Development of a combined model predictive and adaptive Control Strategy for the Operation of a cold District Heating Network

Jens Ullmann[1], Harald Drück[1], Bernd Hafner[2]

[1] Institute for Building Energetics, Thermotechnology and Energy Storage, Stuttgart (Germany)

[2] Viessmann Climate Solutions SE, Allendorf (Germany)

Abstract

Cold district heating networks, also called 5th generation district heat and cold or 5GDHC, reduce thermal losses induced by high operating temperatures using relatively low temperatures for energy distribution and storage. In order to optimize the operation of such a network a model predictive control (MPC) including an adaptive control strategy is developed and investigated for controlling both, the heating and cooling supply. An ice store with a large thermal capacity of 75 MWh represents the main thermal energy store and acts as a heat source for decentralized heat pumps being part of the investigated network. Since the ice store is discharged during winter for heat supply and is charged during summer for cooling purposes it functions as a seasonal thermal energy store. Using model predictive controls over such a long period of time is not feasible due to computational restrictions. Hence an adaptive control part is proposed and implemented into an MPC for an optimum operation of the ice store throughout the year. First system simulation results for the optimum seasonal operation of the ice store are presented using a non-predictive control as well as a model-predictive control.

Keywords: model predictive control (MPC), adaptive control, 5th generation district heat and cold (5GDHC), anergy network, ice store, heat pump

1. Introduction

District heating networks represent a cost effective alternative for the heat supply with large fractions of renewable energies compared to decentralized heating systems installed in each single house. As standard district heating networks using high supply temperatures face the disadvantage of high heat losses, especially when comprising long distance piping, so-called 5th generation district heat and cold or 5GDHC reduces this disadvantage using low supply temperatures. In this contribution a 5GDHC network is being investigated using a large ice store with a water volume of 770 m³ as the main central and seasonal thermal energy store. As the main source for environmental and solar thermal energy a large so-called thermal sun-air-collector (Lott, S. 2022) field is connected to the network. The network includes decentralized heat pumps supplying small buffer heat (hot water) stores of the heating systems of the buildings with temperatures in the range of 25 to 45 °C. When required the heat pump also supports the cooling which is primarily performed using the ice store while regenerating it for the heating period. As the standard, non-predictive control for the CDHN a so-called state machine is being used selecting corresponding modes of operation depending on the ambient conditions and the system conditions. The heating system within the buildings is controlled using a simple stand-alone controller. In order to further optimize the control of the CDHN a model predictive control (MPC) strategy is developed in order to better utilize thermal capacities within the buildings and heat stores and hence reduce unnecessary thermal overheating or losses.

The temperatures within buildings are strongly depending on “disturbance factors” such as the solar irradiance, the ambient air temperature and internal heat sources such as e. g. the number of persons in a building. Regular heating controls take into account only current measurement data for controlling, such as the current ambient air temperature. Model predictive controls predict the future behavior of systems taking into account the predicted disturbance factors such as the forecasted weather conditions or predicted internal loads. Model predictive controls use these predictions in order to compute an optimal control input over a finite time period (prediction horizon) using system simulations. Control inputs are varied within system simulations and an optimum is being determined for a defined target function, such as e. g. a minimum of a cost function, while satisfaction of given system constraints is being ensured. That means the predicted disturbance factors are taken into account during the current control step. This can prevent

doi:10.18086/eurosun.2022.04.14 Available at http://proceedings.ises.org

heating systems from heating up rooms to a set point temperature, which are then finally overheated by in- or external disturbance factors such as solar irradiance shortly after. So, taking predictions into account during the current control step potentially reduces thermal loads and can also optimize the overall thermal energy supply. E. g. the thermal losses of heat stores can be reduced by only heating up the stores when heat supply is required using an MPC.

2. 5th generation district heat and cold (5GDHC)

A simplified scheme of the investigated 5GDHC network is shown in Fig. 1. Heat loss reduction is being achieved using relatively low network (orange hydraulics in Fig. 1) temperatures for heat distribution. These low temperatures are being realized using both, a centralized ice store and a centralized so-called thermal sun-air-collector field as the main thermal energy sources of the heating and cooling system. Thermal energy for heating is shifted from low temperature level supplied by the sources via the network to higher temperatures using decentralized heat pumps combined with buffer stores in each building (red hydraulics in Fig. 1). The thermal sun-air-collector field can either regenerate, or charge, the ice store (green hydraulics in Fig. 1) or directly supply the heat pumps as well (not shown in Fig. 1). Using the “mixed discharge mode” for heating (see table 1) the heat pumps are supplied by both, thermal energy from the thermal sun-air-collectors and the ice store at the same time using a temperature controlled mixer for keeping the heat pump evaporator supply temperature above a specific minimum temperature.

In addition to supplying heat the ice store can also be used for cooling the buildings during summer. This operation mode is called “natural cooling” (blue hydraulics in Fig. 1). If the cooling power provided by the ice store is not sufficient, cooling can be performed by the heat pump, this is called “active cooling” (not shown in Fig. 1). The excess heat produced during active cooling is emitted to the ambient via the thermal sun-air-collectors (required hydraulics not shown in Fig. 1). If the temperature of the ice store rises above a set point value, it can also be pre-conditioned. During pre-conditioning the ice store is actively discharged analog to the active cooling mode.

The design capacity of the ice store is related to the heating and cooling demand of the connected buildings. It is operated as a seasonal thermal energy store being cooled, or discharged, during the winter when energy for heating the buildings is extracted by the heat pumps and being regenerated, or charged, during the summer by cooling the buildings. The domestic hot water is generated exclusively by means of electric instantaneous water heaters (Lott, S. 2022).

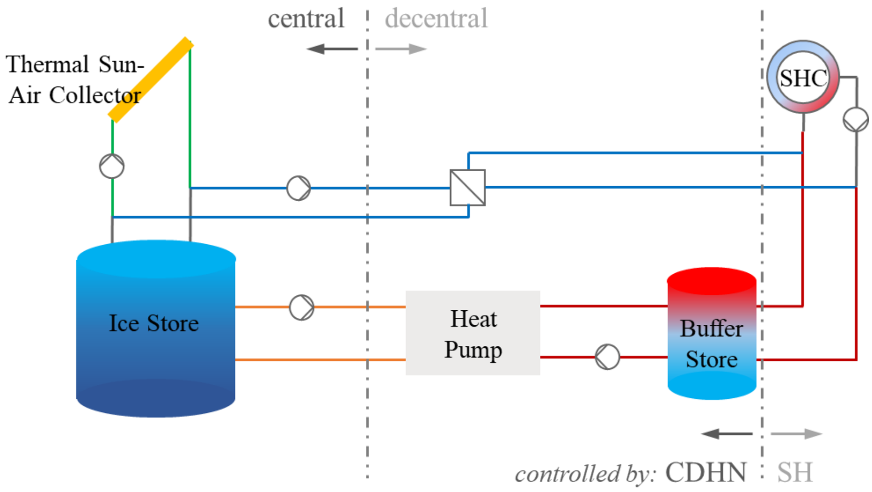

Fig. 1: Simplified hydraulic scheme of the investigated 5th generation district heat and cold (5GDHC) network for space heating and cooling (SHC), orange: low temperature heat supply, red: heating mode, blue: cooling mode, green: regeneration of ice store

The standard control of the investigated CDHN is implemented as a so-called state machine which selects one of 15 different so-called “modes of operation” depending on the actual system and boundary conditions. The state machine controls only the central part of the system as well as the heat pumps and buffer stores. The control of the underfloor space heating (SH) is controlled by a separate two-point controller. There are several operation modes for heating as the “mixed discharge mode” described above, cooling the building or conditioning the ice store. Each operation mode represents a specific set of actor settings controlling e. g. pumps or valves. The state machine is implemented in MATLAB® Simulink. In order to perform annual system simulations using the simulation software TRNSYS the Simulink model of the state machine is integrated as a co-simulation. At the beginning of each TRNSYS time step the state machine model is called returning the operation mode for the TRNSYS simulation to use as well as the setting for each network component or actor. The most important modes of operation are shown in table 1. As an example for the actor settings, the setting of the heat pumps is shown. Other actor settings besides on and off are possible e. g. related to the switching of valves. Considering the decentralized buildings, the TRNSYS building model Type 56 is used for system simulations and is controlled by a simple two-point controller.

Tab. 1: Modes of operation utilized by the state machine used as the standard controller for the CDHN; SoC: state of charge of ice store (see chapter 3.2 for definition)

Mode of operation	No.	Purpose	Heat pump operation
Discharge mode	2	Heating mode using the ice store as main heat source	On
Mixed discharge mode	3	Heating mode using both, ice store and absorber as heat sources	On
Absorber direct mode	4	Heating mode using the absorber as main heat source	On
Regeneration	5	Charge ice store using absorber as heat source	Off
Pre-conditioning (active)	-	Reduce SoC of ice store for natural cooling	On
Natural cooling	-	Coolin of building and charging ice store using building as heat source	Off
Active cooling	-	Cooling of building and use of heat pump and absorber to re-cool excess heat	On

3. Model predictive and adaptive control

As an alternative to the standard control based on actual system data a model predictive control (MPC) was implemented in order to take future system conditions into account when making actual control decisions. The time horizon considered by a model predictive control is usually between one to several days. The thermal capacity of the ice store is very large in comparison to the thermal capacity of the buildings. Hence an MPC is not suitable to optimize the control strategy for the operation of the ice store as a seasonal thermal energy store because the MPC would require very long computation times. Additionally, the MPC would require a full year weather forecast. For an optimum utilization the ice store has to be fully charged (heated up) at the beginning of winter and fully discharged or cooled down resulting in a maximum ice fraction at the beginning of the summer. This aim however can be contradictive to the aim of an MPC which is to minimize energy consumption and maximize energy gains from renewable sources such as the thermal sun-air-collectors. Hence in order to achieve an optimum seasonal performance of the entire heating and cooling system including the ice store an adaptive control strategy needs to be implemented separately and be connected to the MPC. This can be achieved using the so-called state of charge (SoC) of the ice store as the measurable key figure for its control (see Fig. 3). The state of charge by definition reaches its minimum value when the ice store is fully solid with a temperature of 0 °C. The maximum value is reached when the ice store is fully melted and its maximum operation temperature is reached (see definition in chapter 3.2). The permissible or optimum range of the state of charge for a given control step is calculated using the adaptive control strategy (described in chapter 3.2) and is then passed to the MPC as restrictive constraints as shown in Fig. 2. Restrictive constraints represent boundary values of system components that should not be exceeded. As an example of a restrictive constraint the room air temperatures should not drop below 20 °C during the heating season.

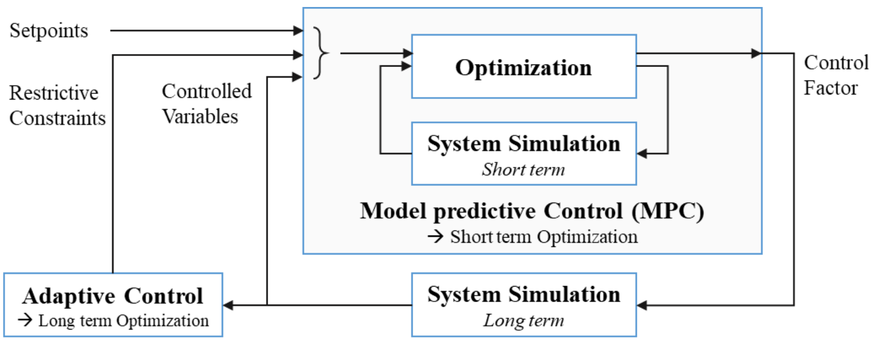

Fig. 2: Simplified procedure of system simulations using model predictive control (MPC) including an adaptive control for the optimum seasonal control of a 5GDHC network for heating and cooling with an integrated ice store.

System simulations using the MPC as system control are performed using TRNSYS including the building model Type 56. The MPC is implemented in MATLAB® using its genetic algorithm for optimization. As well as the standard control the MPC is integrated into the TRNSYS system simulation using the TRNSYS Type 155 (TRNSYS-MATLAB interface). The adaptive part of the control is implemented within MATLAB as an artificial neuronal network (ANN) returning the restrictive constraints in terms of the permissible state of charge of the ice store depending on the actual system and boundary conditions.

3.1. Model predictive control (MPC)

The MPC is used in order to calculate a course over time for the modes of operation which reduces the demand of electrical energy for the heat pumps and increases the amount of gained environmental thermal and solar energy. Therefore, optimization simulations are being performed using the system simulation model which is used for the overall or main (annual) system simulations as well. The optimization simulations are performed varying the course for the operation mode over the prediction horizon (approx. 1 to 3 days) and analyzing the simulation results in terms of the energy demand or gain while keeping the set point room air temperature within the buildings. The simulation results are evaluated using the so-called target function. The target function contains all energy flows or values to be taken into account for the control. Its result is a scalar calculated as shown exemplary in equation 1:

$$\min\begin{pmatrix} Z * \sum_{k=0}^{N_p}\left(\left(R * Q_{el,k}\right)\right) - Y * \sum_{k=0}^{N_p}\left(Q_{renewable,k}\right) \\ + X * \sum_{k=0}^{N_p}\left(Q_{\Delta T,k}^2\right) + W * \sum_{k=0}^{N_p}\left(Q_{HSloss,k}\right) + V * \sum_{k=0}^{N_p}\left(Q_{\Delta SoC,k}\right) \end{pmatrix} \qquad \text{(eq. 1)}$$

$Q_{el,k}$	electric energy consumption of heat pump [kWh]
$Q_{renewable,k}$	in- and output of renewable energy [kWh]
$Q_{\Delta T,k}$	difference between actual value and set point value of energy within room air zones [kWh]
$Q_{\Delta HSloss,k}$	heat losses of the decentralized heat stores [kWh]
$Q_{\Delta SoC,k}$	difference between actual value and set point value of energy within ice storage [kWh]
R, Z, Y, X, W, V	weighting factors
N_p	number of time steps within prediction horizon
k	timestep within prediction horizon

For computational reasons the target function is defined as a continuous function. Therefore, the restrictive restraints to the control such as the deviation from room air temperature or the deviation from the permissible state of charge of the ice store are considered within the target function like the other energy flows or values. Since the weighting factors determine the behavior of the MPC the energies considered for the restrictive constraints are potentiated in order to behave as de-facto restrictive constraints returning very high target function results when differing from set point values. The target function value is then minimized by the MATLAB genetic algorithm (GA). This is performed by repeating the optimization simulation with varying courses of operation modes until the result value of the target function reaches a minimum. The variation of the course of the operation mode is perform by the GA.

3.2. Adaptive control

As the ice store is used as a seasonal thermal energy store for heating and cooling the adaptive control has to ensure it is fully charged at the beginning of the heating season and fully discharged at the beginning of the cooling season. In order to control the seasonal course of the energy state of the ice store, the adaptive control uses the so-called "state of charge" (SoC) as the measurable key figure of the ice store. The state of charge is defined using two reference states: solid ice with a temperature of 0 °C is represented by a value of 0 or 0 % and liquid water with a temperature of 0 °C is represented by a value of 1 or 100 % (see Fig. 3, left). The maximum state of charge of the ice store within the investigated system reaches 125 % at its maximum temperature of 20 °C.

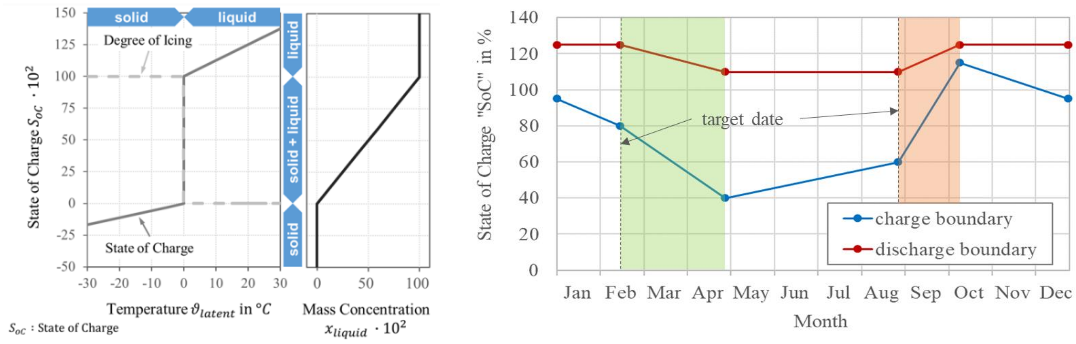

Fig. 3: Definition of the State of Charge or SoC (left) and seasonal course of the State of Charge with boundaries for charging (blue) and discharging (red) of the ice store throughout one year used in order to condition ice store for cooling (green area) and heating (red area) period.

To ensure for example that the ice store is sufficiently discharged at the beginning of the cooling period the adaptive control starts to discharge (or condition) the ice store towards the end of the heating season by using the discharge mode rather than the mixed discharge mode. The mixed discharge mode uses also the sun-air-collector and can result in higher supply temperatures and thus increase the heat pump performance. But accepting a lower heat pump performance in favor of a further discharged ice store can benefit the overall seasonal performance of the system. This is due to higher thermal ice store capacity available as a heat sink for natural cooling. This can very well reduce the amount of active cooling required during the cooling season.

The conditioning of the ice store is activated by the control using the so-called charge (blue line in Fig.3, right) and discharge (red line in Fig.3, right) boundaries as trigger-signals. During preparation for the cooling period (green area in Fig. 3, right) the control keeps the SoC of the ice store below the charge boundary. The charge boundary defines the start or target date and duration of the ice store conditioning. The duration required in order to discharge or charge the ice store is depending on the ratio of the total heat capacity of the ice store to the total heating (or cooling) demand. If the ice store has a high capacity in relation to the heating or cooling demand of the entire system, the target date needs to be shifted to an earlier date because the required duration will extend.

In order to determine the best target date and appropriate duration for the ice store conditioning an artificial neuronal network (ANN) will be trained with data resulting from a parametric simulation study. The parametric simulation study will be performed using TRNSYS system simulations using the standard state machine control varying the ratio of heating demand to ice store capacity as well as the time and duration for charging / discharging (or conditioning) of the ice store. The in- and output data for training the ANN is shown in Fig. 4. As a result, the ANN is trained to return the target date and duration for charging and discharging. The MPC can than retrieve target date and duration from the ANN using the input data at an actual control step.

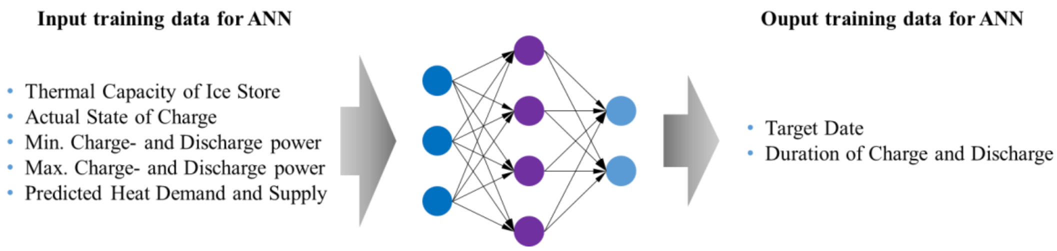

Fig. 4: Training data for artificial neuronal network (ANN) in order to return permissible charge and discharge boundaries for the model predictive control (MPC)

4. Results

First results of the system simulations using the standard state machine control are presented in chapter 4.1. The results comprise exemplary energy quantities required or delivered from the system components as well as exemplary seasonal courses of the state of charge depending on different ratios between heating demand and ice store capacity. The results also show the effect of shifting the charge boundary for the ice store to an earlier target date.

First results concerning the MPC are shown in chapter 4.2. The influence of the building initialization for the optimization simulation is described as well as the general functionality of the MPC and its capability to shift loads and e.g. preheat the buffer store already before the heat demand increases (see Fig. 9). It is also shown that further adaption of the target function weighting factors needs to be performed for the MPC to reduce the electrical energy consumption of the heat pumps though.

The domestic hot water is generated exclusively by means of electric instantaneous water heaters and is therefore not taken into account in the system simulation.

4.1. 5th generation district heat and cold (5GDHC)

First annual system simulations were performed using the standard state machine control. The overall heat demand of the modeled building is 253 MWh/a and the overall cooling demand is 58 MWh/a. The effective usable thermal capacity of the ice store is 75 MWh resulting in a ratio of heat demand to ice store capacity of 3.4. Thermal losses of the distribution network are not considered within this simulation. Because the network temperatures are between -10 °C and 20 °C, the network is estimated to loose very little thermal energy or even gain thermal energy from the surrounding soil. First exemplary results of the annual system simulation are shown in Fig. 5. The narrow columns represent a thermal energy gain into the overall system when being positive and a thermal energy loss from the overall system when being negative (thermal energy loss from thermal sun-air-collector to ambient for cooling purposes during July and August). Concerning the broad columns positive values represent losses or demands such as space heating demand. Negative values represent thermal gains to the system. The ice store's change in internal thermal energy is represented by a broad column as well. A negative value represents a discharging of the ice store and a positive one represents a charging of the ice store.

The seasonal performance factor of the heat pump within this exemplary result is 4.6 regarding heating supply and 3.6 regarding cooling supply. The seasonal performance factor for heating is defined as the ration of heating energy delivered to the building divided by the demand of electrical heat pump energy during the heating season. The seasonal performance factor for cooling is defined as the ratio of delivered cooling energy to the building divided by the electric energy demand of the heat pump during active cooling mode or ice store conditioning.

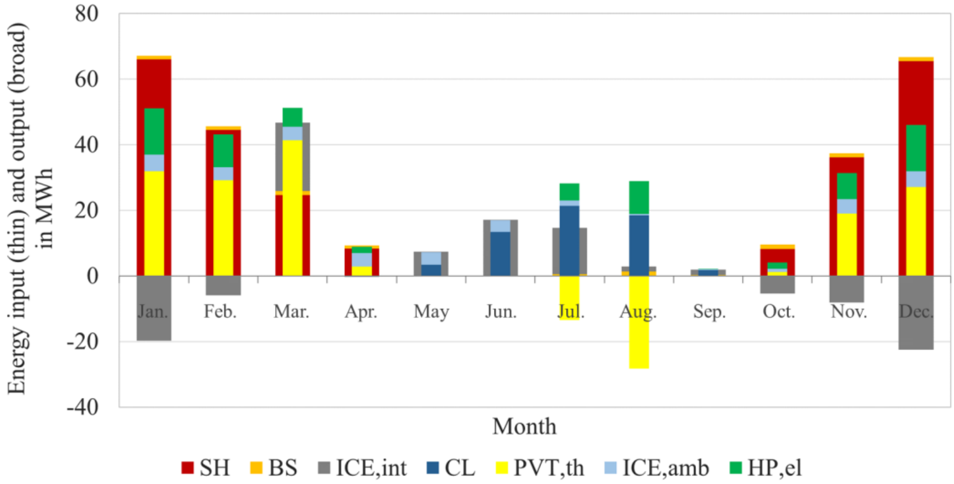

Fig. 5: Energy input (positive inner thin column) and output (positive outer broad column); SH: space heating, BS: buffer stores, ICE: ice store (int: internal energy change, amb: thermal environmental gains), CL: cooling PVT,th: thermal gain from sun-air-collectors, HP,el.: external electrical energy of heat pumps.

The influence of the ratio between heat demand and ice store capacity as well as the target date for the ice store conditioning on the seasonal course of the state of charge is shown in Fig. 6.

The seasonal course of the SoC resulting from the simulation results shown in Fig. 5 for a ratio of heat demand to ice store capacity of 3.4, is represented by the solid blue line in Fig. 6. In comparison the solid red line shows the seasonal course of the SoC for a ratio of heat demand to ice store capacity of 1.7. The lower related heating and cooling demand results in a much slower and lower amplitude of discharging and charging of the ice store.

Fig. 6 also shows the seasonal course of the SoC for two different charging boundaries; solid: CB1 and dotted: CB2 green line, for a heat demand to ice store capacity ratio of 3.4. Compared to CB1, the ice store is discharged earlier using CB2. Since the ice store is only discharged using heating modes during the heating season the ice store can be discharged further using CB2 because the buildings heating demand is higher during this earlier time of the year. This can potentially reduce the overall electrical energy demand for the heat pumps as the effect on the seasonal performance factor for heating is very low, but the ratio of cooling demand and electrical energy for cooling rises from 3.8 to 5.6 when using CB2.

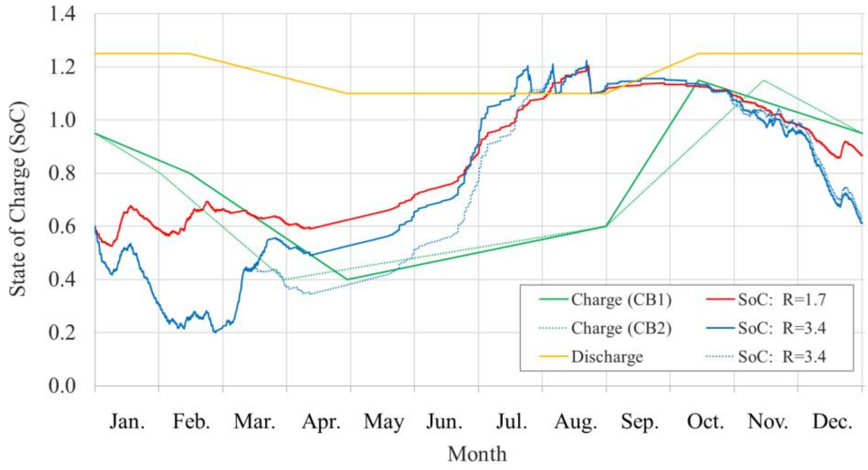

Fig. 6: Seasonal course of the state of charge (SoC) for two different ratios (R) of heat demand to ice store capacity and two different charge boundaries (CB1 and CB2) for R = 3.4.

4.2. Model predictive control (MPC)

Using the software TRNSYS it is not possible to pause a running system simulation and start a new simulation using the actual state of the paused simulation as the initialization state of the new simulation. So in order to perform optimization simulations by the MPC new system simulations have to be performed. These new system simulations have to be initialized according to the actual state of the main system simulation at the beginning of the present prediction horizon. This is possible for most used component models or TRNSYS types respectively. Concerning the initialization of TRNSYS Type 56 (building model) the room air temperatures can be initialized, but the temperatures of the wall structure cannot. This results in high deviations between room air temperatures during optimization simulation and room air temperatures during the main simulation. This deviation is represented in Fig 7 by the difference between the room temperature of the main simulation and the room temperature of the optimization simulation without "settling time".

As no alternative building model is available, a so-called transient or settling time was used as an alternative for quasi-initialization. Thus, the optimization simulation starts at the beginning of the control horizon minus the settling time. During the settling time, the previously determined operation mode course of the main simulation is used. As a compromise, the use of a 48 hour settling time is considered to be a reasonable compromise between simulation effort and the quality of the initialization of the optimization simulation.

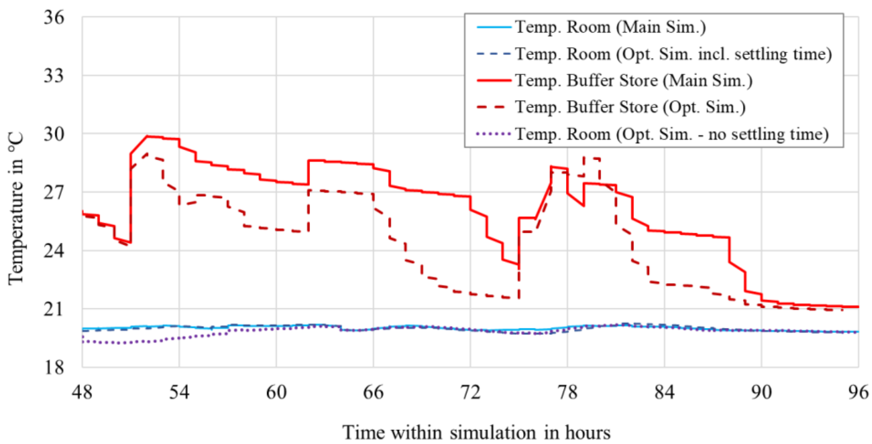

Fig. 7: Comparison between room air temperature and buffer store temperature during main simulation and optimization simulation using "settling time" as well as no settling time for room air temperature.

First exemplary results of annual system simulations using a MPC are shown in Fig 8 in terms of the room air temperatures as well as the ambient and heat store temperatures for the heating season. Additionally, the course of the operation mode being relevant for heating is shown on the right axis. These first results only show a basic functionality as the room air temperatures 1 to 3 demonstrate that the MPC is capable of keeping the set point temperature of 20 °C for most of the heating season. Temperature drops of rooms 2 and 3 at the end of the heating season are probably caused by a high temperature rise within the room 1. The difference between actual and set air temperature of all 3 rooms is first added up and later evaluated by the target function using weighting factors within this simulation. It is estimated that treating all rooms separately by the target function will solve this unwanted behavior.

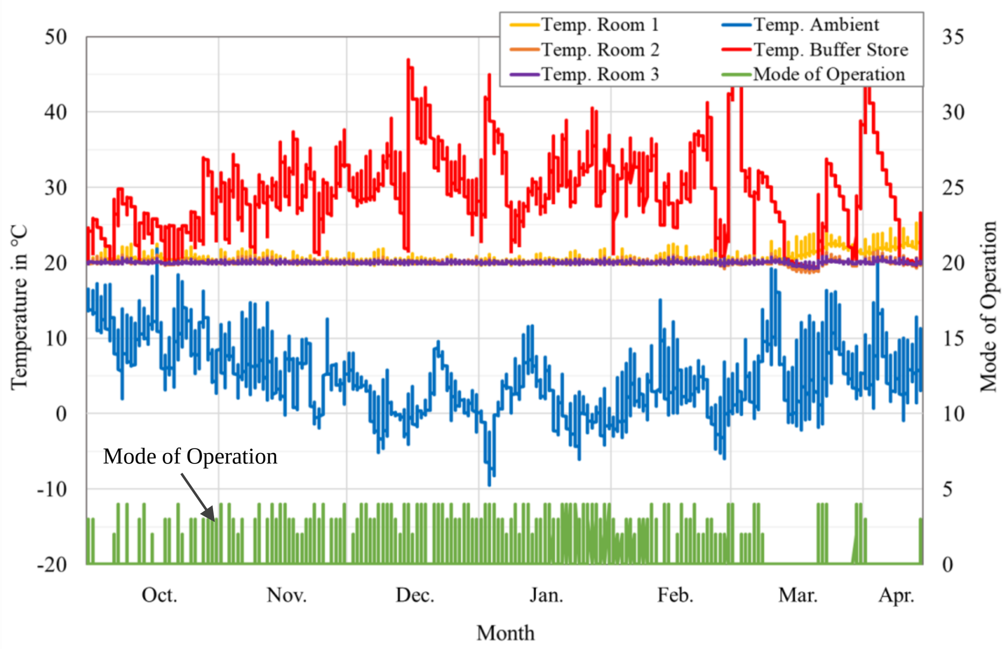

Fig. 8: Exemplarily results for room, ambient and heat store temperatures determined using system simulations applying model-predictive control (MPC) as well as the mode of operation (see table 1) during heating season (October to April).

The electrical energy demand of the heat pumps is not reduced by the MPC while keeping the same comfort level as using the standard state machine control so far. It is estimated that further adaption of the target function parameters will show a distinct increase in the performance of the MPC compared to the actual results.

The results show that the buffer store temperature mainly ranges between 25°C and 35°C during winter months and only occasionally reaches 50°C. The buffer store temperature shows that the buffer store is only heated up when increased demand is predicted. In Fig. 9 this behavior can be well observed on day 5 when the buffer store is heated up to above 40 °C during the first half of the day but the ambient temperature drops not before the second half. The model-predictive control therefore generally exploits the flexibility of the system to shift loads.

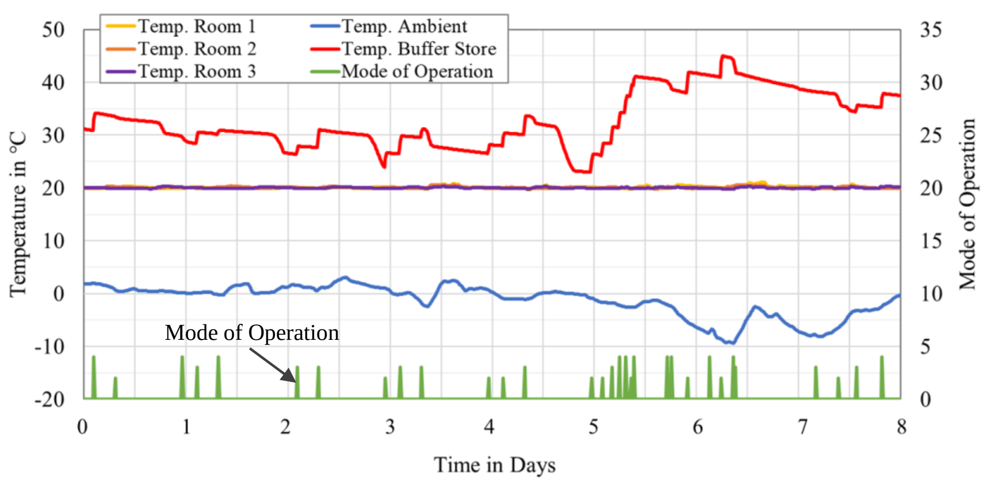

Fig. 9: Load shifting effect of the model-predictive control (MPC) in terms of room, ambient and buffer store temperatures determined using system simulations applying MPC as well as the mode of operation during one week of heating season (see table 1).

Further system simulations have shown that using the same weighting factors of the target function for cooling that are used for heating does not result in good control results for cooling in terms of room air temperature not being kept under set point temperature. Thus different weighting factors will be determined for heating and cooling.

At present the disturbance factors are predicted exactly for optimization, meaning the same disturbance factors (e.g. weather or thermal gains) are used for main simulation and for optimization simulations. Furthermore, the MPC has to be expanded by rules handing large deviations between actual and predicted disturbance factors.

The use of the system model as a functional mockup unit (FMU) using the functional mockup interface (FMI) was no option since TRNSYS version 18 was used and only one tool was available performing FMU model conversion for TRNSYS version 17. Co-Simulation using FMI in general could be an option but would does not solve the problem of initializing building model walls of TRNSYS Type 56.

5. Conclusion and outlook

The introduced 5GDHC network for heating and cooling was modeled using the simulation software TRNSYS for system modeling and MATLB® SIMULINK for modeling the standard state machine as well as the model predictive control. First results of the system simulation using the standard control show high seasonal performance factors (SPF) of the heat pumps of well above 4 during heating season. The seasonal course of the state of charge (SoC) of the ice store depends on the ratio of heating and cooling demand to the thermal capacity of the ice store. The variation of the target date of the ice store conditioning strongly influences the seasonal course of the SoC and hence the heating or cooling capacity of the ice store at the beginning of the heating or cooling period and the SPF of the heat pumps accordingly. In order to determine the control parameters for an optimum seasonal course of the SoC a parameter study will be performed. The parameter study results will be used to train an artificial neuronal network (ANN). The trained ANN can then supply the MPC with optimized control parameters for the SoC boundaries being permissible at the current control step.

In order to further optimize the CDHN control a concept has been proposed to combine a model predictive control and an adaptive control strategy in order to further optimize the operation of the CDHN. The aims of both, the MPC used for short term optimization can be contradictive to the long term adaptive control part used for conditioning of the ice store for the heating or cooling period. Thus the adaptive control strategy overrules the MPC delivering permissible boundary conditions for the state of charge of the ice store at any given time during the year. The permissible boundary conditions are delivered by the ANN that has been trained with the result of the parameter study and returning the control parameters resulting in the optimum seasonal course of the SoC as described above. First results of system simulations presented in this paper show that the MPC is generally functional during the heating season. Room air temperatures are kept above set point values and load shifting can be observed. The weighting factors of the MPC’s target function require further adaption in order to achieve an overall reduction in electrical energy demand of the heat pumps. It is estimated that further work on the parametric values of the target function will result in a reduction of electrical energy demand.

6. Acknowledgments

The activities of IGTE and Viessmann described in this paper are being supported by the German Federal Ministry for Economic Affairs and Climate Action (BMWK) based on a decision of the German Bundestag by Projektträger Jülich (PtJ) within the project ‘Development of integrated solar supply concepts for climate-neutral buildings for the “city of the future” (Sol4City)’ under grant numbers 03ETW019 A\B. The authors gratefully acknowledge this support and carry the full responsibility for the content of this publication.

7. References

Dittmar, R., Pfeiffer, B.-M., 2004. Modellbasierte Prädiktive Regelung. De Gruyter, ISBN-13: 978- 3486275230.

JUNGWIRTH, J. Lastmanagement in Gebäuden. München, Technische Universität München, Diss., 2015. München, 2015, urn:nbn:de:bvb:91-diss-20150128-1221398-0-6.

Prívara, S., Široký, J., Ferkl, L., Cigler J., 2011. Model predictive control of a building heating system: the first experience: Elsevier; Energy and Buildings 43 (2–3) (2011), pp. 564–572.

Zakulaa, T., Armstrong, P.R., Norford, L., 2014. Modeling environment for model predictive control of buildings. Elsevier, Energy and Buildings 85 (2014), pp. 549–559.

WIMMER, R.W. Regelung einer Wärmepumpenanlage mit Model Predictive Control, 2004, IMRT Press c/o Institut für Mess- und Regeltechnik, ETH Zentrum, https://doi.org/10.3929/ethz-a-004904606.

SOLAR ENERGY LABORATORY, UNIVERSITY OF WISCONSIN-MADISON. TRNSYS 16 Nutzerhandbuch. Getting started. Wisconsin.

MathWorks®, 2022. Global Optimization Toolbox Documentation (r2022a). Retrieved May 03, 2022 from https://de.mathworks.com/help/gads/.

Lott, S., Fischer, S., Drück, H., Hafner, B., 2022. Quasi-Dynamic Testing of Thermal Sun-Air-Collectors and Numerical Simulations of a Cold District Heating Network, EuroSun 2022 Conference Proceedings (to be published).