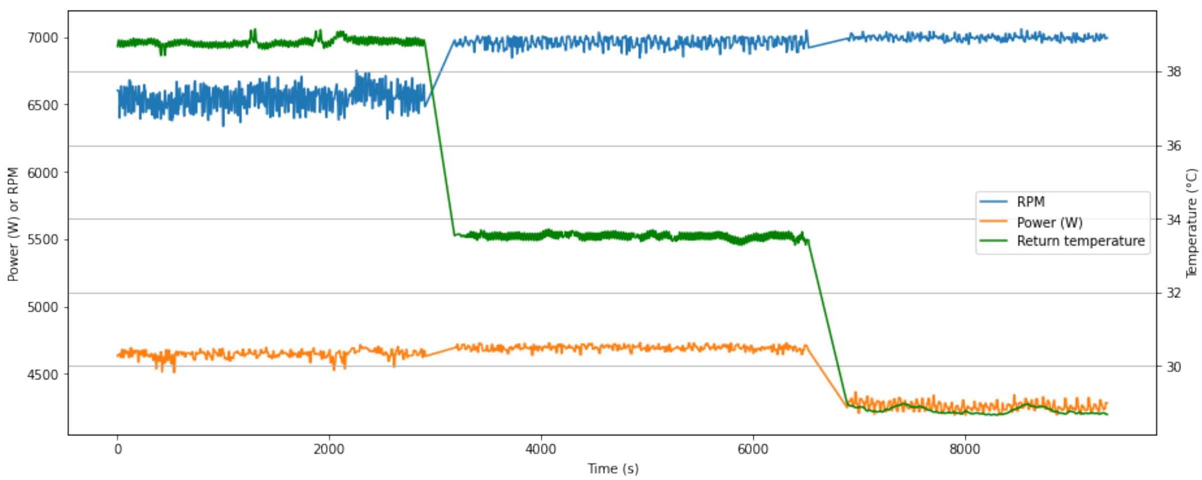

Figure 6.3: Plot of power consumption, compressor rpm and return temperature

Another observation is that the compressor RPM is lower when the return temperature of the heating water is higher. In Figure 6.3 the power consumption of the heat pump, the compressor RPM and the return temperature of the heating water are plotted. It can clearly be seen that the compressor RPM increases when the return temperature becomes lower. However, the power consumption does only change slightly, it is 4648W when the temperature of the water is 38.5°C and is 4694W when the temperature of the water is 33.5 °C, a decrease of 0.98%. When the return temperature is lowered further to 28.5°C the compressor RPM does barely change, from 6959 to 6993 on average which is an 0.49% increase, while the power consumption drops to 4261W, a 9.2% decrease.

6.2 Ideal conditions

In this section the resulting measurements of the ideal measuring case are discussed. Different types of filtering are compared. Next to comparing the different filtering methods a comparison is drawn between the different methods to obtain the COP value.

6.2.1 Unfiltered

In this section the results are presented without additional filtering, the only criteria used for selecting the data is a running compressor and a power consumption of at least 4000W.

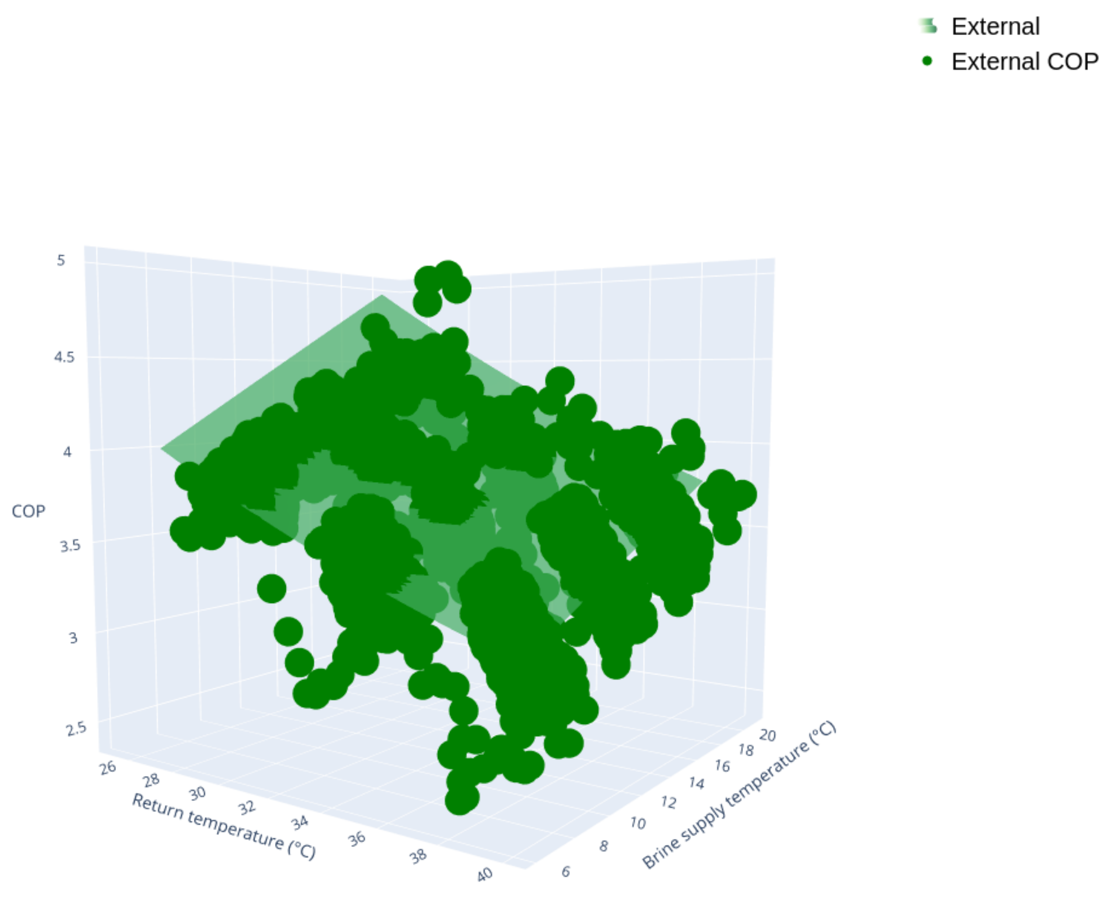

Figure 6.4: 3D plot of observations and fitted model

In Figure 6.4 it can be seen that there is data that does not fit the fitted model. This is because selecting the data only by looking at the fact that the compressor is running and the power consumption of 4000W does not mean that an actual steady-state of operation is reached.

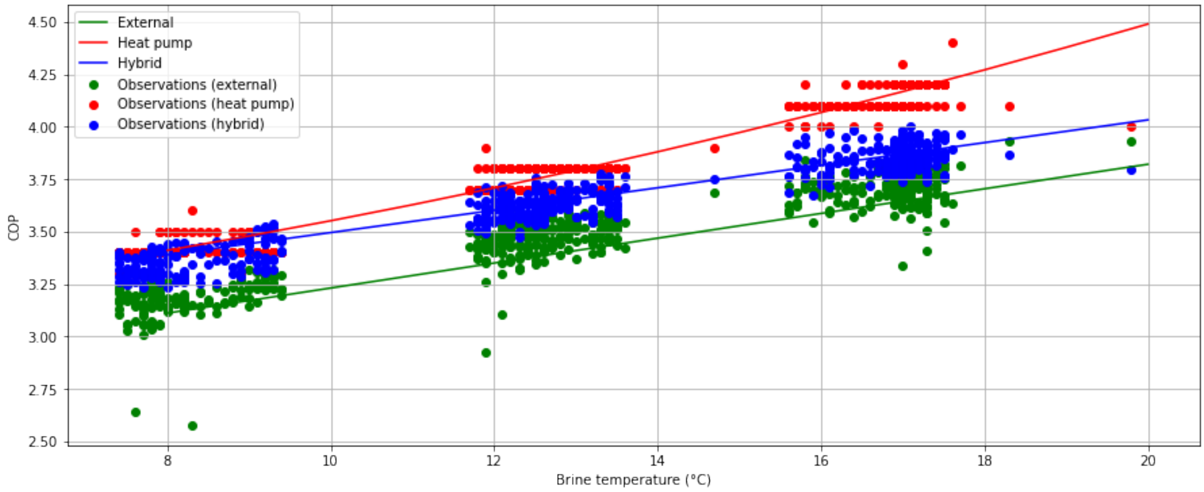

Figure 6.5: Comparison of different model fits at a return temperature of 38.5°C

Similar to Figure 6.4 Figure 6.5 shows a lot of spread of the data points in an assumed steady state. In Figure 6.5 a difference can be seen in the COP reported by the different methods to obtain this value. The difference between the hybrid method and the external calculation method can be explained by the difference in the externally measured power consumption and the power consumption reported by the heat pump.

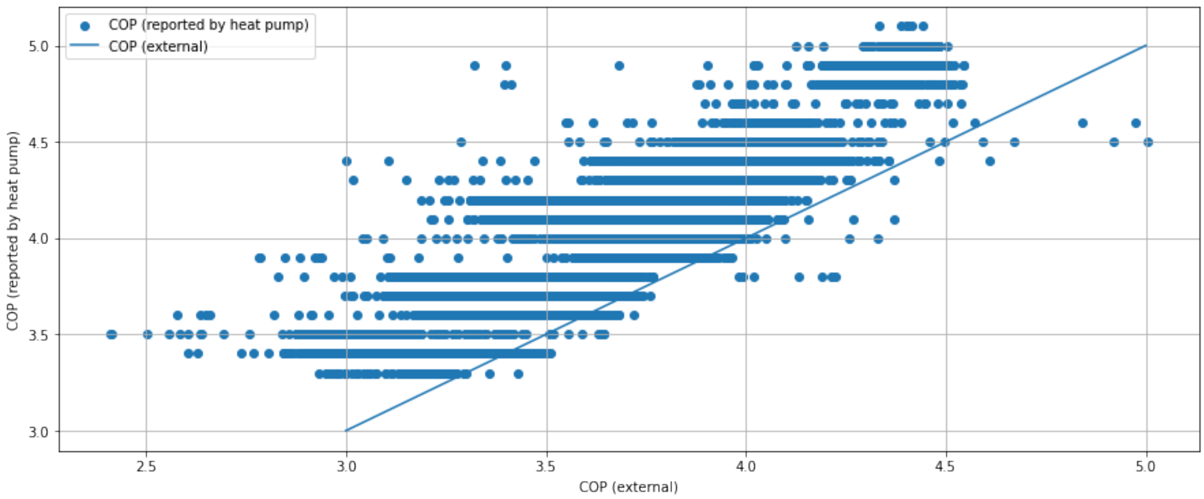

Figure 6.6: Plot of the COP reported by the heat pump against the COP measured with external sensors

In Figure 6.6 the COP as reported by the heat pump is plotted against the COP as measured using the external sensors. A clear bias is observed in the reporting of the COP by the heat pump, with the latter consistently being more optimistic.

6.2.2 Non steady state removed

To remove the non steady-state data the method described in Section 5.2.6 has been used. The data is smoothed with a rolling average with a window size of 12 and for Equation 5.16 $\delta = 30$ and $\Delta_{max} = 0.3$ is used.

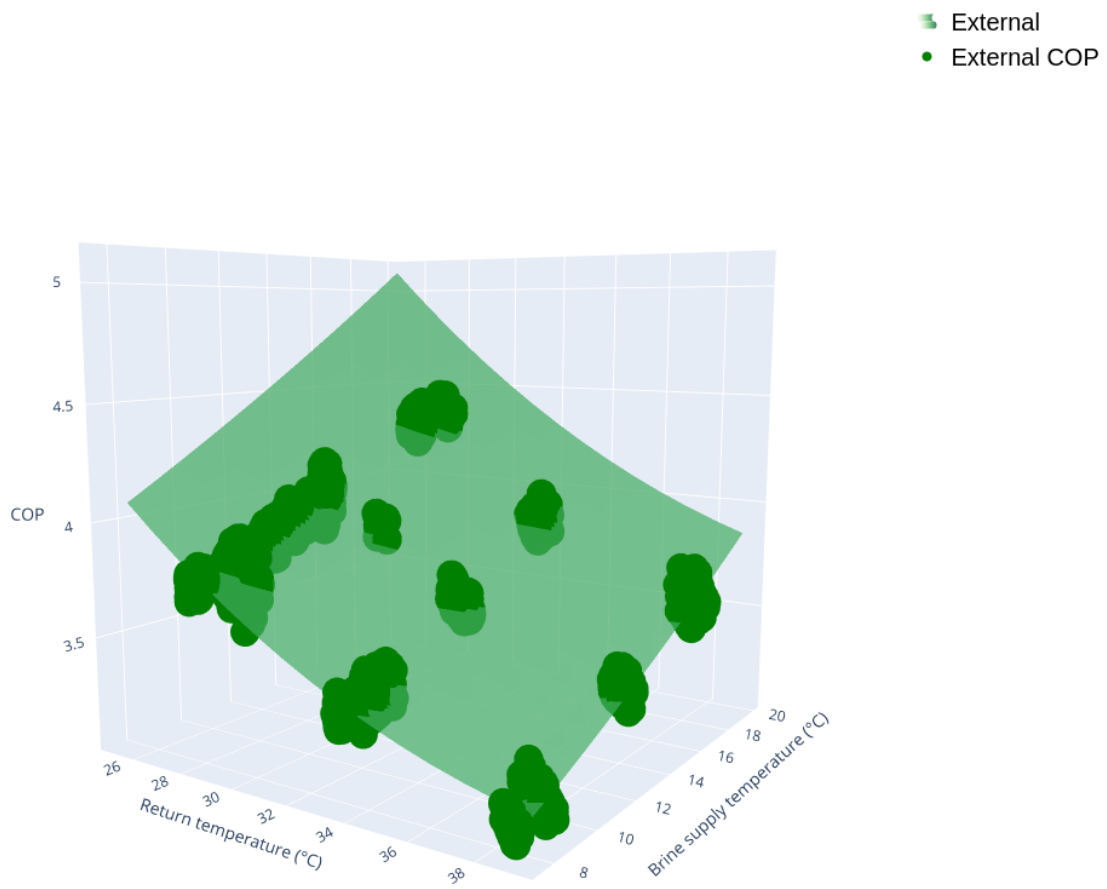

Figure 6.7: 3D plot of observations and fitted model

In Figure 6.7 it is shown that removing the non steady-state data points makes sure the data points and resulting fit better, since the non steady state outliers have been removed.

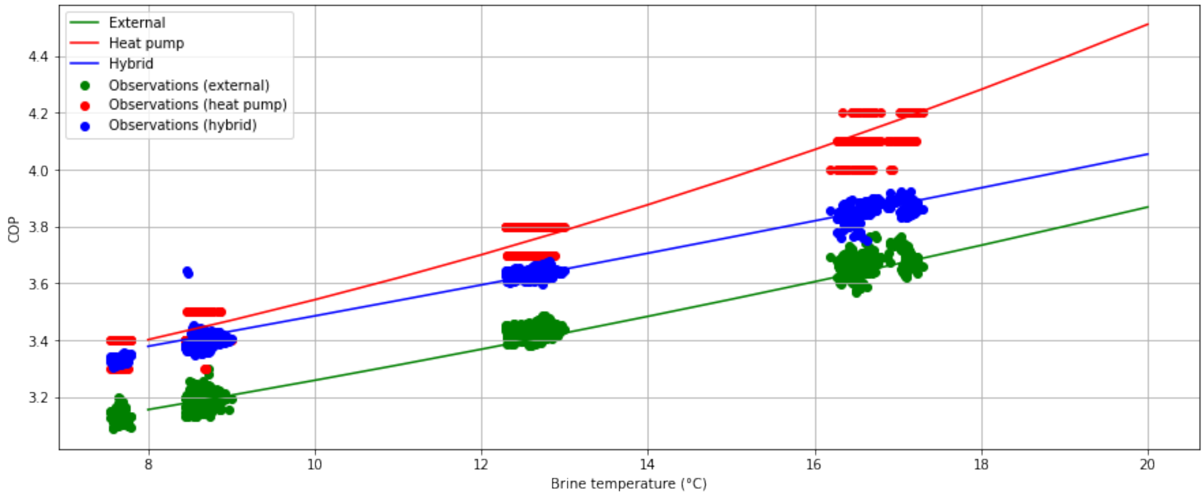

Figure 6.8: Comparison of different model fits at a return temperature of 38.5°C

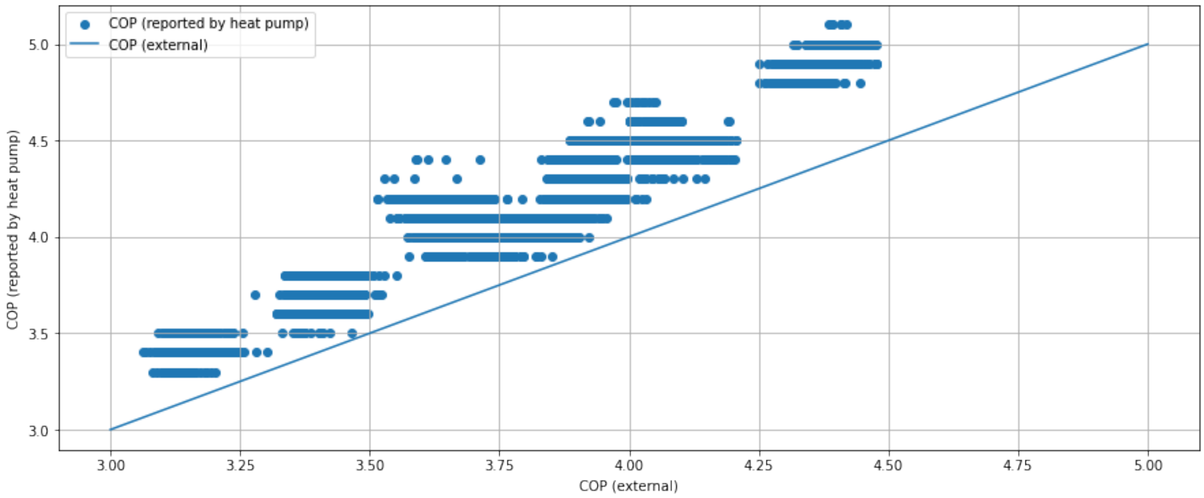

Figure 6.9: Plot of the COP reported by the heat pump against the COP measured with external sensors

6.2.3 Non steady state removed and moving average

For selecting the data the same parameters as Section 6.2.2 are used. For the moving average over the selected parts a window of 12 is used, the same window as found during the simulation study.

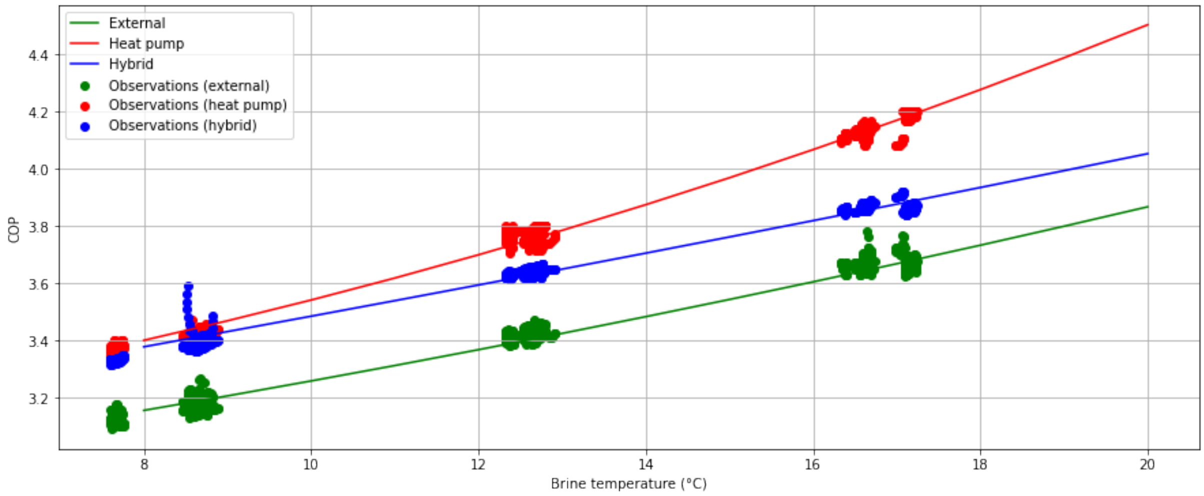

Figure 6.10: Comparison of different model fits at a return temperature of 38.5°C

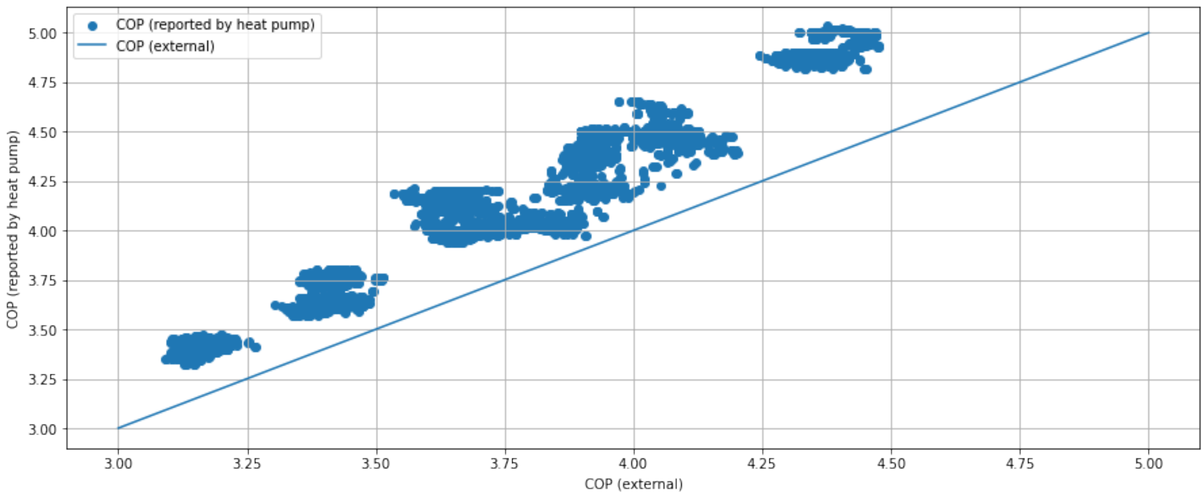

Figure 6.11: Plot of the COP reported by the heat pump against the COP measured with external sensors

6.2.4 Comparison of fitted models with different filtering

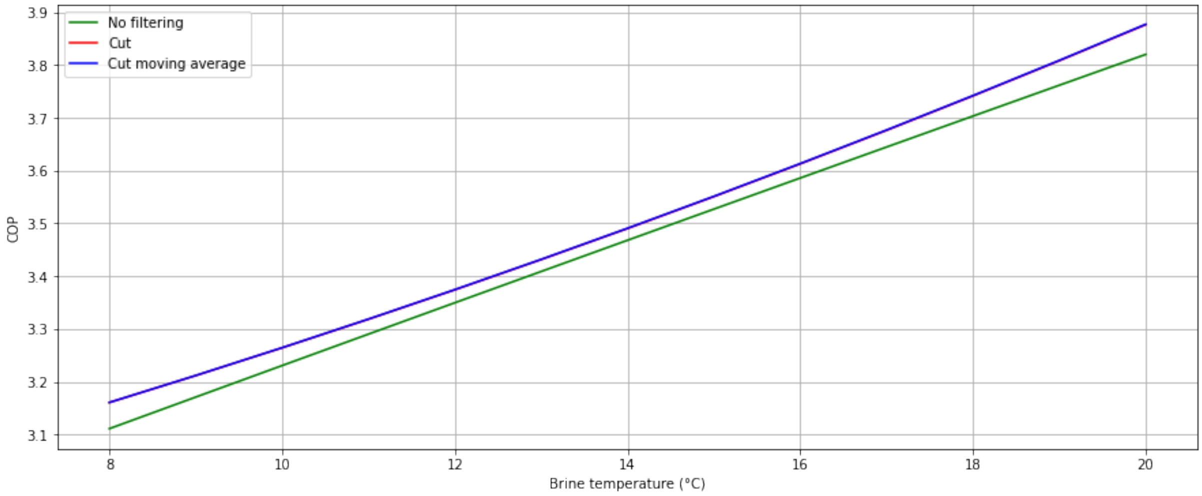

Figure 6.12: Comparison of different model fits at a return temperature of 38.5°C with external data

The resulting models of the different filtering methods are shown in Figure 6.12. The lines for "Cut" and "Cut moving average" do overlap in the figure. The fit with the unfiltered data gives lower results than the other two options, this is caused by the fact that the non steady state data point as seen in Figure 6.4 give lower COP values.

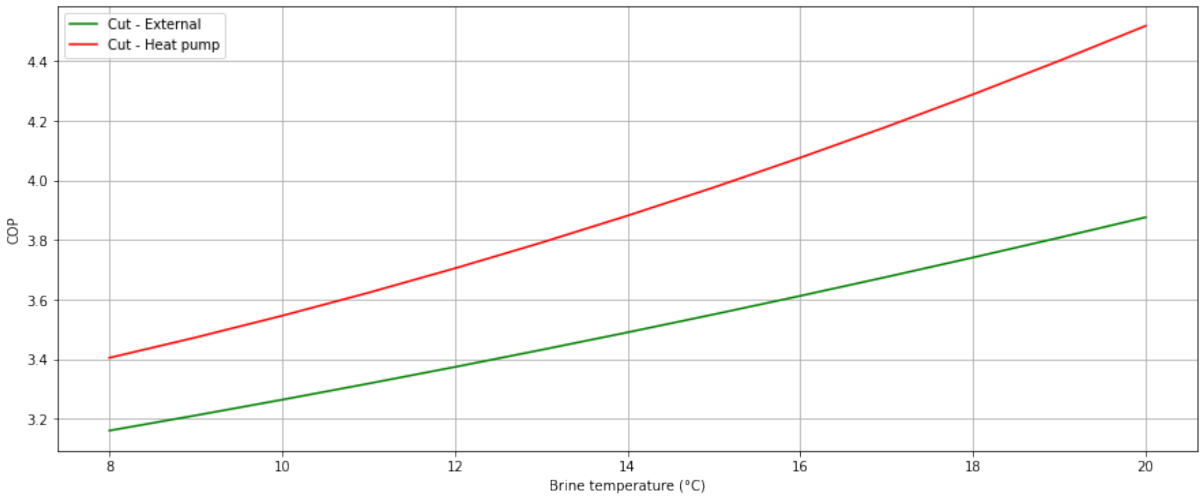

Figure 6.13: Comparison of resulting models from external and heat pump data at 38.5°C return temperature.

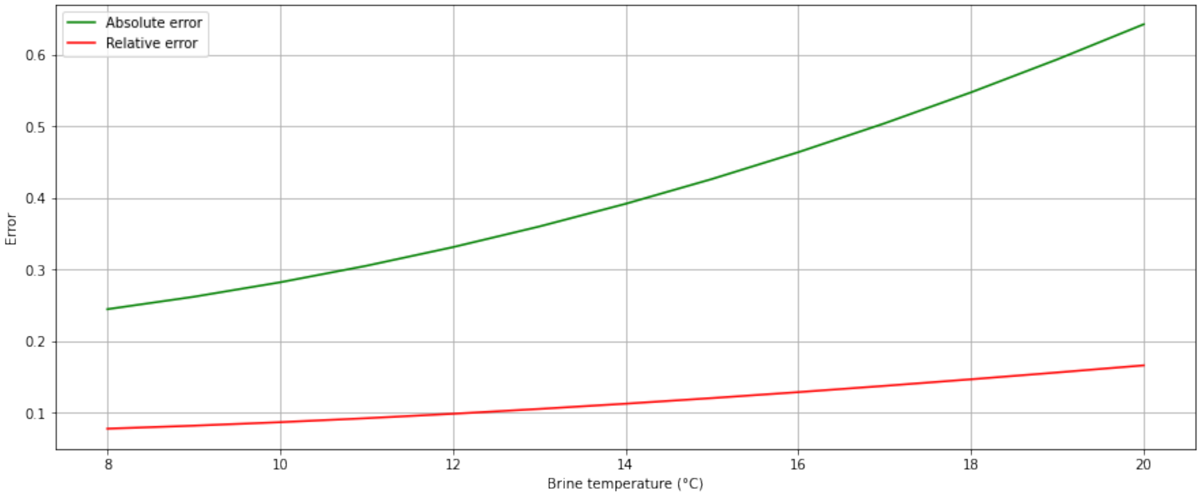

Figure 6.14: Deviation of fitted model with heat pump data with respect to external data

In Figure 6.13 the resulting models from the external and heat pump data are plotted. The heat pump data consistently results in a higher COP. In Figure 6.14 the error and the relative error from the model fitted with heat pump data with respect to the model fitted with the external data is shown. Both the error and relative error do increase with higher brine supply temperatures. Part of the error can be attributed to the difference in the power consumption as reported by the heat pump and the power consumption as measured externally. Since the heat pump does not report the flow of the water in the heating system it is not possible to calculate the COP with only heat pump data. The heat pump does report the heat energy added to the heating water on the display, but this value cannot be collected automatically and is therefore not used to compare it with calculated values of the heating output.
For comparisons in the next section the models fitted with the non steady state data removed are used as the baseline model.

6.3 Non-ideal conditions

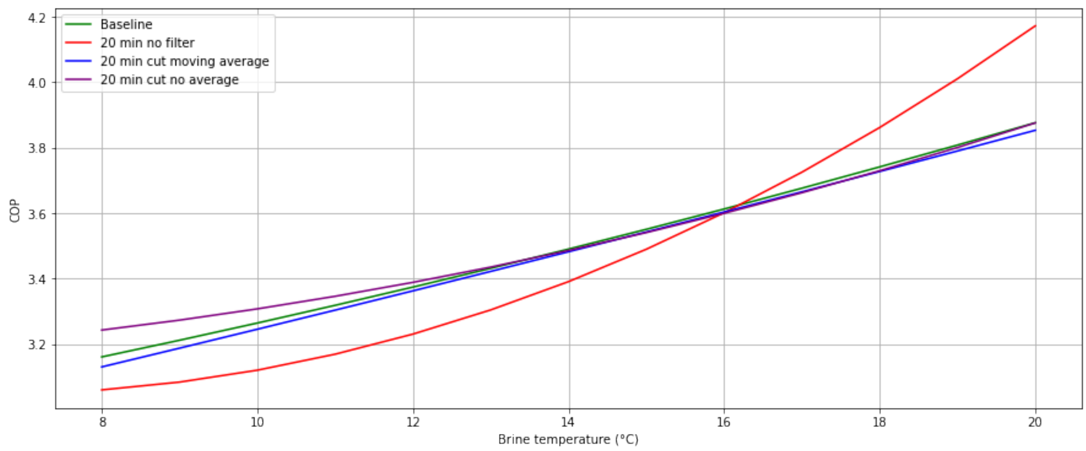

Figure 6.15: Comparison of different filtering methods with heating time of 20 minutes

In Figure 6.15 the different filtering methods are compared against each other with data from 20 minutes heat up time and the baseline model. To compare the resulting models with different heat up times the filter with moving average over the different parts will be used.

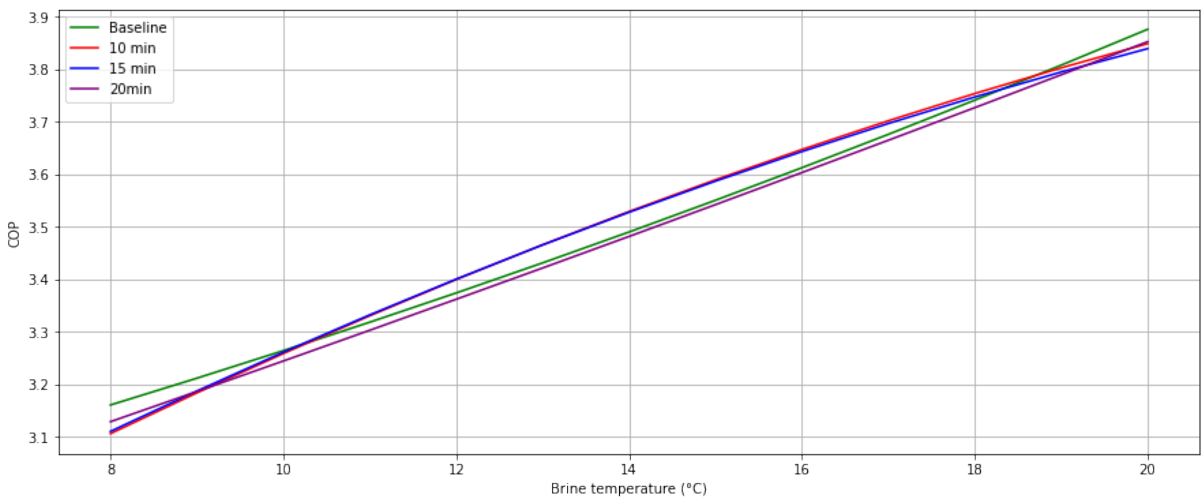

Figure 6.16: Comparison of different model fits at a return temperature of 38.5°C with external data

The models generated from the different runs appear to closely match the baseline model. The model created with data from 20 minutes of heat up time has a maximum deviation from the baseline of $3.1 * 10^{-2}$ and a maximum relative error of 1.0%, and has the lowest maximum deviation, while the data from the heat up time of 15 minutes has the highest maximum deviation of $6.2 * 10^{-2}$ and a maximum relative error of 1.6%.

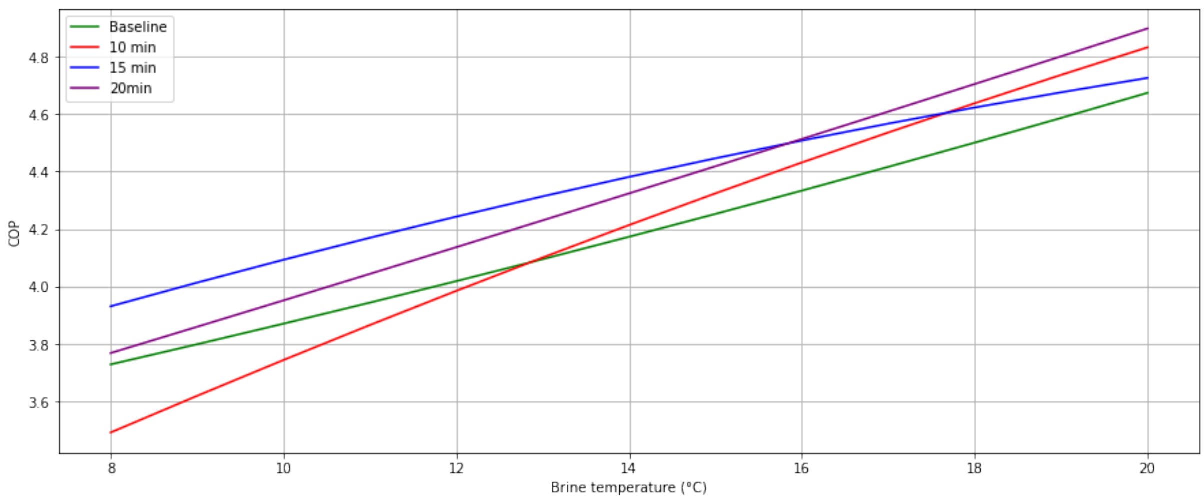

Figure 6.17: Comparison of different model fits at a return temperature of 28.5°C with external data

The models do have a higher deviation from the baseline when comparing with the baseline at a lower return temperature of 28.5°C. In this case the maximum deviation of all the models is $2.3*10^{-1}$ compared to the baseline model, which results in a relative error of 6.3% for the model with 10 minutes heat up time and a relative error of 4.9% for the model with 20 minutes heat up time.

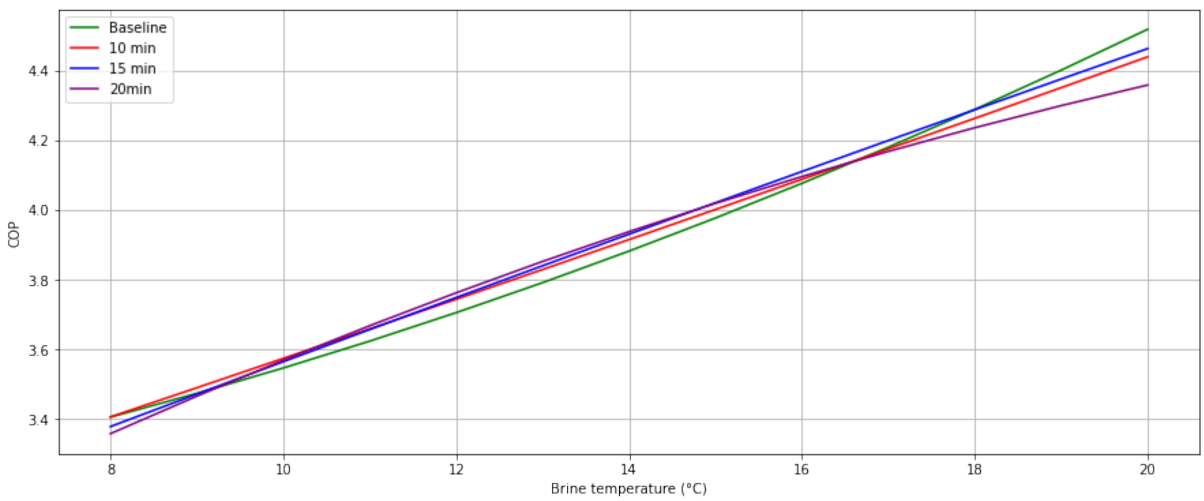

Figure 6.18: Comparison of different model fits at a return temperature of 38.5°C with heat pump data

With the data from the heat pump the maximum relative error is 4.8% compared to the baseline created with heat pump data.

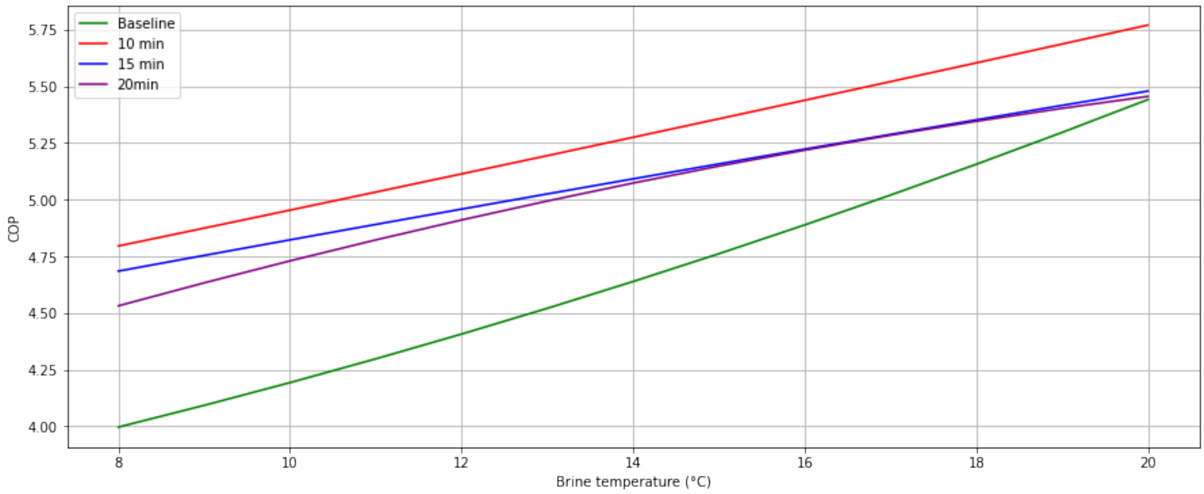

Figure 6.19: Comparison of different model fits at a return temperature of 28.5°C with heat pump data

At a lower return temperature of 28.5°C the models deviate more from the baseline model, especially at lower brine temperature. The maximum deviation for the 10 minute heating model is $8.0 * 10^{-}1$ while the deviation for the model with the heating times of 15 and 20 minutes are $6.9 * 10^{-1}$ and $5.4 * 10^{-1}$ respectively. The relative errors are 20%, 17% and 13% respectively.

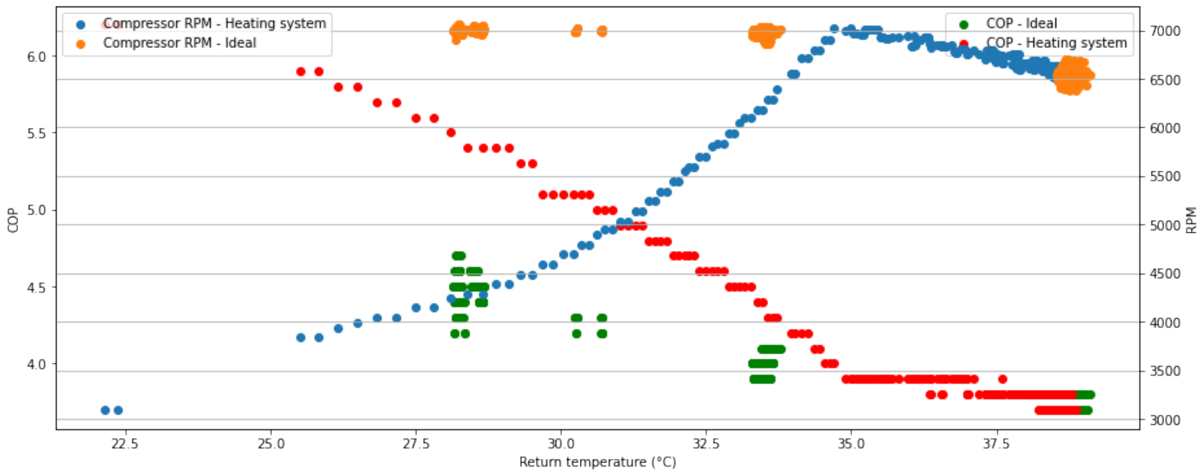

Figure 6.20: Comparison of collected data from the heat pump in ideal and non-ideal condition with brine temperature of 12.5°C

In Figure 6.20 the collected data from both the ideal and non-ideal case is shown. It shows that during the non steady state heating phase the heat pump reports a higher COP compared to a steady state situation. An observation is that in the case of the system that is heating up the compressor of the heat pump is still in the process of starting up before reaching its maximum RPM. It can also clearly be seen that due to the heating of the system less data is available at lower return temperatures for the model to fit on.

6.4 Discussion

With the models fitted to the collected data of the heat pump more accurate plannings can be made by the energy management services. With the external sensors a maximum error of 1.6% is achieved at a return temperature of 38.5°C. With the tested heat pump this is the steady state operation and therefore most important error. With the data from the heat pump the largest relative error is 4.8% with the non-ideal data compared to the data in ideal situations. The downside of the the heat pump data with this particular heat pump at least is the more optimistic report of the achieved COP, within the during the experiments observed regions of operation the COP reported by the heat pump was up to 15% higher.
The models can be used in the DEMKit simulation which currently assumes a fixed COP for a heat pump. With this model the effects of the outdoor conditions can be taken into account. When using the model in dEF-PI it can be used to describe a device of the adjustable type. It will then describe how much heat energy will be produced given the input energy. The description can also use the ramp up time to set certain conditions on use of the heat pump.
An implementation of such a model could for instance lead to more accurate predictions of the load profile. The generation of the load profile can now take the conditions into account and adapt the usage of the heat pump accordingly. It is possible to have changing conditions during the desired run time of the heat pump, making solving for a planning a hard problem. A possible solution is to simplify the behaviour over a certain window and use changing conditions to determine the final load profile.

7 CONCLUSION

This chapter will answer the stated research questions and present identified future work.

7.1 Research questions

In Chapter 1 the main research question is stated as follows:

How can a model of the behaviour of hybrid heating systems in residential building be made more accurate using machine learning?.

This question will be answered by first answering the sub-questions.

7.1.1 Sub-questions

What models exist for the components of the hybrid heating system?

In Section 2.1 different models for different parts of the hybrid heating system are discussed. For most parts of the hybrid heating system usable models are already available, except for the natural gas boiler where no usable model was found. Most models found are grey box models, these models use simplifications to make modelling simpler and computationally less complex. For example for the heat pump the design model was mentioned. This model models the complete physical behaviour of the heat pump, making it very complex. A simpler grey box model was also found which was deemed to be accurate enough.

What machine learning techniques exist to improve the accuracy of the model(s)?

In Section 2.3 different types of machine learning are discussed. Supervised learning is deemed the best approach for learning the behaviour of parts of the hybrid heating system seems both the input conditions and the resulting output conditions can be made available. Two machine learning methods are discussed that can be used in conjunction with existing models. Bootstrapping, where the problem of getting the required data is solved by training the machine learning model first on a synthetic dataset and hybrid modelling where machine learning is used to predict the error of the existing model in order to compensate for the error of the existing model.

What are the data requirements to sufficiently learn such a model using machine learning techniques?

In Chapter 4 the simulation study is used to determine how much data is needed in ideal conditions. To make a model under ideal conditions 200 samples at 9 different regions of operation of the heat pump are needed. The experiments from Chapter 5 are used to make an actual model and test model creation in non-ideal conditions.

How can such models be used in the planning for or controlling of the hybrid heating system?

In Chapter 4 it is mentioned that the current model for heat pumps in DEMKit assumes a fixed COP, this can be replaced by models that do take boundary conditions into account. Models can be used in dEF-PI to expose the possible energy flexibility. An implementation is future work to verify the effects.

7.1.2 Main question

How can a model of the behaviour of hybrid heating systems in residential building be made more accurate using machine learning?

Machine learning can be used to more accurately model hybrid heating systems in residential building by using it to improve existing models. This can be done by using an existing model to pre train the machine learning model or by using a machine learning model to correct a grey-box model. Since usable grey box model are needed for these techniques to start, it was opted to use machine learning techniques such as model fitting to improve an existing model by finding suitable parameters.

7.2 Future work

The following four points for future work have been identified:

- A method to determine the correct filtering parameters for different heating systems is needed. The parameters used are known to work in the current test setup, but are probably not suitable for other test setups or real heating system installations. Therefore a method is needed, to preferably automatically, determine the correct filtering parameters for a system.
- Experiments need to be performed with multiple different heat pumps. Experiments and modelling have been done on one heat pump, more experiments are needed to verify that learning the models also works on different heat pumps. Another consideration is the fact that a heat pump made for a ground source is used. The working principle for an air to water heat pump is the same, but different optimizations done by manufacturers may lead to different results.
- Collect data from a real hybrid heating system to verify creating models in a real system. In the current experiments non-ideal situations have been simulated by slowly heating the return temperature of the heating water. Data from real systems is needed to test learning model with actual data.
- Implement the machine learning with a control algorithm to study the effect of the learned models on generated plannings. The model can be used to make better plannings and make better predictions about the final load profile of the heat pump.

7.3 Discussion

During the experiments the return temperature of the heating water to the heat pump oscillated. This is caused by the fact that the system during the test is relatively small and the return temperature is actively controlled. These oscillations due to the control system are not present in real world heating systems, this might influence the results.

Exactly repeating experiments with the same brine supply temperature is difficult with the current experiment setup. The PI-controller used to control the brine temperature has a physical slider to set the setpoint of the brine temperature that is very sensitive to small adjustments, making selecting the same temperature multiple very difficult.

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