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Using history based irradiance forecasts for supporting the predictive control of solar thermal systems

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Abstract

Results from a modeling study, aimed to investigate into the possibilities for including a model predictive control MPC scheme in a simply structured combisystem are reported. The system modelled uses a flat plate collector system, a single storage - assumed to be well mixed - and an electrical auxiliary energy. The control can act on the aux. heating for the storage tank. A fixed set point thermostatic control gives the benchmark for the MPC control applied. As MPC asks for predictions of the disturbance of the system – which here are the variations of the meteorological operation conditions of the collector system and the heating load governed by the ambient temperatures (and general the load requirements) – two forecast options are applied here, the hypothetical perfect knowledge of the future conditions and a simple forecast scheme, based on a statistical analysis of historical data of the location of interest. As quality measures for the control schemes, the aux. energy consumption and the deviation of the room temperature from a desired level are used to assess the different control schemes.

Key words: solar combisystem, model predictive control (MPC). Irradiance forecast

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1. Introduction

For the energy management of solar energy system, e.g. combisystems for assisting heat and hot water supply, advanced control techniques, making use of forecast information on the environmental conditions (irradiance, ambient temperature, …) are reported to be beneficial (see e.g. Candanedo et al. 2010, G. Goertler et.al., 2000., Pichler et al. 2014). To investigate, on one hand, whether these findings hold for very simple structured systems with a minimum of controllable parameters and, on the other hand whether a simple forecast, based on statistical information gained from historical data, can be used for the characterisation of the future disturbances

The simulation based case study aims to investigate into the possibilities for including a model predictive control MPC scheme in a simply structured combisystem are reported. The system uses a flat plate collector system, asingle storage - assumed to be well mixed - and electrical auxiliary haeting. The control can act on the aux. heater of the storage tank. A fixed set point thermostatic control gives the benchmark for the MPC control. As MPC asks for predictions of the disturbance of the system – which are given here by the variations of the meteorological operation conditions of the collector system and the heating load governed by the ambient temperatures (and generally the load requirements) – two forecast options are comparedhere, the hypothetical perfect knowledge of the future conditions and a simple forecast scheme based on a statistical analysis of historical data of the location of interest. As quality measures for the control schemes, the aux. energy consumption and the deviation of the room temperature from a desired level are used to assess the different control schemes.

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2. System modeled and location

Our analysis refers to a basic combined solar system to assist space heating and hot water supply using flat plate collectors. This system modeled comprises of 11m^2 of flat plate collector and a unique storage tank with a volume of 900 litres. As the tank should serve a low temperature (floor heating) system here the storage temperature is low (see section 4), the contribution to the hot water supply is limited to pre-heating as served from this storage. For the modeling, we assume the characteristics of a standard medium quality collector type. The storage tank, having medium losses, is modeled as well mixed. For the heating load, a "test-box" approach is taken representing a room of 25m^2 floor area, loosing heat to ambient through 50m^2 of wall with good insulation standard (see deOliveira et al. 2013). The hot water demand profile – used as constant daily profile here is given in fig, 1 (giving the profile for one flat, taken from Defra 2008).

The auxiliary space heating for both heating and hot water service is dome by direct electric heaters.Whereas the final heating for the hot water is assumed to be completely controlled by the requirements of the, the control of the main auxiliary heating to the storage tank offers the possibility of the application of different control strategies.

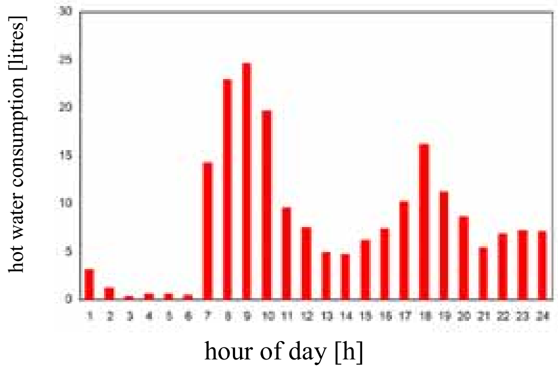

Fig. 1: Hot water consumption profile used here. This profile refers to one flat (taken from Defra 2008).

The system is assumed to be operated at Kristiansand, Southern Norway. Data on global horizontal irradiance and ambient temperature supplied by GEOMODELSolar, Slovakia [GEOModel, 2014] are used as basic input. The data on horizontal irradiance are transferred to irradiances on a 45° tilt surface looking to the south. As time period the month of May is selected. The irradiance and the temperature profiles – defining the heating load) for this period is given in fig.1 and fig.2. The average irradiance in this period is 239 W/m2, the average temperature is 9°C ranging from 2°C to 18°C.

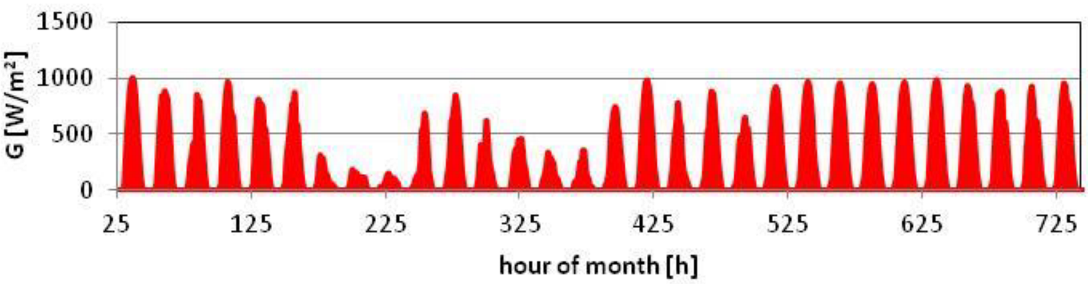

Fig.2 Irradiance profile for the inspected period

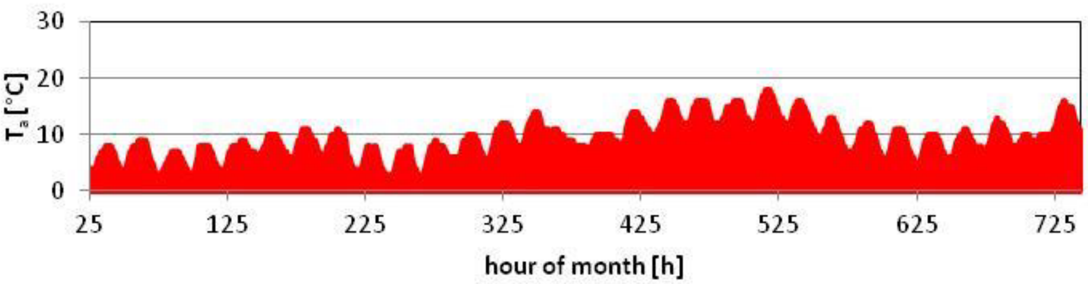

Fig.3 Temperature profile for the inspected period.

3 History based Irradiance forecasts

As mentioned, a data based forecast scheme is used here (Arachchige 2014). It is a Markov scheme, trained on historic time series of the irradiance. Data from 6 years (i.e. from the months of May) are analyzed for this. The month specific probability distributions of expected irradiance sum in dependence of the previous day irradiance sum are derived from this set.
To illustrate this approach, fig.4 gives examples for the conditional probabilities of the next day irradiance sum for two classes of the previous day sum.

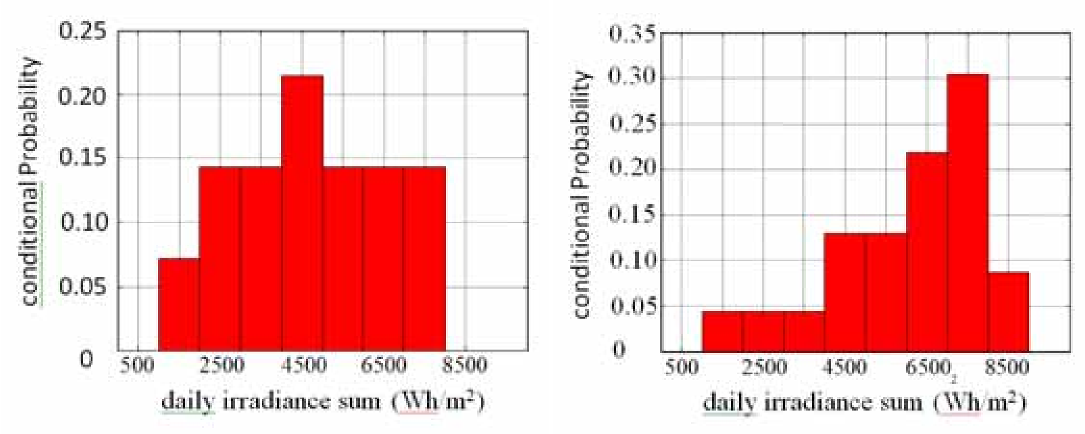

Fig.4: Example for the probability distribution of next day irradiance sum based on actual sum H. left chart refers to 4 kW/m^2 ≤ H < 5 kW/m^2, right chart to 6 kW/m^2 ≤ H < 7 kW/m^2,

These probability distributions can be interpreted as giving forecast information on the basis of today's irradiance. In this paper the most basic information is used in form of the mean of the next days irradiance sum as forecast of mean of next days sum (this proved superior to the application of the most probable sum, Arachchige 2014, basically the probability distributions can form the basis for probabilistic forecast scheme). Given the expected irradiance sum defined by the previous day, hourly resolved irradiance data can be presented in form of typical hourly irradiance profiles derived from the historical data.Fig.5 shows examples for three classes of previous irradiance sum.

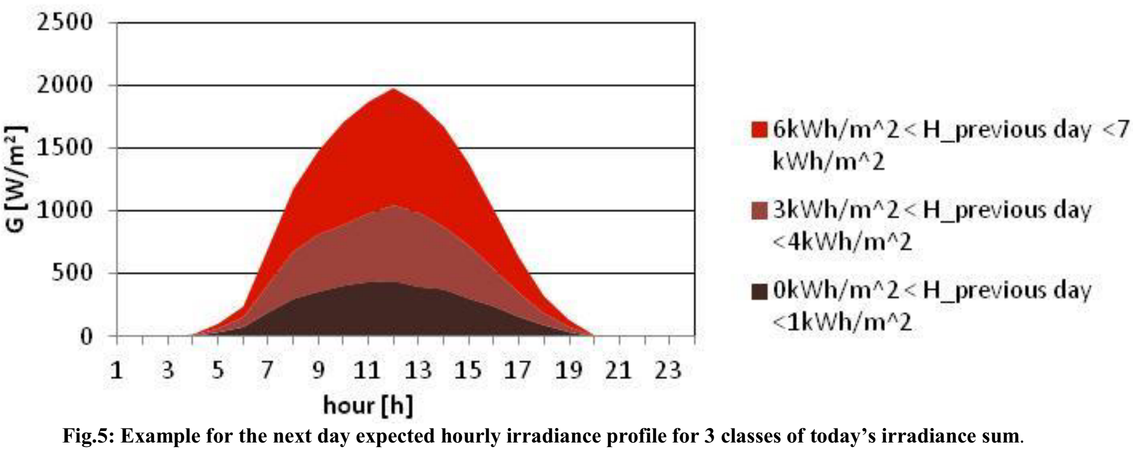

Fig.5: Example for the next day expected hourly irradiance profile for 3 classes of today's irradiance sum.

A simple way to extend this day-ahead forecast to a 2-day-ahead forecast is given by reapplying the day-ahead transition matrices on the outcome of the 1-day-ahead forecast. As the matrix information is condensed here to the information on the expected next-day mean this scheme results in a quite simple procedure.
Fig. 6 gives a 6-day snapshot of the outcome of the next day and the 2-day-ahead prediction for the month of May inspected. The scatter of measured and predicted irradiances for the 2 forecast horizons using data for the whole month are given in figs.7 and 8.

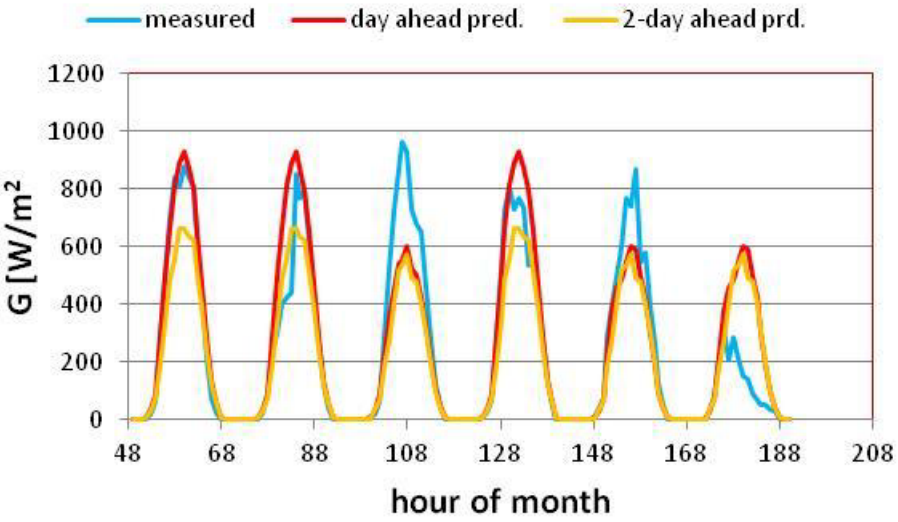

Fig.6: 6 day example of measured irradiances and the outcome of the day ahead and 2-day ahead forecasts.

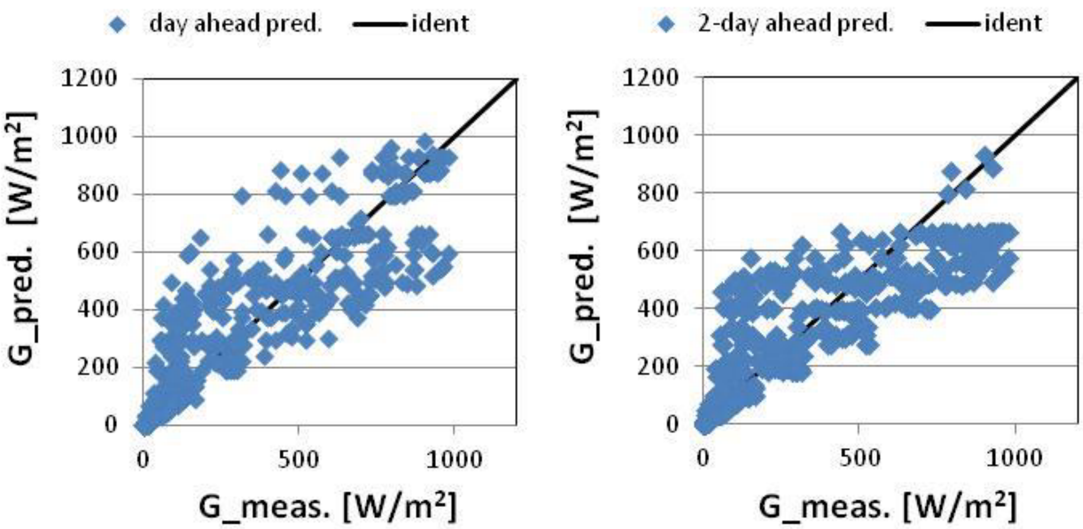

Fig 7: Scatter plots of measured hourly irradiances and day ahead and 2-day ahead forecasts for the data month of May.

Prediction of the ambient temperature is mimicked by a repetition of the data set of yesterdays.

4. System operation and control

For the system described above, the control is done via the operation of the auxiliary heating of the storage tank. Aim is to keep the room temperature as close as possible to a desired level with a minimum consumption of auxiliary energy. The basic control option aiming at the first goal is given by a simple thermostat control of the room temperature. Energy consumption and "comfort loss" (deviation of room temperature from the desired level) achievable with this control will be compared here to the respective measured under two variants of advanced control scheme "model predictive control" MPC. The two variants are given by an ideal (not realistic) scheme disposing of the complete knowledge of the future disturbances, i.e. of a perfect forecast, and a scheme applying the forecast information as given above. In the following, the control schemes will be desrcibed with a little more detail and their performance depicted by a 5 day snapshot of system operation. A first analysis of this system was presented in Lie et al. 2014.

4.1 Thermostat control

The thermostat controller works as follows (here for the room temperature). The power of the auxiliary heating $\dot{Q}_{aux,i}$ is given by (T_r *and* T_r^{ref} refer to actual and desired room temperature).

$$Q_{aux,i} = \begin{cases} Q_{aux,i-1}, T_i \in \left[T_r^{ref} - \delta T_r, T_r^{ref} + \delta T_r\right] \\ 0, \qquad\qquad\qquad T_r > T_r^{ref} + \delta T_r \\ Q_{aux}^{max}, \qquad\qquad\quad T_r < T_r^{ref} + \delta T_r \end{cases} \qquad \text{eqn.1}$$

The reason for the dead-band of width δT_r is to avoid excessive switching in the control input. Typically, δ δT_r must be increased when the measurement noise increases. In the sequel, we use $\delta T_r = 1K$. The reference temperature (desired room temperature) is set to $T_r^{ref} = 20°C$. For the auxiliary heating a maximum power of 4 kW is set.

An example for the evolution of various temperatures in the system during 5 days of simulation is depicted in fig.8.

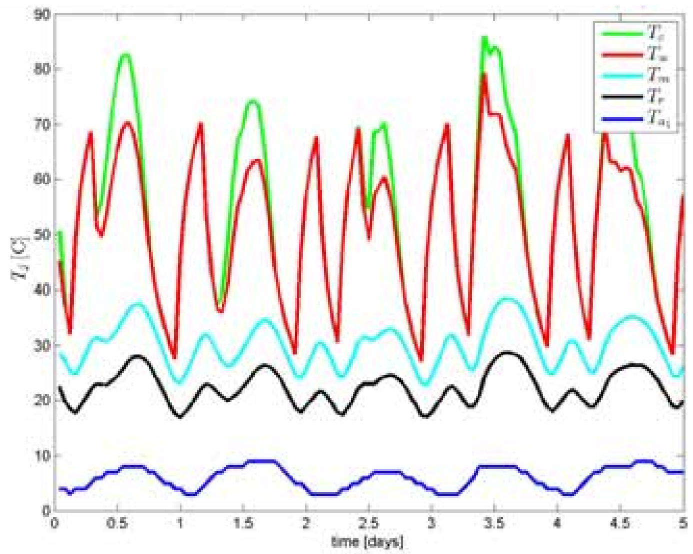

Fig.8: Temperature profiles for the system operating under thermostat control. Shown are the evolutions of Tc: collector temperature, Tw: storage temperature, Tm: floor temperature, T_r: room temperature, T_{a1}: ambient temperature.

The respective heat flows are given in fig. 9.

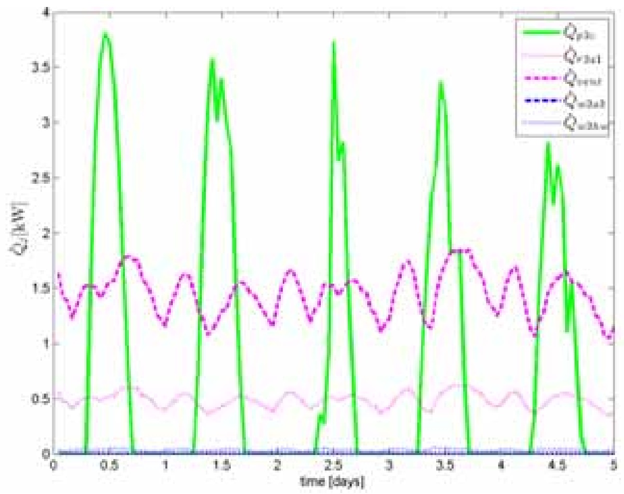

Fig.9: Selected heat flows for the time section given in fig.8.
—Q_p2c: heat uptake by collector fluid;
—Q_r2a1: transmission losses room to ambient, —Q_vent: ventilation room to ambient.

3.2 MPC perfect disturbance knowledge

With Model Predictive Control (see e.g. Pichler et al. (2014)), we consider the repetitive optimization of a cost function constrained by the system model and possible other constraints. Here we choose a cost function V given as

$$V = \int_t^{t+t_h} \left[w_{T_r} \left(T_r - T_r^{ref} \right)^2 + \dot{Q}_{aux}^2 \right] dt \qquad \text{eqn.2}$$

where T_r^{ref} is a given reference temperature of the room, T_ris the actual temperature, and $\dot{Q}_{aux}$is the auxiliary heat input to the water storage tank, which is our control input/manipulated variable. For the results presented it may be vary in a range of 0-4KW. Using this formulation, we have to utilize some prediction a time t_h into the future of the "disturbance variables" of the system. To simplify our discussion, we consider only predictions of the "disturbances" solar irradiation, ambient temperature and hot water consumption (given as constant pattern here). These disturbances govern the temperature level in the storage tank and thus the requirements for auxiliary energy. In the cost function, w_T is a weight factor that can be used to shift the emphasis amongst the two terms in in the cost function, and t_h is the future time horizon upon which the cost function is computed for.

To prepare the optimization for the use of a nonlinear Programming solver, we discretize the cost function V and instead use

$$V' = \sum_{t=1}^{N} \left(w \ \ (T_r - T_r^{ref})^2 + Q_{aux,i-1}^2 \right); \ \ T_r\text{: } room\ temperature, \ \ T_r^{ref}\text{: desired room temperature, } w \ \ \text{:} weight \qquad \text{eqn.3}$$

3.2.1 Setting of free parameters

In principle we could use a varying discretization time t - this is common in MPC - but is less useful in our case because of the periodic nature of the disturbances over our future horizon t_h which is chosen to be t_h=2d. In the same way, the time step applied to sample the "disturbances" can be selected with some freedom, expecting better results for smaller steps. Here a step size of 2h and 4h where compared, leading to no significant changes in the results. The results given here refer to Thus, a calculation time 4h is chosen here,

For setting the control deviation weight w_T $\in \{ [\![10]\!]^2$ kW/K^2 ,$[\![10]\!]^4$ kW/K^2 } was tested. As no significant changes in the room temperature appeared w_T=$[\![10]\!]^2$ kW/K^2 is the calculation time in the results given here.

3.3. Results of MPC using perfect disturbance knowledge

The first application of the MPC refers to the case of a perfect prediction. Fig. 5 gives the temperature profiles for the system with the MPC control discussed. Differences to the system behavior under thermostat control are remarkable. The respective heat flows are given in fig. 10.

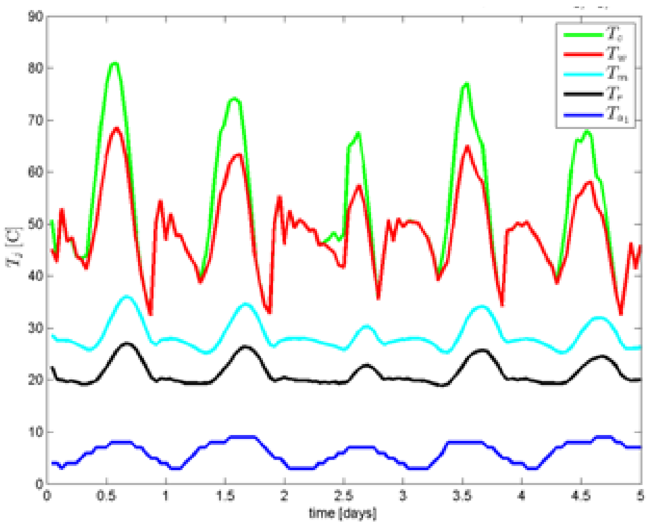

Fig.10: Same presentation as fig.8, but for the system operating under MPC control, using the perfect knowledge of the future evolution of the disturbances.

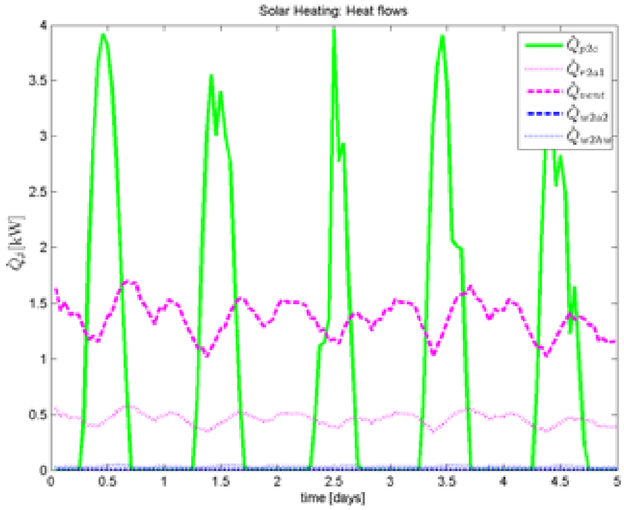

Fig.11: Same presentation as fig.9 but for system under MPC control with perfect forecast.

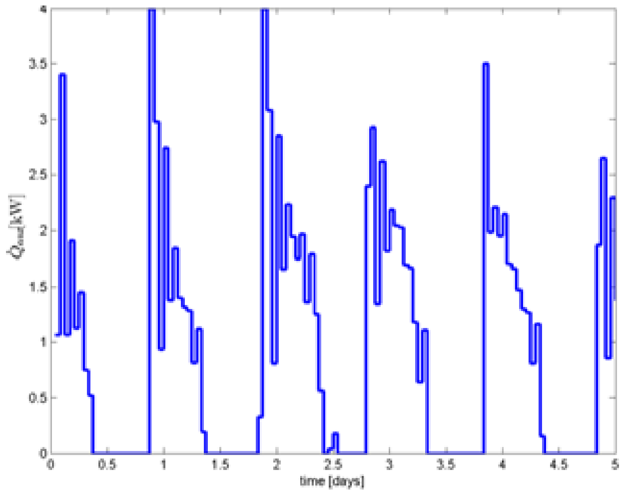

Fig.12: Time pattern of aux. heating under MPC using the perfect knowledge of the future evolution of the disturbances.

3.4. Results of MPC using realistic forecasts

Here the forecasts as described in section 2 are used. The resulting pattern for the temperatures and the operation of the auxiliary heating are given in fig. 13 and fig.14.

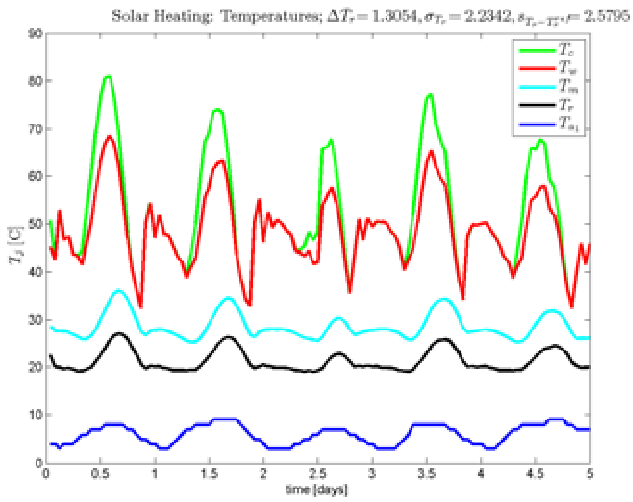

Fig.13: Same presentation as fig.8, but for the system operating under MPC control, using the forecasts as given in section 2.

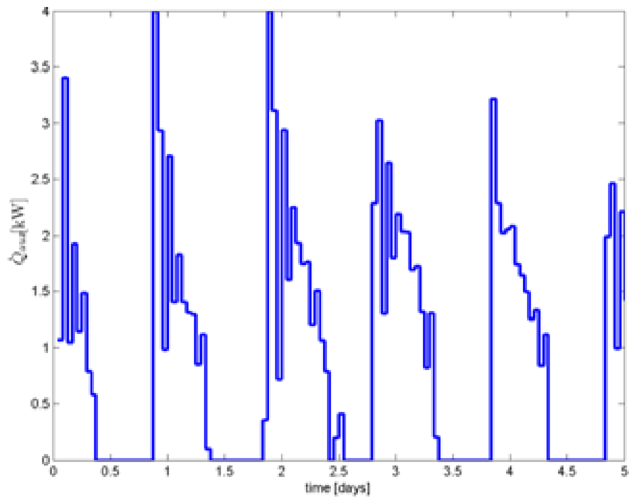

Fig.14: Same presentation as fig.12 but for MPC using the forecasts given in section 2.

It can be remarked, that the change from perfect forecast to the "realistic" forecasts given here does not result in big changes in the operation of the auxiliary heating. Next section will give compare the quality measures fir the 3 control scheme discussed.

3.5. Comparing auxiliary energy need and temperature stability under the 3 control schemes

Table 1 compare normalized aux, energy consumption and deviation from desired temperature for the 3 controls schemes in the period inspected.

Table 1: Quality measures for the system performance under the different control schemes, The "temperature deviation" i.e. the standard deviation of the excursions from the desired temperature and aux. energy are given normalized to the respective value for the thermostat control.

	temperature deviation	rel. aux. energy
Thermostat	1	1
MPC perfect	0.71	0.790
MPC realistic	0.72	0.796

It can be remarked that the MPC schemes directly lead to an improvement of the results of the thermostat control (however it has to be remarked, that there is also still room for improvement in optimizing parameters of the thermostat control). Concerning the two MPC variants, the change from the perfect forecast to the simple statistical forecast does result in small quality loss only. This may have been partly caused by the low complexity of the studied system. These specific findings however, have to be validated over longer time periods, covering, amongst other a larger variety of meteorological situations.

4 Conclusion and outlook

From the case study presented, it can be concluded, that a model predictive control (MPC) scheme can used with profit for a simple solar combisystem with rather limited number of controllable actors. Concerning the quality requirements on the necessary forecast information on the meteorological conditions acting as disturbances, this study indicates, that a comparatively simple forecast scheme may be applied here.
Future extensions of this work will have to cover the handling of more complex systems with an increases number of controllable actors. The control scheme may be extended here in the direction of stochastic dynamic programming, able to make use of probabilistic forecasts. In this context, the forecast scheme presented here, which can offer a basic probabilistic forecast has to be validated versus more elaborated forecast schemes based on meteorological modeling (see e.g. Lorenz et.al, 2009).

5 References

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