Task 55 Towards the Integration of Large SHC Systems into DHC Networks

SOLAR HEATING & COOLING PROGRAMME
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A-D4.1
Supervisory control of large-scale solar thermal systems

IEA SHC FACT SHEET 55.A-D4.1

Subject:	Supervisory control of large-scale solar thermal systems
Description:	Overview on different approaches for supervisory control strategies, deciding on operating modes and set points for the controls of the different plants and components integrated in solar thermal systems.
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Introduction

The control of large-scale solar thermal systems and heating grids - respectively hybrid energy systems - in which they are embedded, goes along with several control tasks, which are carried out in different control layers. At a higher level, supervisory controllers, often referred to as energy management systems, decide on the operating mode of the different plants and components, and provide the reference signals for their controllers. These modes of operation of the different plants and components are then carried out by the respective controllers at plant and component level, and by those responsible for the operation of the district heating network. The control of large-scale solar thermal systems thus can be divided into the following 3 main categories:

1. **Supervisory control (energy management systems), which will be the focus of this FACT SHEET, IEA SHC FACT SHEET 55.A-D4.1.**
2. Control of heat distribution networks, which is one focus of IEA SHC FACT SHEET 55.A-D4.2.
3. Control strategies for the integrated plants and components, i.e. the actual solar plant, but possibly also heat pumping systems or other plants and components. The control of large-scale solar plants is the focus of IEA SHC FACT SHEET 55.B-D3.1.

There are basically 2 methodologically different approaches for supervisory control:

In most of the applications supervisory control consists of an application-specific set of rules deciding on the general mode of operation and the set points for the lower-level controllers of the integrated plants and components. In the simplest variation the rules only consider the current state of the system; this represents the current state of the art for the supervisory control of large-scale solar thermal systems. More advanced strategies additionally consider forecasts for the future solar heat production or heat demand, but still rely on a set of comparatively simple and application-specific rules.

A very systematic alternative approach for the supervisory control is the application of optimization-based predictive supervisory controllers, i.e. control strategies based on solving a mathematical optimization problem and the consideration of knowledge on future boundary conditions. These approaches, often referred to as energy management systems, do not focus on specific applications, e.g. solar thermal systems, but aim to cover as many technologies, energy sectors, storages, etc., as possible in a modular and systematic way. The same framework could therefore be used for the supervisory control of almost any hybrid energy system. Even if the potential of these approaches has been proven within different demonstration projects, they are currently in a development phase and have not yet fully penetrated the market.

Both rule-based and optimization-based approaches for the supervisory control of large-scale solar thermal systems are displayed in detail in the two main chapters of this fact sheet. In the chapter on the *State of the art – Supervisory control by rules for the choice of the operating mode based on expert knowledge* approaches only considering the current state of the system and approaches additionally considering forecasts are discussed. In the subsequent chapter on the *Advanced concept – Optimization-based predictive supervisory control* different approaches are presented in a very general manner, and the aspects specifically important for large-scale solar thermal systems are highlighted appropriately.

Since both approaches significantly benefit from appropriate short-term forecasts for the solar yield to be expected for a certain operating temperature, the future heat demand, etc., different possibilities for on-line forecasting are discussed in *Appendix A – On-line forecasting*, and one specific, practically suitable approach is explained in more detail.

Content

State of the art – Supervisory control by rules for the choice of the operating mode based on expert knowledge

The state of the art is to derive the respective operating mode of the different plants and components from measured variables, and if available, other information, e.g. forecasts, by means of simple rules. This includes, for example, the adjustment of the set point for the feed temperature levels according to the weather conditions, typically based on the ambient temperature, or to decide on a specific operating strategy for the operation of on-site thermal storages. However, the operating strategies applied vary considerably among different applications and especially among different technology providers. Nevertheless, a distinction can be made between two basic approaches:

1. Strategies only considering the current state of the system
2. Strategies additionally using forecasts

Examples for these 2 approaches are examined in more detail in the following based on a typical, widely spread configuration consisting of a decentral collector field, an on-site buffer storage, on-site consumers and a bi-directional connection to a DH network. A simplified scheme of this configuration is given in Figure 1, however, the possibility to feed into the DH network is often realized directly, i.e. not via the buffer storage, what is displayed simplified in this scheme.

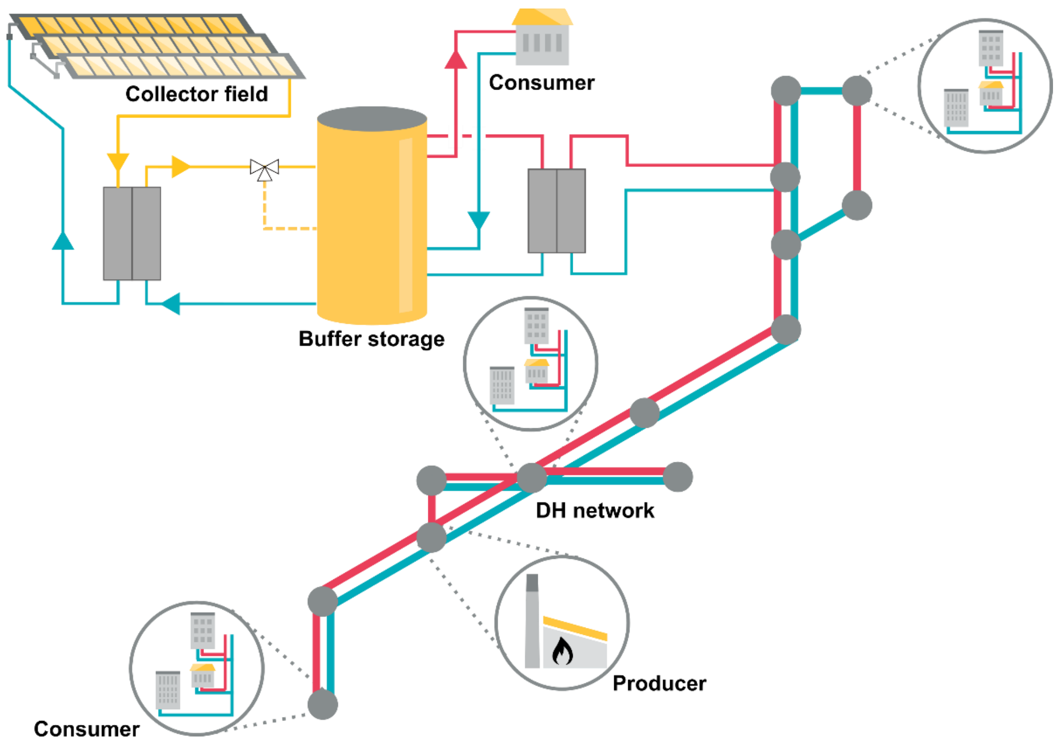

Figure 1: Scheme of a typical large-scale solar thermal system with a decentral, bi-directional connection to a DH network

Strategies only considering the current state of the system

The decision on the mode of operation finally comes down to 2 (possibly 3) main decisions, first whether the collector field should be operated or not, second whether heat should get fed into or obtained from the DH network, and possibly third at which position of the buffer storage the heat from the collector field should get fed in, in case the buffer storages have different inlets. Indirectly these decisions also determine the temperature levels the different plants and components are operated at, however, these levels are typically control parameters or externally imposed, e.g. by the consumer or the DH network. The heat consumption takes place anyway, so in simple, state-of-the-art configurations (without demand side management) no decision must be taken to this end.

The decision on starting or stopping the operation of the collector field are taken based on the current levels of measured temperatures among the collector field and the state of the buffer storages. In both cases, deciding to start or stop implies a certain sequential control for gradually switching on/off the different actuators as certain temperature levels are achieved, finally ending in normal operation mode or no operation of the collector field.

The decision on the interaction with the DH network, i.e. whether to feed into the DH network, to obtain heat from the DH network, or neither of these, is taken based on the current state of the buffer storage. This is typically done very simply, by starting to feed in respectively to draw when certain thresholds of the state of the buffer storage are reached.

The decision on the inlet position to be used to feed into the buffer storage is also taken based on the current state of the buffer storage. This is typically simply done by switching between the inlets when certain thresholds of the state of the buffer storage and the current temperature level provided by the collector field are achieved.

In all these decisions the evaluation of the current state of the buffer storage is very important. The current state is in most cases only determined by the current values of vertically distributed temperature sensors. The next step of complexity is to use the available temperature levels to estimate the temperature levels in between the measurement positions and to use the resulting temperature distribution to estimate the current amount of heat stored and possibly also the current exergy level. The best estimation of the current state of the buffer can be achieved by additionally simulating the vertical temperature distribution online using a suitable mathematical model, and to continuously correct the current simulated state by the currently available measurement values. However, such complex and sophisticated approaches are typically only used when also more complex control strategies are applied.

The threshold levels used for the decisions described above typically vary with the seasons of the year, indirectly considering to some extent the conditions of the near future, and that the required temperatures for feeding into the DH network, typically fixed by contracts, are always given. Often a certain correlation to the ambient temperature is fixed, but it could also be the case that the set point is defined by the supervisory controller of the entire DH network.

Even if these control strategies are based on comparatively simple rules, it could be reasonable to optimize these strategies by determining the optimal values for the different threshold levels through numerical simulation studies and possibly even by numerical optimization algorithms. This is not state-of-the-art yet among the most solar thermal systems connected to DH networks, but is getting more common and particularly supported by application-oriented R&D projects.

Strategies additionally using forecasts

The strategies described in the previous section can be improved by additionally using forecasts to consider a likely near future. With this an operating mode can be selected that expands the expert rules from considering only the current state of the system to considering also the near future (defined by the forecast horizon, typically 24 or 48 h).

To do so, forecasts of dominant influencing factors that are outside the influence of the supervisory controller must be available. For the configuration considered (see Figure 1) forecasts for the solar heat production and the heat demand of the on-site consumers are required. Multiple forecasting methods exist in literature; a review on the different methods and a more detailed description of a comparatively simple, general and widely applicable forecasting method is given in the Appendix.

The decisions finally needed to be made by the supervisory controller remain the same as described in the previous section, however, the way how the forecasts are considered in detail again strongly vary among different applications and especially among the different technology providers.

An exemplary, simple rule-based supervisory control strategy for configurations as described in Figure 1 is described in more detail in the following.

Exemplary, simple rule-based supervisory control strategy considering forecasts

The strategy is based on the following framework conditions:

- The owner of the solar thermal system (collector, buffer storage, on-site hydraulic network) can buy/sell heat from/to the DH network operator and has to provide the demanded heat for the on-site consumers.
- 2 possible modes for using the solar heat currently produced:
  - *Buffer feed:* Storing the heat in the local buffer storage to keep it available for the on-site consumers.
  - *DH network feed:* Feeding the solar energy currently produced into the district heating network.
- In case the needs of local consumers cannot be met, heat must be purchased from the district heating network.
- Explicit consideration of the different tariffs for
  - the heat fed into the DH network,
  - the heat sold to the on-site consumers, and
  - the heat purchased from the DH network.

To determine the mode of operation for the next period, the supervisory controller periodically executes the following steps, e.g. every 15 min or every hour:

1. **Evaluation of the current state of the buffer storage:** In the first step, the state of the buffer storage is evaluated by using a mathematical model of the buffer storage. For this, the parameters of the model of the buffer storage are adapted by using the current values from the temperature sensors installed. For the model a partial differential equation describing the vertical temperature distribution is recommended, however, depending on the complexity of the buffer storage also more complex models could be necessary. For the numerical simulation the buffer storage is discretized over the height, e.g. in 100 layers. To evaluate the current state of the buffer storage, strictly speaking the energy useful for the consumers, the exergy of the buffer storage is evaluated, using a given reference temperature, defining the zero level as corresponding to the minimum temperature accepted by the on-site consumers, e.g. 50°C.
2. **Forecasting the future solar yield and the heat demand of the onsite-consumers:** In parallel to the first step, the course of the future solar yield as well as the future heat demand of the on-site consumers are forecast. Since the feed temperature required from the solar collector field results from the chosen mode of operation, the forecasts for the solar yield must be calculated for the different possible set points for the feed temperature. In this simple case, these are the set points for the 2 different modes of operation, *Buffer feed* (e.g. 75°C) and *DH network feed* (e.g. 90°C), where the set point for *Buffer feed* is a control parameter and the set point for *DH network feed* is imposed by the DH network operator/control.
3. **Decision on the operating mode:** In the last step, a *decision-making algorithm* is used to decided how to use the available heat. This is done by evaluating the following three cases:
    a. In case the heat in the storage is enough to provide the consumer with heat, the heat should be fed into the DHG ➔ *DH network feed*
    b. In case the heat in the storage together with the expected heat from the solar thermal plant is still not enough to supply the consumer, the heat should be used to load the storage ➔ *Buffer feed*
    c. In case the heat in the storage is not enough to fully supply the consumers, but together with the future solar heat for *DH network feed* produces a surplus, then a mixed mode of operation is necessary, and the temporal behavior must be closer evaluated. Therefore, the heat demand of the consumers, considered to be counted negative, is reduced by the heat from the storage. The remaining, negative heat demand must be provided by solar. In a next step the heat demand is accumulated for every timestep (e.g. 15 minutes) of the forecast horizon. In case this accumulated course shows a negative heat demand, solar heat must be fed into storage (*Buffer feed)* at the earliest time possible to supply this demand. Then the accumulated course of the demand is calculated one more time and it is evaluated again, if a negative heat demand is occurring and which is the earliest time possible to supply it by solar. By this the storage losses can be minimized, since the heat is fed into the storage as late as possible and only in case it is

needed. This routine stops in case the accumulated sum for the heat demand is zero or positive, means something stays in the storage and the remaining time steps which are not used for loading the storage (*Buffer feed*) can be used to generate additional profit by feeding the solar heat into the district heating grid (*DH network feed)*.

A schematic overview on the strategy is given in Figure 2.

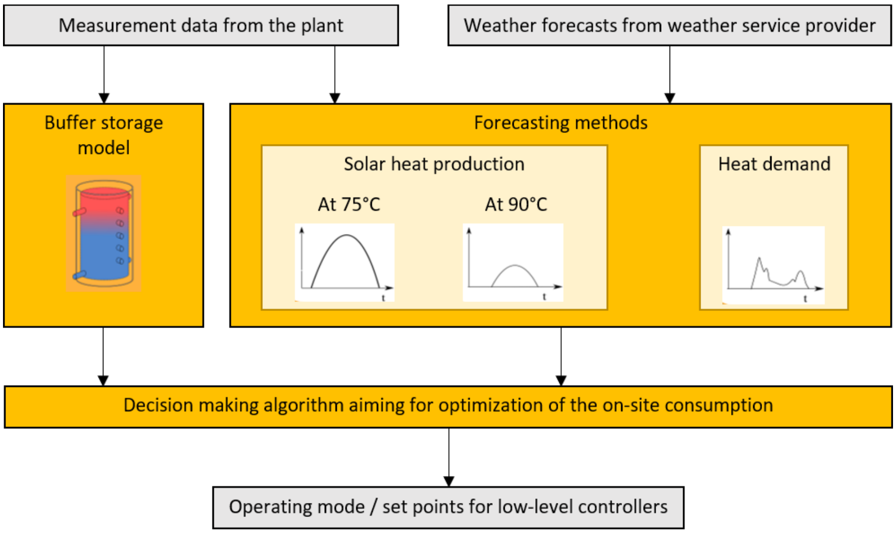

Figure 2: Scheme of an exemplary supervisory control strategy considering forecasts.

Unfavorable operation due to large forecasting errors can be avoided or at least mitigated by repeatedly executing the algorithm, e.g. every 15 min or hourly. The considered current state of the system as well as the forecasts are thus regularly updated taking the newly available measurement data into account.

A more detailed description of this exemplary algorithm can be found in [1], however, only in German.

For sure it could be reasonable to optimize the strategy also in this case by determining the optimal control parameters, e.g. the set points for the feed temperature of the collector field for the different operating modes, or the prediction horizon, through numerical simulation studies and possibly even by numerical optimization algorithms. Big potential would lie in the continuous variation of the temperature levels the different components should be operated at. However, this would significantly increase the complexity, quickly leading to problems which only could be handled reasonably and robustly with systematic approaches. The most promising approaches for this are optimization-based concepts, which will be the focus of the next chapter.

Advanced concept – Optimization-based predictive supervisory control

A very systematic alternative approach for the supervisory control is the application of optimization-based predictive supervisory controllers, i.e. control strategies based on solving a mathematical optimization problem and the consideration of knowledge on future boundary conditions. The available approaches for optimization-based predictive supervisory control are not limited to solar thermal systems, in fact they aim to cover as many technologies, energy sectors, storages, etc., as possible. The coupling of the different energy sectors will continue to increase, and it is obvious that a joined consideration of all producers and consumers, storages, distribution grids, and all coupled sectors theoretically must lead to the best overall operating behaviour. Because of the many possibilities of the detailed structure and configuration of the different hybrid energy systems to be considered, it is not reasonable to develop specific approaches for single sectors, but instead holistic approaches should be pursued. This is already the case for most of the approaches currently available. Even if the different approaches are often clearly derived from specific sectors, the general principles used have a common basis. For this reason, the approaches for optimization-based predictive supervisory control are presented in a very general manner in the following, and the aspects specifically important for large-scale solar thermal systems are highlighted appropriately.

These optimization-based predictive supervisory controllers are generally referred to as energy management systems (EMS). Their main task is to control the entire energy production (among all plants and sectors) while fulfilling the demand of the different consumers and ensuring that all restrictions are fulfilled, e.g. the storage capacities of thermal buffer storages or electrical batteries and the transport capacities of pipes or power lines.

The idea of optimization-based control is to formulate the control problem as an optimization problem, which then is periodically solved. Casting the control problem into an optimization problem requires the formulation of two main parts: First, the dynamics of the considered (hybrid) energy system must be described through the constraints of the optimization problem, and second a so-called cost-function of the optimization problem penalizing or rewarding a certain operating strategy must be formulated. This optimization problem is then solved, leading to an optimal control schedule for a given horizon, e.g. 24 or 48 hours. However, only the first time instance of the control signals is applied to the system, strictly speaking as set points of the lower-level controllers of the integrated plants and components. After a certain period, e.g. 15 min or 1 hour, the formulation and solution of the optimisation problem is repeated using updated measurement values, i.e. the current state of the systems, and forecasts. This repeated update and solution of an optimization problem is typically referred to as *moving horizon model predictive control* (MPC) approach in control theory.

A schematic overview of the structure of such an optimization-based predictive supervisory control (Energy Management System) is given in Figure 3.

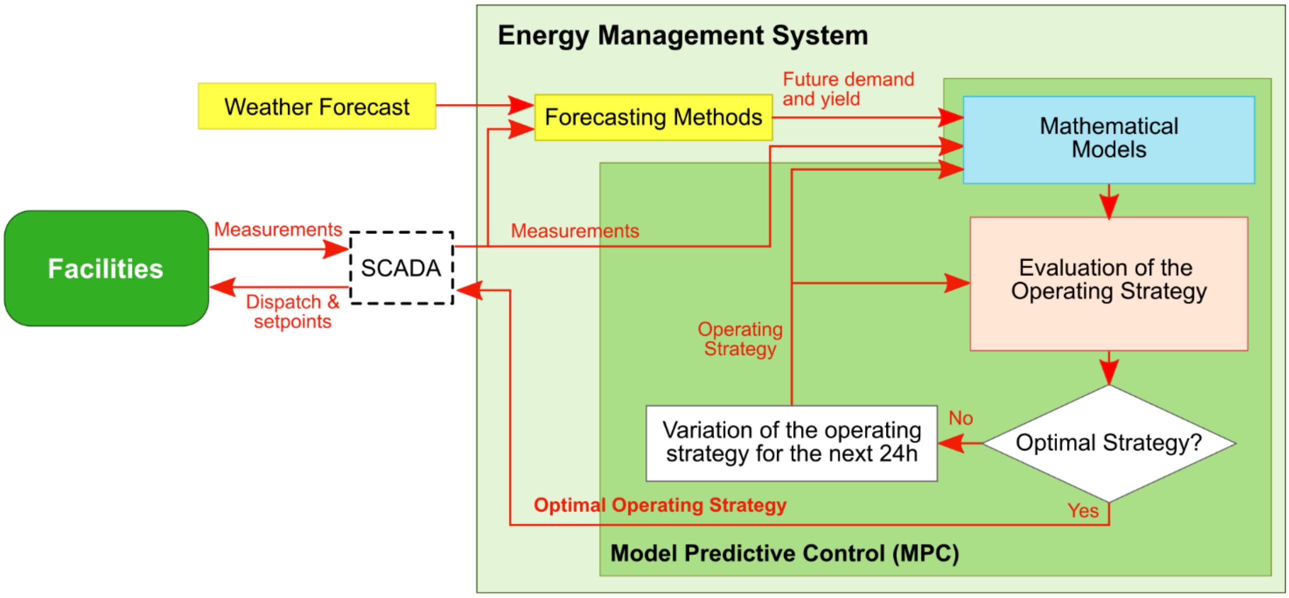

Figure 3: Structure of an optimization-based predictive supervisory control (Energy Management System)

The main difference in the different approaches available, respectively investigated in research, is in the mathematical models used:

First, *linear* or *non-linear models* could be used, consequently leading to linear, respectively far more complex and computationally expensive non-linear, optimization problems. Since the control must be real-time capable, even though the step-sizes are comparatively large, a trade-off between model complexity and speed must be made. Non-linear approaches would allow for more complex, and thus more precise models, however, obtaining optimal solutions for the resulting non-linear optimization problems is very hard. For most non-linear optimization problems optimality of the result cannot be guaranteed. Therefore, linear models are more widely used in both industry and academia.

Second, certain discrete decisions must be taken by the supervisory controller, e.g. the decision between two operating modes or simply the decision whether a certain controllable plant, e.g. a gas boiler, should be in operation or not. To do so additional Boolean or integer variables need to be added to the models, leading to *mixed-integer linear programmes* (MILP), which are currently the most common approach for optimization-based predictive supervisory control of hybrid energy systems in both industry and academia, see e.g. [2], [3], [4]. Many years of research and development on the application of MILP (not only) for the predictive supervisory control of hybrid energy systems have devised fast algorithms like *branch-and-bound* or *branch-and-cut* as well as efficient heuristics that are able to derive proven optimal solutions for such MILPs under tight time constraints, see e.g. [5], [6], [7]. To allow for a wide and efficient application the derivation of the mathematical models and the optimization problem needs to be largely automated, see e.g. [2], in order to decrease the effort necessary for the development and implementation of such a control at a certain system.

However, the reduced complexity and thus accuracy of the models also goes along with disadvantages. The decision variables correlating to the different production units are typically the demanded power / heat flow or the mass flows corresponding to a certain temperature spread. In the first step, constant efficiencies over the entire operating range are assumed. Especially in the thermal sector these two assumptions, fixed temperature levels and constant efficiencies imply significant disadvantages. First, efficiencies of certain producers often depend on the load they are operated at. However, this could be modelled sufficiently well within the MILP framework by using piece-wise-affine (PWA) functions, see e.g. [2]. The use of fixed temperature levels implies a much bigger problem, since efficiencies of certain producers, losses, and in particular the yield of solar thermal plants strongly depend on the temperature levels they are operated at. For sure, the most accurate approach to model all these phenomena would be to go for non-linear models and consequently to mixed-integer non-linear programming (MINLP). However, the authors do not consider this to be a practically suitable, widely and systematically applicable approach, since the complexity and computationally effort increases dramatically, and what is still more problematic, the optimality of the result cannot be guaranteed. A reasonable approach to overcome this problem while remaining within the MILP framework is presented in [8], describing the idea of heat flows with a set of mass flows at different, constant temperatures. A promising approach could also be to benefit from the extension of commercial solvers to non-convex mixed-integer quadratically-constrained programming (MIQCP) problems, e.g. [6], allowing for direct modelling of heat flows at variable temperatures and therefore allowing the EMS to compute optimal control schedules not only in terms of energy flows, but also at which specific temperatures. However, these investigations are at a very early stage of research at the moment this fact sheet was created.

The optimal prediction horizons and time intervals the optimization problem should be resolved strongly depend on the detailed configuration, in particular on the storage capacities. In most cases longer horizons lead to better results, but also more complex and difficult to solve optimization problems. Especially for very large storages, i.e. seasonal storages, this has to be considered. In this case a cascadic combination of a mathematically less complex, long-term optimization solved at longer intervals, and a more detailed and more frequently solved short-term optimization may be a sufficient approach.

Appendix A – On-line forecasting

For the case the large-scale solar thermal systems with a bidirectional connection to DH networks go along with on-site consumers and an on-site buffer storage, not only forecasting the solar heat production, but also forecasting the heat demand of the consumers should be considered. However, most of the forecasting methods are rather general and thus in principle applicable to any domain.

To be suitable for a wide and systematic practical application the forecasting methods preferably should fulfill the following three requirements:

1. Simple implementation: The methods should not require high computational effort or depend on third party software to be easily implementable on commercially available controllers, without license costs.
2. Automatic adaption: The methods should automatically adapt to variations over the year (e.g. seasonal changes, newly erected buildings) minimizing the (re-)parametrization effort.
3. Wide applicability: The methods should be capable of describing a large variety of different solar collector installations (hot water/process heat, size, orientations and climate conditions) and a large variety of consumers (single house/heating grid, size, office/industry/household).

The literature on forecasting methods is dominated by methods designed for the electrical sector, with many publications dating back to 1966. In contrast to this, forecasting methods of the solar heat production and the heat demand are smaller and younger research fields. However, due to the preliminary work for the electrical sector a rich variety of forecasting methods is already available. The methods available in literature are based on regression models, e.g. [9], [10], [11], stochastic models (usually based on ARMA models), e.g. [9], [10], or combinations of both, e.g. [12], [13]. Additionally, machine learning methods (usually based on neural networks) have been applied too, e.g. e.g. [14], [15]. The stochastic models as well as the machine learning approaches are typically rather complex, what is not necessary for this task, and hinders their practical utilization. Thus, regression-based approaches are in principle more suitable for practical implementation.

A suitable approach, fulfilling the three mentioned requirements of being simple to implement, automatically adapting itself and widely applicable very well, for forecasting the heat demand is presented in [16]. A generalization of the method and its extension to forecasting the solar heat production is presented in by [17] respectively [18].These two methods share a general approach, which can be applied to other sectors or technologies as well.

In the following, first the general approach is described and then specified for forecasting the solar heat production and the heat demand.

General approach

The approach bases on the description of the influence of external factors x on the solar heat production respectively the heat demand. Such external factors are for example the global radiation or the ambient temperature. If a forecast for these external factors $\hat{x}$ is available, e.g. from weather service providers, a prediction for the correlating produced respectively consumed heat flow $\hat{\dot{Q}}$ can be computed. The simplest model for the correlation of the external factors and the heat flow is linear, which can be written as

$$\hat{\dot{Q}}(t) = \beta_0 + \beta_1 \hat{x}_1(t) + \beta_2 \hat{x}_2(t) + \beta_3 \hat{x}_3(t) + \cdots, \tag{1}$$

with the regression parameters β. Forecasts for $\hat{x}$ from weather service providers are typically available with a sampling time of one hour. Thus, the prediction is also calculated every hour of the day

$$\hat{\dot{Q}}[n] = \beta_0 + \beta_1 \hat{x}_1[n] + \beta_2 \hat{x}_2[n] + \beta_3 \hat{x}_3[n] + \cdots, \tag{2}$$

with the discrete time variable n.

In addition to the influence of external factors, the solar heat production and the heat demand show a periodicity, which cannot be entirely related to external factors x. In the case of the solar heat production, for example local shading can occur at a certain time of the day, which is independent of the global radiation. Likewise, at the heat demand, the user might consume heat for showering at a certain hour of the day, which is independent of the weather. This periodicity is considered by using not only one linear regression model, but a linear regression model for each hour of the day $m = 1,2, \dots, 24$. These 24 linear regression models only differ at their regression parameters $\beta[m]$, which leads to the final prediction model:

$$\hat{\dot{Q}}[n] = \beta_0[m] + \beta_1[m] \hat{x}_1[n] + \beta_2[m] \hat{x}_2[n] + \beta_3[m] \hat{x}_3[n] + \cdots \tag{3}$$

The 24 regression parameters $\beta[m]$ are determined from historical data. For this, $\dot{Q}$ and x of the respective hour of the previous N_d days is stored. This leads to an overdetermined system of N_d linear equations, and the parameters are calculated in order to minimize the sum of squared errors (least squares approach) by using the computationally cheap pseudo-inverse. Continuous redetermination of these regression parameters ensures that the forecasting method automatically adapts to variations over the year.

This procedure is always recommended, if the variable that should be forecast depends on external factors and shows a periodicity that cannot be described by forecasted external factors.

An additional correction of the prediction $\hat{\dot{Q}}$ should help to increase the accuracy of the forecast of the near future by making use of the latest prediction error $(\dot{Q} - \hat{\dot{Q}})$. To keep the method simple, a scaled linearly decaying function Φ is used, adding the weighted latest available prediction error to the following time steps, correcting the prediction. The correction can therefore be written as

$$\tilde{\hat{Q}}[n] = \hat{\dot{Q}}[n] + \left(\dot{Q}_0 - \hat{\dot{Q}}_0\right)\,\Phi\,. \tag{4}$$

While the correction makes sense in general, it can also be the source of problems and thus needs evaluation for each application, where special focus must be given to variations of the sign of the prediction error.

The specific prediction models (3) for forecasting the solar heat production and the heat demand are presented in the following two sections respectively. The correction (4) does not change and is therefore not further discussed.

Forecasting the solar heat production of large-scale solar thermal plants

The specific application of the method for large-scale solar thermal plants should be discussed for flat plate collectors, accounting for about 70% of all solar thermal systems installed in Europe [19]. The solar heat production from a flat plate collector during steady-state operating conditions can be approximately expressed by the static energy equation according to the European Standard ISO 9806; see e.g. [20]:

$$\dot{Q}(t) = A_{\mathrm{coll}} K(\theta)\eta_0 I_{\mathrm{g}}(t) - A_{\mathrm{coll}} c_1 \Delta T(t) - A_{\mathrm{coll}} c_2 \Delta T(t)^2 \tag{5}$$

with the temperature difference

$$\Delta T(t) = \bar{T}_{\mathrm{fl}}(t) - T_{\mathrm{amb}}(t) \tag{6}$$

where A_{coll} denotes the gross collector area, I_{g} the global radiation received by the collector surface, $\bar{T}_{\mathrm{fl}}$ the arithmetic mean fluid temperature between the inlet and the outlet of the collector and $T_{\mathrm{amb}}$the ambient temperature. The coefficients represent the optical efficiency η_0, the heat loss coefficients c_1 and c_2. The function $K(\theta)$ represents the incident angle modifier (IAM) which describes the dependency of the optical efficiency η_0 on the angle of incidence θ of the global solar radiation I_{g}, which varies from collector to collector and is typically estimated through experiments [21] and given in the data sheet.

However, even though the Standard EN12975:2006 is accepted and widely used, the analysis of measurement data from solar thermal plants shows that applying this data sheet method, with its parameters taken from the data sheet of the collector, does not always lead to satisfying results for forecasting the solar heat production. The main reasons for this lie in the thermal inertia, shading and pollution. To overcome these problems, the parameter sets (η_0, c_1, c_2, A_{coll}) must be different over the day and be continuously re-determined throughout the operation.

The static collector model (5) is identical in structure to the prediction model (3) with the regression parameters $\beta_0 = 0$, $\beta_1 = A_{\mathrm{coll}} K(\theta)\eta_0$, $\beta_2 = -A_{\mathrm{coll}} c_1$ and $\beta_3 = -A_{\mathrm{coll}} c_2$ and the external factors $\hat{x}_1 = \hat{I}_{\mathrm{g}}$, $\hat{x}_2 = \Delta\hat{T}$ and $\hat{x}_3 = \Delta\hat{T}^2$, where I_{g} and T_{amb} are obtained from a weather service provider and the forecasted temperature difference is computed according to (4) by $\Delta\hat{T} = \hat{\bar{T}}_{\mathrm{fl}} - \hat{T}_{\mathrm{amb}}$ assuming the mean fluid temperature to be constant $\hat{\bar{T}}_{\mathrm{fl}}(t) = \hat{\bar{T}}_{\mathrm{fl}} = \mathrm{const.}$, what is reasonable since the solar thermal plants are operated with constant set points for the outlet temperatures in the considered time frames and also the return temperatures can be assumed constant for the considered time frames.

Exemplarily two different forecasts for the solar heat production of a large-scale solar thermal plant are displayed in Figure 4. It can be concluded, that the usage of the parameters from the collector field would lead to systematic errors (grey), sunny days could be forecasted very well (left), and days with rapid cloud movements could be forecasted well in average but with stronger temporal deviations (right).

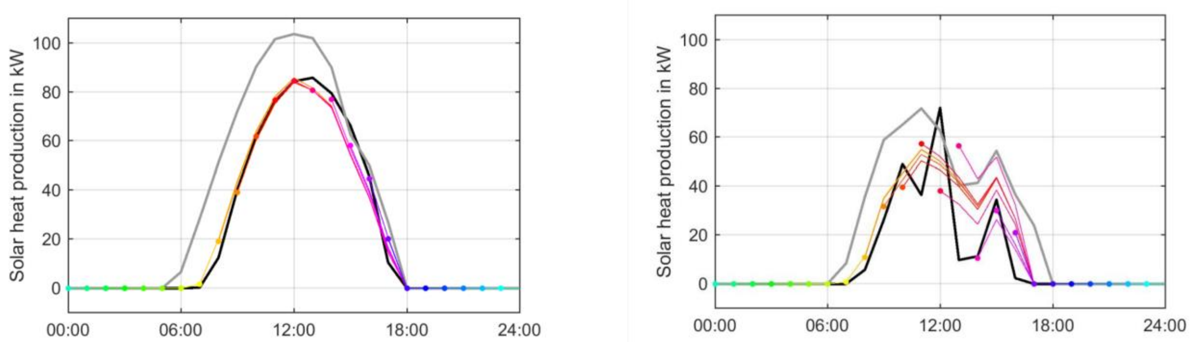

Figure 4: Exemplary forecasts for the solar heat production of a large-scale solar thermal plant

Explanations: left: sunny day; right: day with rapid cloud movements.
black: heat actually produced; colour: hourly re-determined forecasts (starting with green, going via yellow to red and blue); grey: forecast achieved with parameters from data sheet.
net collector area of 138 m²; location: Graz, Austria;

Forecasting the heat demand

Even though the heat demand of consumers is influenced by many different external factors, considering the ambient temperature as only external factor in forecasting is enough to get suitable results for all non-industrial consumers, if the parameters are periodically, e.g. hourly, re-determined, and separate regression models are used for each hour of the day. Thus, the prediction model analogous to (3) for forecasting the heat demand can be set to

$$\hat{\dot{Q}}[n] = \beta_0[m] + \beta_1[m]\hat{T}_{\mathrm{amb}}[n] \,. \tag{7}$$

A distinction between workdays and weekend days in most cases additionally improves the forecasting quality significantly. Hence, separate hourly regression parameters should get considered for workdays and weekend days.

Exemplarily two different forecasts for the heat demand of an office building are shown in Figure 5. It can be concluded, that the heat demand can be forecasted sufficiently well for days with relevant heat demand, as for example for the day in spring displayed on the left-hand side. However, the head demand in summer (right-hand side) is much more. However, in this case the overall demand is extremely small, around 3% of the connection load, thus it is for sure sufficient to approximately forecast the average demand of the next day.

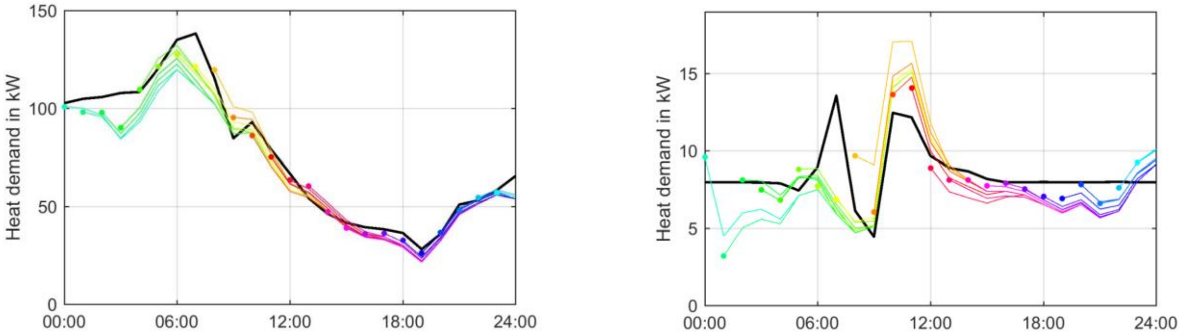

Figure 5: Exemplary forecast of the heat demand

<u>Explanations:</u> left: spring; right: summer.

black: heat actually consumed; colour: hourly re-determined forecasts (starting with green, going via yellow to red and blue).

office building (connection load: 300 kW), location: Austria.

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