Predictive Rule-Based Control Strategy for Optimizing the Operation of Solar District Heating Plants

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Abstract

For large-scale solar district heating plants, there is often the choice either to provide solar heat to on-site consumers or to feed it into a district heating grid. Plant operators get a better price if they sell the heat to the on-site consumers instead of to the grid. Current state-of-the-art control strategies typically decide on the basis of temperature thresholds on the mode of operation: if the heat should be stored for selling it later to the consumers or it should be fed into the district heating grid. Such strategies, however, can lead to frequent rapid mode switches throughout the day and sometimes the storage is loaded insufficiently, so that heat has to be bought back from the grid. If, the other way around, the storage tank is loaded to a higher extent than needed, this leads to increased storage losses. To address these problems, this contribution presents a predictive rule-based control strategy that takes information on the predicted future conditions into account. By doing so, it ensures that the storage is only loaded to an extend which can be sold to the on-site consumers, thus reducing storage losses, increasing efficiency and maximizing monetary profit for heat sales.

Keywords: profit optimization, predictive control strategy, rule-based control, solar district heating

1. Introduction

It is known since decades that the basis of our energy system has to be transformed from fossil fuels to renewable energy, and, with increasing impact of climate change, this need has become painfully obvious, (IPCC, 2021). Often, strategies for such a change focus on the electric sector, regarding all demands other demands, including heating, just as contributions to the load profile. But **#heatIsHalf**: Process heat and space heating are responsible for almost 50 % of the world end energy consumption, (REN21, 2023). At the same time, the electric grid is already often overstressed by current demand and fluctuating production, (Ghavi, 2024). Here, thermal solutions that do not rely heavily on electric energy can offer a solution.

Heating grids are particularly useful and versatile for providing renewable heat to households, and large-scale solar plants can be an important source of heat, in particular when combined with large-scale thermal storage (up to seasonal storage). Thus, optimal operation of such systems is an important task, but, as it is often the case with fluctuating renewable energy, a challenging one.

Beyond just the technical aspects, renewable energy systems are embedded in an economic framework as well, and at the moment, they have to compete with other energy sources that create enormous damage (called *negative externals* in economy) and are nevertheless often still subsidized by governments to a larger extent (though often less visible) than renewables, (EEA, 2023). This is a rather unfair competition, with emission trading systems and carbon taxes only slowly and slightly levelling the field. A more reasonable economic system would not require necessary measures for our survival to provide attractive interest rates for investors as well – but, at the moment, we have to live with what we have. Thus, also the economic performance of renewable energy systems has to be optimized as good as possible when designing operation strategies.

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2. Description of the System and the Challenge

Large-scale solar district heating (SDH) plants, as sketched in Figure 1, often consist of a large-scale solar thermal field, a storage, on-site consumers and a direct connection to a local district heating grid (DHG).

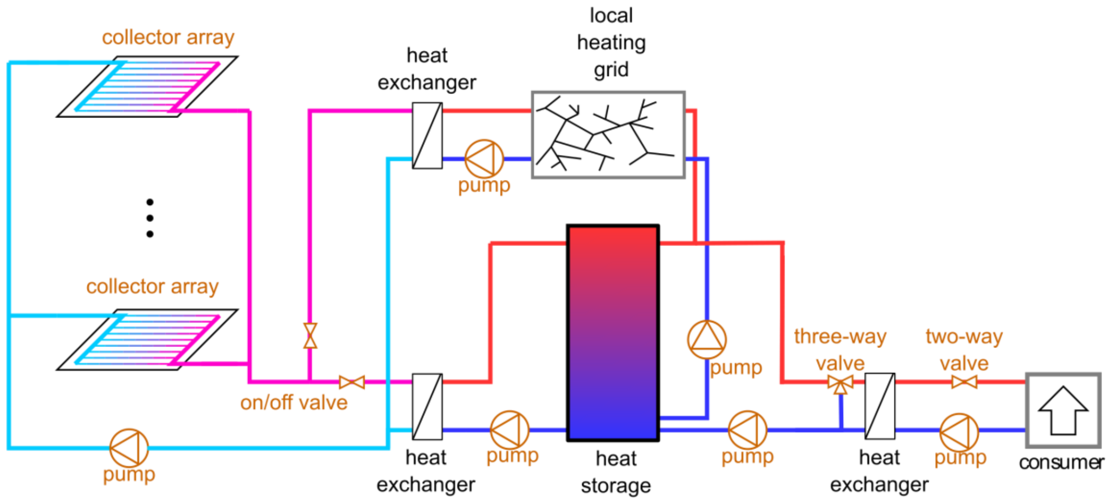

Figure 1: Schematic representation of a typical large-scale solar thermal plant as investigated in this contribution.

Via the connection to the DHG, the SDH plant can generate additional profit by feeding the solar heat into the grid in case the production exceeds the needs of the on-site consumers. Vice-versa, in case there is not enough solar heat available, the grid acts as auxiliary heating and additional heat can be purchased to avoid comfort losses for the on-site consumers. Therefore, simply speaking, this kind of SDH plants can run in two general operation modes:

- **`HSt`**: transfer the solar heat to the local heat storage in order to sell it to the on-site consumers.
- **`DHG`:** transfer the solar heat to the district heating grid to directly generate profit.

In order to decide on the operation mode, state-of-the-art high-level control strategies are based on simple state machines considering the loading state of the storage and the actual ambient temperature. The idea is that in case the ambient temperature falls below a certain threshold, the storage is loaded to a higher extend and vice versa. This strategy takes into account the fact that the heat demand is correlated with the ambient temperature; it also tries to keep the heated volume in the storage as small as reasonably possible.

While such strategies are simple and transparent, they can lead to *multiple mode switches*, which have a negative effect on the system, and to *profit losses* by a suboptimal storage management. For example, profit losses can occur for a sunny day followed by a cool night. Then a lot of solar heat is fed into DHG over the day since the ambient temperature is relatively high and the storage gets only partially loaded. During night, that heat has to be bought back from the DHG at a higher price in order to supply the consumers. Tackling this issue by loading the storage to a higher extend as default would in general lead to higher storage losses, which again reduce the monetary profit.

3. A Predictive Algorithm

A way to deal with issues of multiple mode switches and profit losses is to use a control strategy that also considers the *expected* solar heat output and heat demand of the consumers, (Gölles+, 2021). Such predictive control strategies can be based on mathematical optimization, with an optimization problem often formulated as a mixed-integer linear program, (Moser+, 2020). Such optimization-based approaches are both powerful and versatile, and for operation of trans-sectorial energy systems beyond a certain level of complexity, they are usually the best choice. This power, however, comes at a price, both the one-time effort of setting up the optimization problem and the computational resources required to repeatedly solve it. In addition, optimization-based decisions often lack explainability. For rather simple systems like the SDH-DHG interaction, a rule-based predictive approach can provide reasonable performance and transparent decisions, while requiring significantly less effort.

For this special case, we present such an algorithm, based on (Unterberger, 2021). The goal of the algorithm is to decide when to run in `mode = HSt` or `mode = DHG`. The number of mode switches is to be minimized, while the storage is managed in a way such so that

- the on-site demand can be satisfied with solar heat, if possible,
- no excess heat is sold to the DHG and has to be bought back later for a higher price,
- only heat really required is stored, in order to minimized storage losses.

In order to determine the optimal operation schedule, the following steps are executed for a forecast horizon of 24 hours (and periodically repeated to update the strategy in order to incorporate new information):

Step 1 – calculate available heat in the storage: The storage is separated in multiple volume elements (e.g. 100), each with a certain temperature. The temperature of the elements is obtained from a cubic interpolation between the measurements of the temperature sensors in the storage. The available heat in the storage is calculated with respect to a reference temperature for which the heat is still useful for the connected consumers.

Step 2 – calculate the forecasts for the expected solar heat output and heat demand: The expected solar heat output and the heat demand is calculated by using forecasting methods. Advanced methods, e.g. adaptive linear regression or machine learning models based on Bayesian regression or Recurrent Neural Networks, (Murphy, 2022), continuously adapt to latest measurements and take seasonal changes into account. The expected solar heat output is counted positive while the expected heat demand is counted negative.

Step 3 – set default mode to `HSt`: For all future time steps before sunrise and after sunset, the `optimal_MODE` array is set `HSt` for the respective indices. By doing so, a day is started and finished by loading the storage in order to use the heat for the on-site consumers at the earliest or latest time possible, which increases local consumption.

Step 4 – determine optimal time for switching to mode `DHG`: Ideally, during each day, there is only one transition from mode `HSt` to `DHG` and back. A supply-consumers-first policy is enforced by the algorithm, as the heat is only fed into the DHG in the case the demand of the on-site consumers is fully satisfied. The optimal switching time is determined in three sub-steps:

- First, the currently available heat is used to iteratively reduce the expected effective heat demand (i.a. predicted demand minus demand satisfied by the operation strategy) along the forecast horizon, by assuming to fully cover it by heat from the storage. This ensures that the storage is emptied quickly (reducing storages losses) and guarantees that no overloading of the storage occurs, as the storage is typically designed to store the heat of a full day of sunshine. If the current heat in the storage is sufficient to satisfy the heat demand for the next 24 h, all available solar heat can be fed into the DHG. Otherwise, it has to be decided along the forecast horizon at which time the solar heat should be fed into the storage or into the DHG in order to fully satisfy the demand.
- Second, the cumulative sum of the predicted demand, reduced by the heat from the storage, along the forecast horizon is calculated, in order find times where this effective demand is negative and therefore not fully satisfied. The index `idx` of the first element where the cumulative sum is negative determines the time for which part of the solar heat must be fed into the storage beforehand, in order to maximize self-consumption and minimize heat purchases from the grid. In order to find the best possible time to feed solar heat into the storage, it is evaluated if `idx` corresponds to a time between sunrise and sunset: In case the demand occurs after sunrise but before sunset, the first available solar heat after sunrise is used to reduce the effective heat demand. In case the demand occurs after sunset, the latest available solar heat before sunset is used to reduce the effective demand. This is done in order to reduce mode switches by extending the mode for feeding heat into the storage at the beginning or end of a day. The corresponding elements of the schedule are set to `HSt`.
- After this step, the remaining cumulative sum is re-calculated until it no longer shows any negative heat demand and the schedule is set to `DHG` for the remaining time.

Step 5 – apply mode to the system: Finally, the current mode of operation of the plant is set to the first value of the schedule.

The Algorithm is illustrated in Figure 2, and an example of its application is shown in Figure 3 and Figure 4.

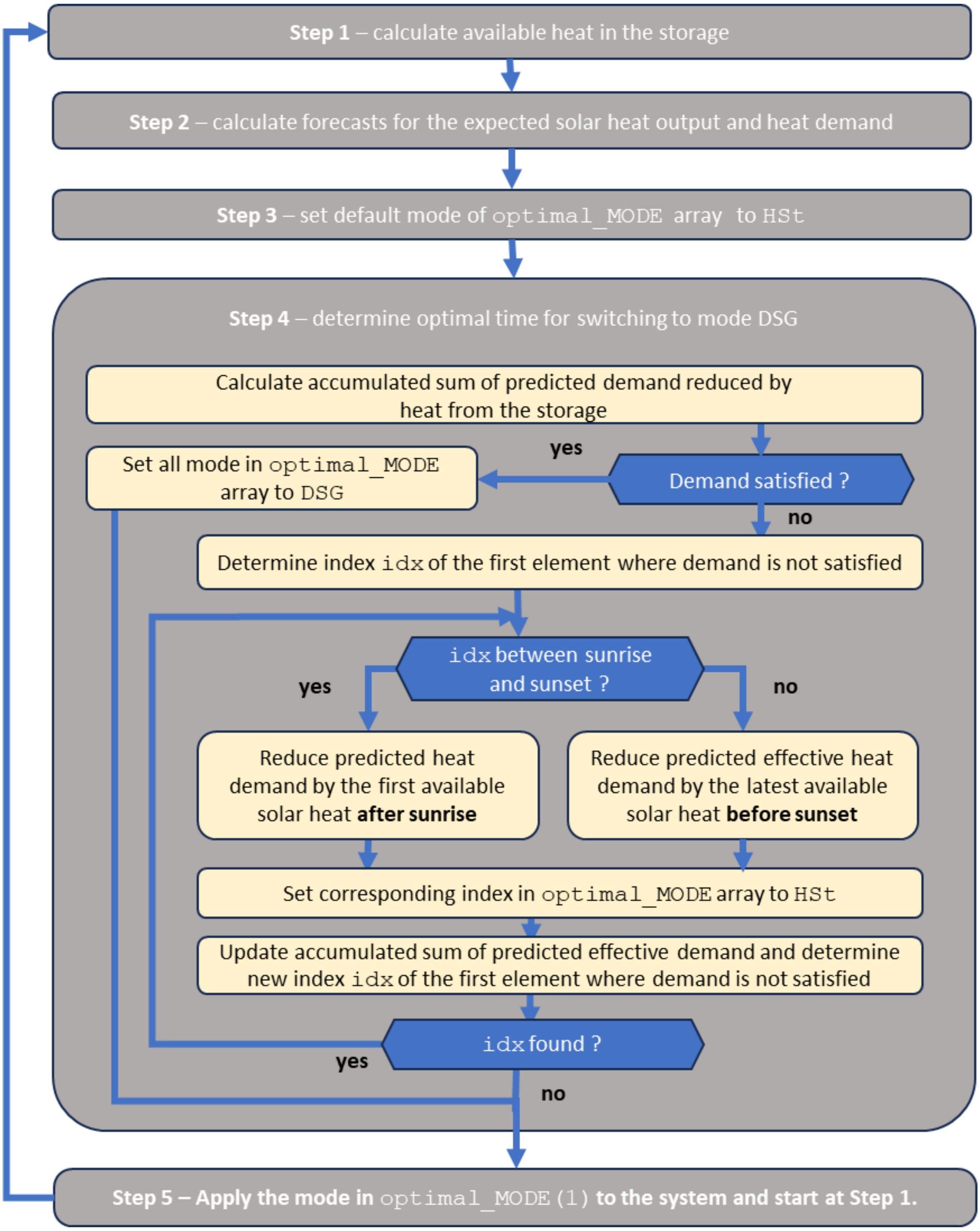

Figure 2: Flow-chart for the proposed algorithm, where the mode values `HSt` or `DHG` are stored in an array `optimal_MODE`

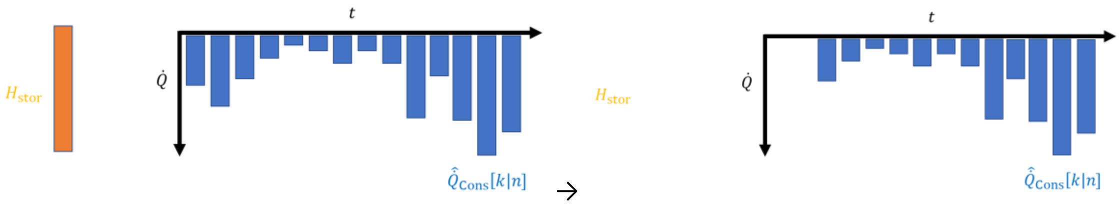

Figure 3: Example for the action of the proposed algorithm, Step 3 (all heat from storage is used to reduce the effective consumption as early as possible, in order to reduce storage losses)

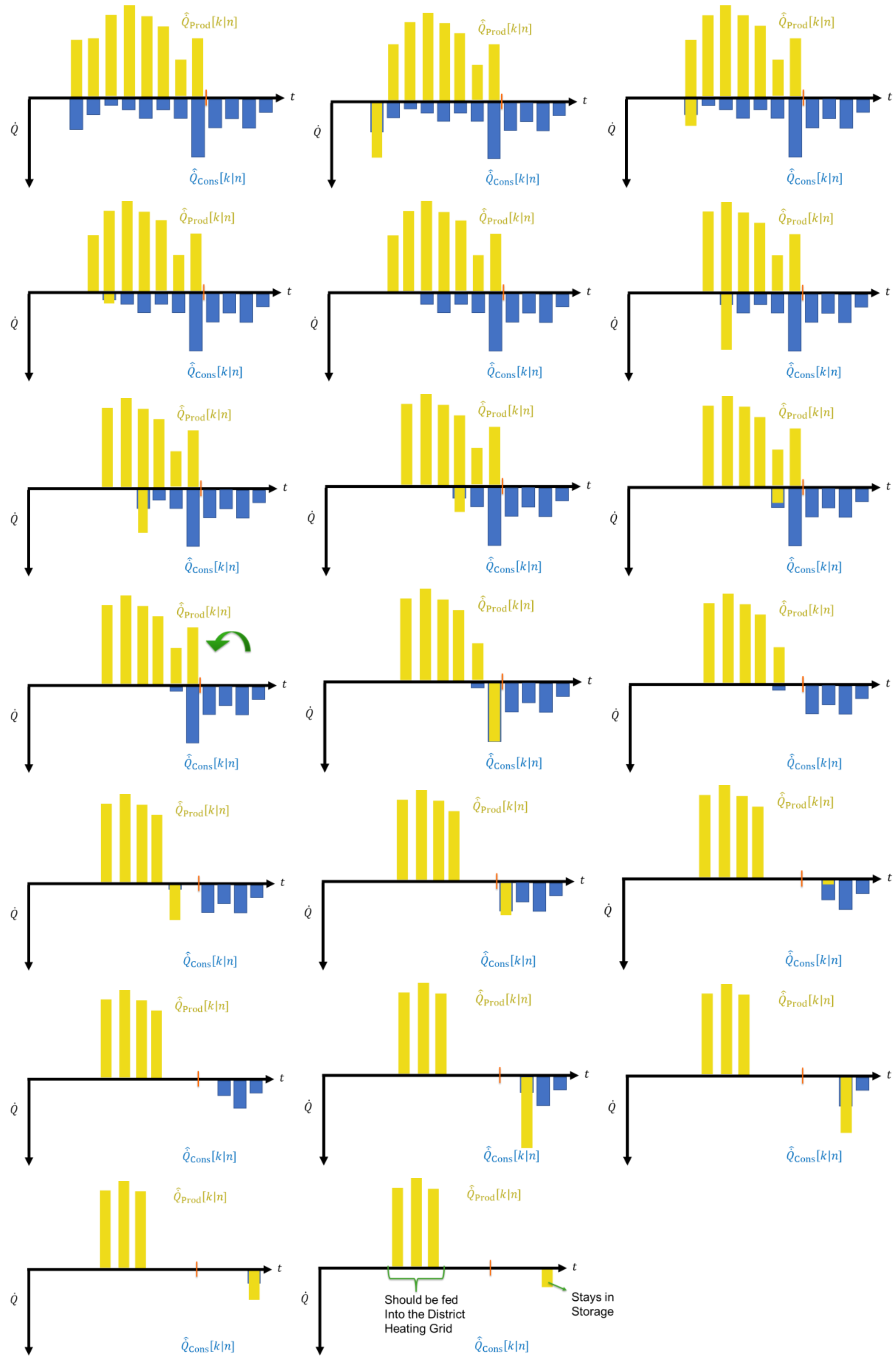

Figure 4: Example for the action of the proposed algorithm, Step 4 (predicted production $\hat{\dot{Q}}_{\mathrm{Prod}}$ is matched against predictive consumption, in order to reduce the effective consumption $\hat{\dot{Q}}_{\mathrm{Cons}}$)

4. Methodology for Validation of the Algorithm in a Simulation Study

A state-of-the-art control strategy, as described in Sec. 2, has been compared to one described in Sec. 3 in simulation studies for a representative week during transition time (the period between summer and winter), which is typically most sensitive to the quality of the control strategy, in particular the storage management. The study, described in more detail in (Unterberger, 2021), is based on data for a solar plant located in the south of Austria. The ambient conditions for the investigated week, regarding solar radiation on the collector surface I_g' and the ambient temperature T_{amb} are shown in Figure 5.

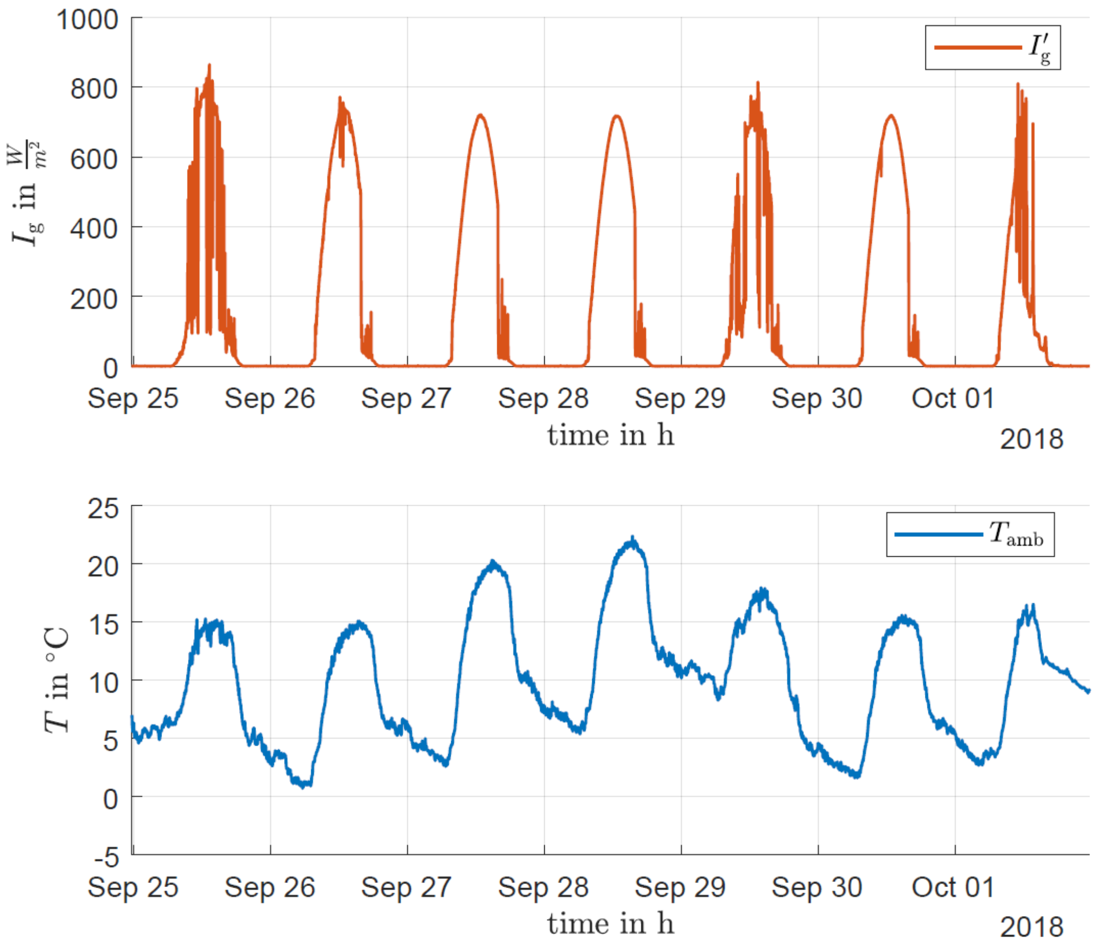

Figure 5: Ambient conditions, solar radiation I_g' on the collector surface and ambient temperature T_{amb}, for a representative week in the transition period measured on site and used as input for the simulation studies.

The overall simulation model describing the plant has been implemented in MATLAB®/Simulink for a simulation step size of 1 min. For the different components like collector field, heat exchanger and storage, simulation-oriented models based on partial differential equations were used. The models for the different components had been verified with measurement data from the real plant. For the components of the hydraulic heat distribution system such as pumps and valves only static models had been used since their dynamic characteristics play a minor role for a step size of 1 min. These models had been parametrized by information from the data sheet as well as by measurement data from the plant.

For the low-level controllers, PI-Controllers have been used which have been extended by a static feedforward control in case of the collector field as it is state-of-the-art in such systems. Furthermore, switching between modes was assumed to take 1 minute until heat can be supplied again, which is based on the experience with the plant.

For the forecast of the future solar heat $\hat{\dot{Q}}_{\mathrm{Sol}}$ and the predicted heat demand $\hat{\dot{Q}}_{\mathrm{Con}}$, the adaptive forecasting methods from (Nigitz, 2019) and (Unterberger$^+$, 2021) have been used with a forecast horizon of 1 day and with a sampling time of 15 min, considering the last past weeks of measurement for the parameterization.

For the state-of-the-art high-level controller that only considers the current state of the system, the parameters haven been taken from the real plant controller, which had been optimized by the plant operator for years leading to thresholds of $T_{\mathrm{HSt,warm}}$ = 15 °C and $T_{\mathrm{HSt,load,OFF}}$ = 72 °C. For the predictive high-level controller, additionally considering future information, the only parameter, the reference temperature for the evaluation of the heat in the storage (lowest usable temperature), was set to T_{ref} = 55 °C.

5. Results of Validation

The results for the state-of-the-art controller, only considering the current state of the system, are shown in Figure 6 and for the predictive high-level controller additionally considering future information in Figure 7. In each of the figures, the upper graph shows the different energy flows with $\dot{Q}_{\mathrm{Con}}$ as the heat demand of the on-site consumers, $\dot{Q}_{\mathrm{Sol,HSt}}$ as the solar heat fed into the heat storage, $\dot{Q}_{\mathrm{Sol,DHG}}$ as the solar heat fed into the DHG and $\dot{Q}_{\mathrm{Aux}}$ as the heat provided to the storage by DHG, which acts as an auxiliary heating system.

Additionally, in Figure 7 the predicted heat demand $\hat{\dot{Q}}_{\mathrm{Con}}$ and the predicted solar heat $\hat{\dot{Q}}_{\mathrm{Sol}}$ are shown as black dotted lines. The middle graph of each figure shows the mode, with `mode` = 1 in case heat is fed into the heat storage, while for `mode` = 2 the heat is fed into the DHG. The lower graph shows the temperature of the topmost temperature sensor $T_{\mathrm{HSt,upper}}$ inside the heat storage, together with the critical value $T_{\mathrm{HSt,crit}}$ indicating the threshold for loading the storage via the auxiliary heating. This means in the case that the most upper temperature sensor $T_{\mathrm{HSt,upper}}$ in the storage drops below $T_{\mathrm{HSt,crit}}$, the storage is heated up until $T_{\mathrm{HSt,upper}}$ is above $T_{\mathrm{HSt,crit}}$ plus a safety margin ΔT.

The state-of-the-art control strategy, based only on the current state of the system, has to heat up the storage by heat from the DHG three times during this week, at the beginning of September 30th. This happens even though the day before, September 29th, there would have been sufficient solar radiation available to heat up the storage to a higher extent. This is an undesirable behavior, since heat must be bought back at a higher price, which reduces the profit of the plant operator. In the middle graph of Figure 6, it can be seen that switching between modes happens rather often, in total 54 times.

In the first graph of Figure 7, it can be seen that no auxiliary heating is necessary. Furthermore, in the second graph, it can be seen that the modes switches are drastically reduced, in total only 14 times, even if the forecast especially for the solar heat output deviates for some days as can be seen in the first graph. In the third graph, it can be seen that the most upper temperature sensor never drops below the threshold, but also that the heat storage is better managed since the storage is always emptied close to the critical threshold in times before solar heat is expected. An economic analysis, using feed-in tariffs and heat consumption prices for the plant investigated in (Unterberger, 2021), yields a 3 % increase regarding the overall profit.

6. Conclusions and Outlook

The proposed algorithm has several important features, which may help to tap the full potential of SDH plants:

(1) *Performance*: The algorithm takes into account predictions and thus can outperform state-of-the-art approaches that are solely based on the current state of the system:

- *Reduction of storage losses:* By starting and ending a day with loading the storage as well as loading the storage only to the extend which is used by the consumers storage losses are minimized.
- *Reduction of mode switching:* The algorithm determines the optimal window when to feed into the grid and avoids repeated changes of the mode of operation.
- *Priority for supply of on-site consumer:* Heat is only fed into the DHG if the local demand of the consumers can be satisfied (according to the predictions)

(2) *Transparency and simplicity:* The algorithm is rule-based and thus transparent. It can be implemented even on rather simple controllers, which is in contrast to optimization-based control, which requires more computational resources and offers a lower level of explainability.

(3) *Automatic Adjustment:* When using adaptive forecasting methods, the algorithm automatically adapts to seasonal changes or changing consumer behavior, reducing parameterization efforts to a minimum.

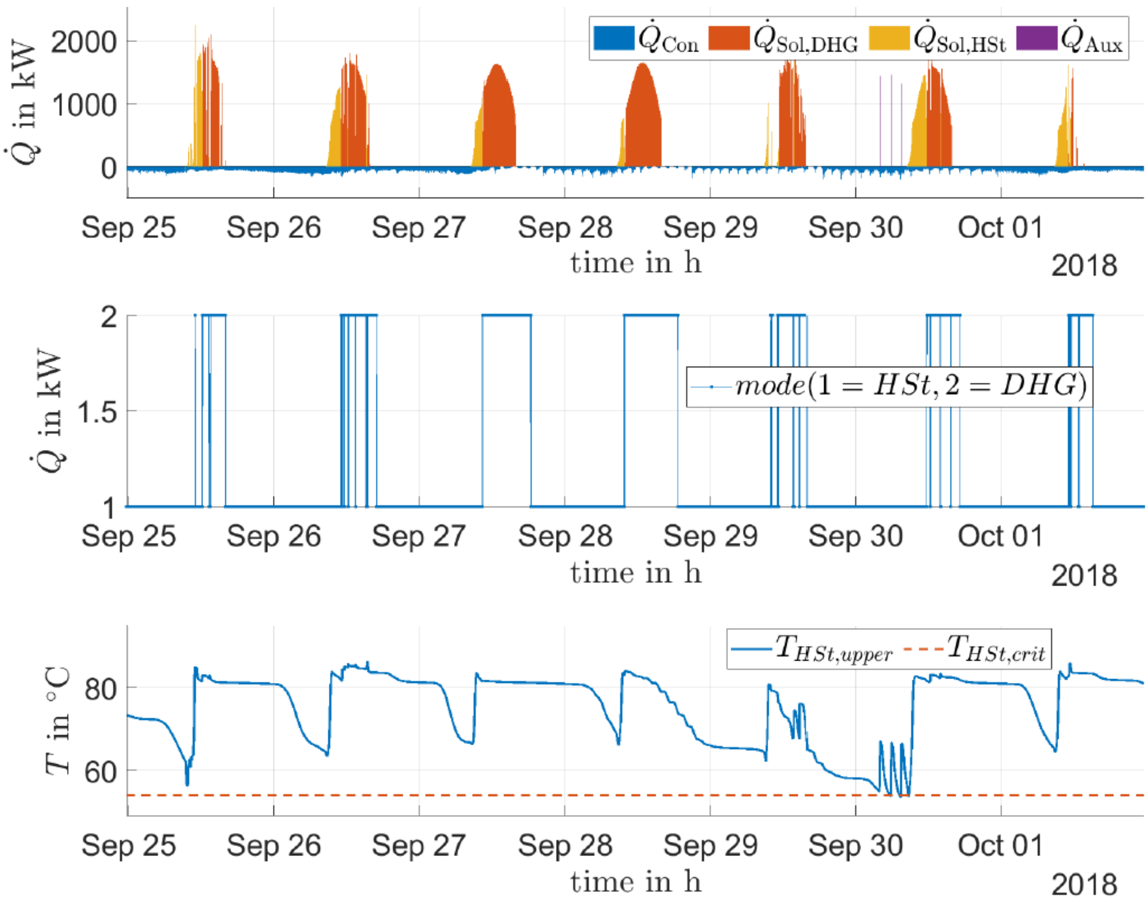

Figure 6: Simulation results for state-of-the-art control strategy

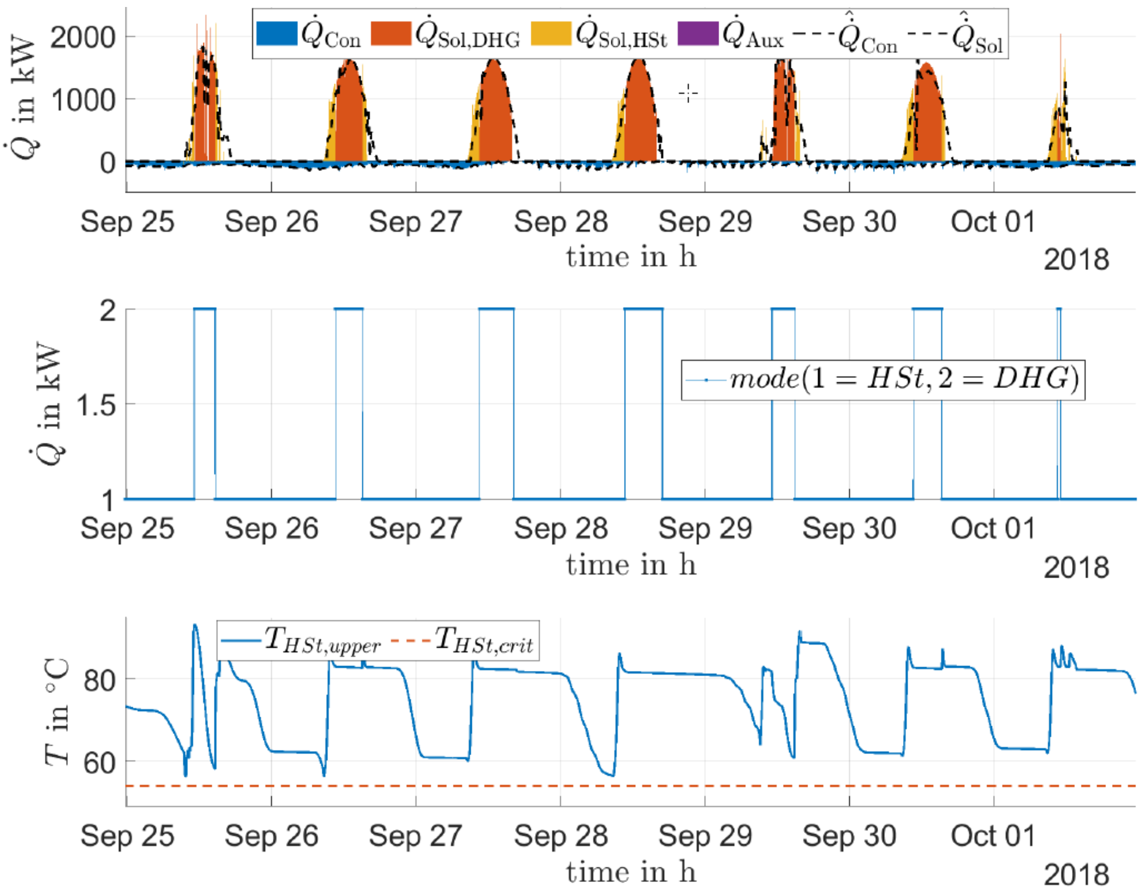

Figure 7: Simulation results for the proposed predictive rule-based control strategy

In simulation studies, the developed predictive rule-based control strategy leads to only one third of the number of mode switches and about +3 % regarding the overall profit.

As next steps, more extensive simulation studies (for several weeks, preferably even a whole year) with a more detailed analysis of contributions to the results, a consistent inclusion of storage losses, comparison also to optimization-based control and the test at a real SDH system are planned.

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