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Model predictive control for a smart solar tank based on weather and consumption forecasts

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Abstract

In this work the heat dynamics of a storage tank were modelled on the basis of data and maximum likelihood methods. The resulting grey-box model was used for Economic Model Predictive Control (MPC) of the energy in the tank. The control objective was to balance the energy from a solar collector and the heat consumption in a residential house. The storage tank provides heat in periods where there is low solar radiation and stores heat when there is surplus solar heat. The forecasts of consumption patterns were based on data obtained from meters in a group of single-family houses in Denmark. The tank can also be heated by electric heating elements if necessary, but the electricity costs of operating these heating elements should be minimized. Consequently, the heating elements should be used in periods with cheap electricity. It is proposed to integrate a price-sensitive control to enable the storage tank to serve a smart energy system in which flexible consumers are expected to help balance fluctuating renewable energy sources like wind and solar. Through simulations, the impact of applying Economic MPC shows annual electricity cost savings up to 25-30%.

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Keywords: Model predictive control; solar heating; smart solar tank; smart energy systems

1. Introduction

Economic Model Predictive Control (MPC) has previously been used to reduce the electricity costs of heating and cooling in buildings [1,2,3]. For a smart solar tank [4] the same MPC framework can be

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applied in order to save energy and reduce electricity costs. For the system considered in this paper, the electricity consumption of the auxiliary heating elements in a storage tank must be controlled. The heating elements can be turned on in periods when the amount of solar energy alone cannot meet the heat demand, e.g. hot water and space heating in a residential house.

The MPC exploits knowledge about the future inputs, so to minimize electricity costs a good tank model is required, along with excellent forecasts of both solar radiation and consumption patterns. In this paper we estimate the parameters in a storage tank model from measured data with a maximum likelihood method. With this model we design an Economic MPC to control the power consumption of the heating elements according to a price. By adding a price signal to the objective of the controller, the MPC will minimize the electricity costs for the individual tank by shifting power consumption to periods with cheap electricity. As the electricity costs are reduced the trade-off of considering prices and not power consumption alone is to use more power, but at the right time.

The performance of the MPC in terms of power consumption and electricity costs is investigated for different consumption patterns in a one-year simulation period. The influence of uncertainty in the forecasts of both solar radiation and consumption is also examined. We assume that electricity prices are known each hour at least 12 hours ahead, which is true for the day-ahead Elspot market in Denmark [5]. These prices reflect the power demand of the overall energy system and also indicate the amount of cheap renewable energy sources available, such as wind power.

2. Solar thermal collector and storage tank

The smart solar tank consists of a solar collector with area of 9 m^2, and a storage tank with a total volume of 788 l. The tank itself contains an inner tank for domestic hot water and a pressureless outer tank for space heating. The tank can be heated by the solar collectors. To help cover the remaining heat demand, three smaller electric heating elements of 3 kW each are installed in the tank, as shown in Figure 1b.

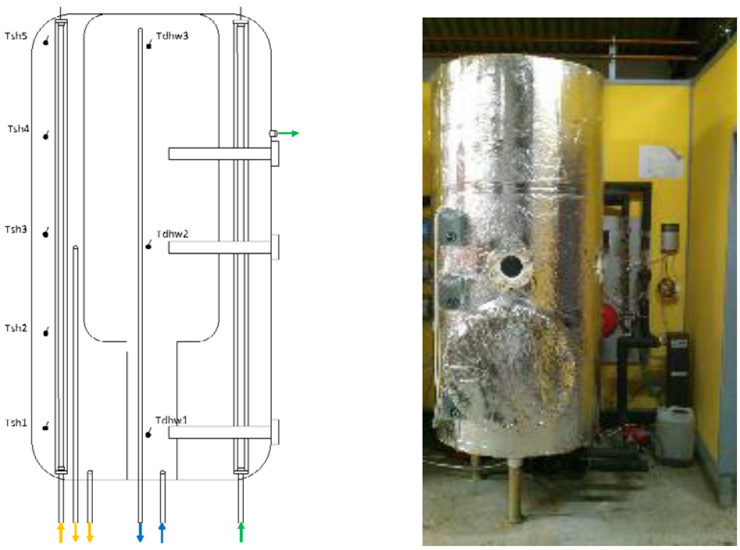

Fig. 1. (a) Sketch of the tank with inlets, outlets and eight temperature measurement points. (b) Photo of storage tank in lab

Solar energy is transferred to the tank by feeding water into the tank through a stratification device. In this way, beneficial thermal stratification is built up during solar collector operation [4,6]. Space heating is transferred from the upper part of the tank and the return inlet to the tank goes through another stratification device.

2.1. Tank model

We model the storage tank separated from the solar collector such that the energy balance is

$$Q_{\text{tank}} = Q_{heater} + Q_{solar} - Q_{consumption} - Q_{loss} \tag{1}$$

The contribution from the solar collector Q_{solar} and heat consumption $Q_{\text{consumption}}$ are forecasted inputs. The heating element input power consumption Q_{heater} is controllable. The loss is modelled as proportional to the temperature difference between the internal tank temperature and the ambient room temperature. The actual energy in the tank Q_{tank} cannot be physically measured, but is assumed to be dependent on the measured tank temperatures. Eight temperature measurements from different layers of the tank are combined to represent an overall tank temperature (T_t) proportional to the stored energy. Using an average from the eight sensors (n = 8) we get the tank temperature

$$T_t = \frac{1}{n}\sum_{j=1}^{n} T_j \tag{2}$$

Based on (1), the heat dynamics of the tank can be described as a simple first order differential equation

$$C_t \cdot \dot{T}_t = Q_h + \hat{Q}_s - \hat{Q}_c - UA \cdot (T_t - \hat{T}_i) \tag{3}$$

Q_h is the controllable power consumption for the electric heating elements with efficiency η. C_t is the specific heat capacity of the tank, while the energy contribution from the solar collector Q_s and the house consumption Q_c are both forecasted inputs. We use the forecasts computed from measurements in domestic households in southern Denmark based on [7,8]. The ambient temperature T_i should also be forecast, but is assumed to be a constant 20°C in further simulations.

The model data to be used for model estimation was based on a storage tank that uses stratification pipes for optimal injection of the return water. Therefore a layered model with more than one temperature state should possibly be considered. However, for the given data set and a time scale of minutes, a first order model with only one layer was found sufficient for describing the heat dynamics of the tank.

The solar thermal power is simulated from measured climate data recorded at the local district heating plant in Sønderborg. A standard flat-plate collector is used as the simulation model, as described in [9]. The solar thermal power is forecast with the method described in [7], where a conditional parametric model is applied for forecasting the hourly solar thermal power up to 36 hours ahead. The forecasting model takes numerical weather predictions of global radiation as input. Based on past data, the collector thermal performance is modelled and takes local effects into account, such as the orientation of the collector and shading from objects in the surroundings.

2.2. Model parameter estimation

CTSM was used to estimate the unknown parameters of a continuous discrete stochastic state space model. The model consists of a set of stochastic differential equations describing the dynamics of a system in continuous time and a set of algebraic equations describing how measurements are obtained at discrete time instants.

$$\begin{aligned} \mathrm{d}x &= (A(\theta)x + B(\theta)u + E(\theta)d)\mathrm{dt} + \sigma \mathrm{dw} \\ \mathrm{y} &= C(\theta)x + e \end{aligned} \tag{4}$$

The model includes a diffusion term to account for random effects, but otherwise it is structurally similar to ordinary differential equations. Therefore conventional modelling principles can be applied to set up the model structure. Given the model structure, any unknown model parameters can be estimated from data, including the parameters of the diffusion term. The parameter estimation method is a *maximum likelihood* (ML) method and a *maximum a posteriori* (MAP) method [10,11,12,13].

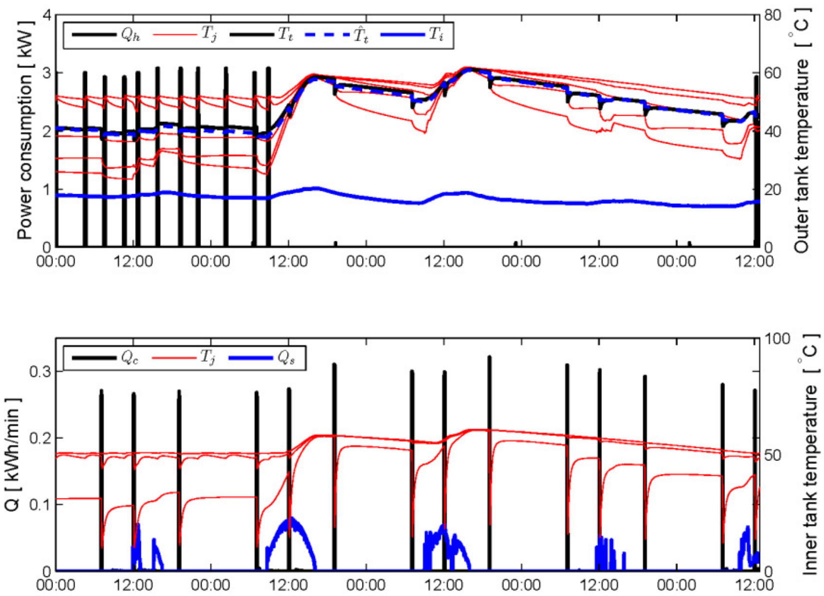

Fig. 2. Data measurements from real storage tank used for parameter estimation. The estimated tank temperature has been also been plotted

The model parameters $\theta = [C_t \quad UA \quad \eta]$ were estimated in the continuous time stochastic state space model (4) with $x = y = T_t$ and $d = [Q_s \quad Q_c \quad T_i]$ that contains the forecast disturbances from (3). It is assumed that the measurement error is normal-distributed. with a variance of 1°C such that $e \in N(0,1)$. The process noise was assumed to have standard deviation $\sigma = 0.001$.

The parameter estimation was based on the data shown in Fig. 2. The estimated parameters of (3) were found to be:

$$UA = 8.29\ (\pm\ 0.0278)\ \mathrm{W/K} \qquad C_t = 3881.3\ (\pm\ 0.00167)\ \mathrm{kJ/K} \tag{5}$$

It should be noted that the heating element efficiency was fixed at $\eta = 1$ and the tank temperature representing the stored energy was assumed to be an average of all eight temperature measurements. The fit of the resulting estimated tank temperature $\hat{T}_t$ is also compared to the average tank temperature T_t in

Fig. 2, and reveals a nice match. Note that the consumption pattern Q_c in this data set is deterministic and the same amount of energy is deliberately drawn from the tank at 7 am, 12 pm, and 7 pm.

3. Economic MPC

Traditionally the heating elements in a storage tank are controlled by a thermostat that is either on or off and keeps the temperature close to a temperature set point in a hysteresis loop. Instead of specifying a temperature set point for the tank, a set of constraints on the tank temperature and on power consumption is specified. For the MPC strategy, as long as the temperature is within some bounds, there is no need to force it to a certain temperature. In this way knowledge about the future weather and heat consumption can help to minimize the power consumption of the heating elements. Adding a price signal to the objective will then not only try to minimize the power consumption, but also the electricity costs. So the finite static MPC optimization problem to be solved at every sampling time t is

$$\begin{aligned}
\text{minimize} \quad & \sum_{k=t}^{t+N-1} p_k u_k \\
\text{s.t.} \quad & x_{k+1} = Ax_k + Bu_k + Ed_k \\
& y_k = Cx_k \\
& 0\,\text{kW} \le u_k \le 9\,\text{kW} \\
& 50\,°\text{C} \le y_k \le 95\,°\text{C}
\end{aligned} \tag{6}$$

At each sampling time, t, we minimize the electricity costs over the prediction horizon N, given the forecasts available at time t. The first control action u_0 of the solution is implemented on the process and the procedure is repeated at the next sampling instant. This is usually referred to as receding horizon control. The model (3) is discretized into a discrete time state space model defined by the matrices (A,B,E,C) with the estimated parameters (5). The constraints on temperature and power consumption must also be satisfied.

4. Simulation

Fig. 3 shows a simulation of the resulting MPC with the estimated tank model. The scenario is based on real measured solar radiation and consumption patterns from residential houses in southern Denmark during a whole year from May 17 2010. The simulation is a closed loop simulation with a 24-hour prediction horizon based on forecasts subject to uncertainty and actual electricity prices from the Nordic Elspot market [5].

In Fig. 4, one week in March 2011 of the simulation from Fig. 3 has been extracted. During the first few days the heating elements mostly use power during night-time when the prices are low. In the remaining period a lot of solar radiation heats up the tank and the heating elements are practically not used. The temperature stays within the predefined interval that defines the storage capability.

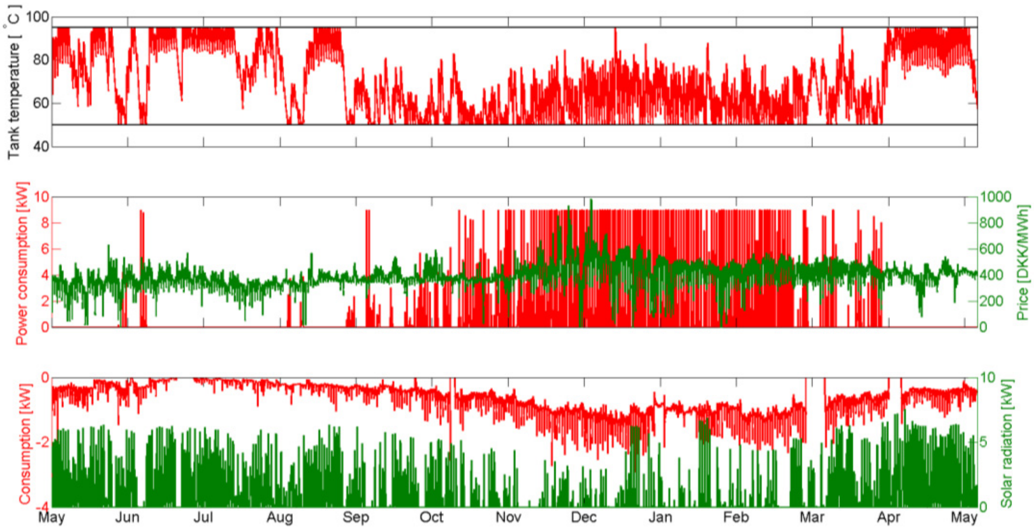

Fig. 3. A one-year simulation starting May 17 2010 with 24 h prediction horizon using uncertain forecasts. The upper plot shows the tank temperature, the middle plot contains the electricity price and the optimal power consumption for the heating element, and the lower plot contains the solar heat input and the house consumption demand. The heating element is turned on when the electricity price is low.

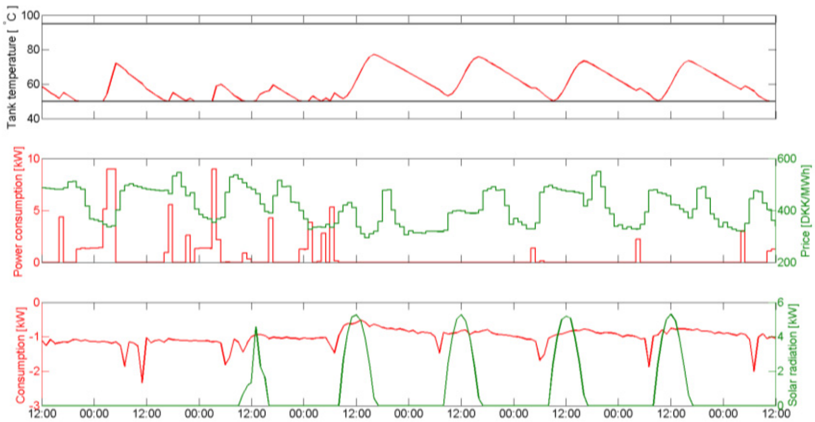

Fig. 4. Shows the same as Fig. 3. but contains only one week in March 2011 to make it easier to read the details.

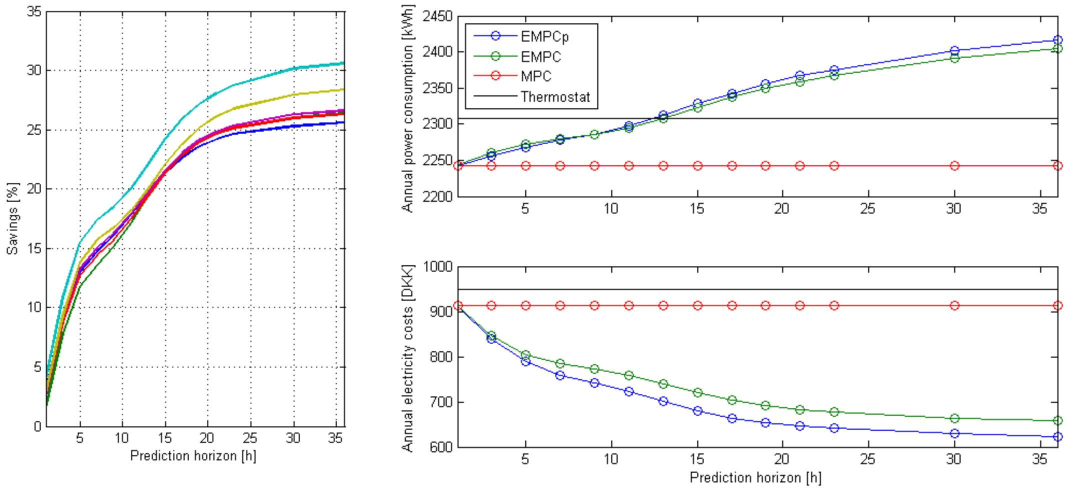

Fig. 5. (a) Annual savings in percent compared to conventional thermostat control for the six different houses. (b) Annual power consumption (upper) and electricity costs (lower) for house #2 as a function of the prediction horizon N for four different control strategies. Closed loop Economic MPC with perfect forecasts (EMPCp), with real forecasts subject to uncertainty (EMPC), a constant electricity price of 1 (MPC) and a Thermostat control keeping the temperature at 60°C.

5. Results and discussion

For a whole year the annual power consumption and electricity costs were found from closed loop MPC simulations for four different control strategies. The results can be found in Fig. 5a, while a simulation for one of the houses is shown in Fig. 5b. For a prediction horizon N larger than 24 hours, the cost savings do not increase by much as the prediction horizon increases further. This is mainly due to the maximum input power and the storage capacity of the system. Information about the solar radiation or the consumption next week will not change the optimal power consumption due to these system constraints. Furthermore, using perfect forecasts, i.e. knowing the future inputs exactly, does not increase the savings significantly. The annual savings of considering the price with an Economic MPC are 25-30% for the given simulation scenarios for six different houses.

Note that the power consumption for the Economic MPC grows larger than for the ordinary thermostat control as the prediction horizon increases. However the costs go down. Consequently, to save more money, more electricity must be used for control. However, the increased power consumption can be justified when the electricity price reflects the amount of renewable energy in the power system.

Another result of the investigations is that in the MPC strategy in which only power consumption is minimized and where prices are not considered, the annual power consumption is constant regardless of the prediction horizon. Since the sampling period is so high (1 h) compared to the dynamics (< 5 min), the amount of power (9 kW) that can be delivered instantaneously in every one-hour sampling period is higher than the instantaneous demand at any time. So the control signal matches the consumption at every sampling time even for a one-hour prediction horizon. Also the control is only active at the lower temperature bound, because it is not possible to actively cool the tank.

Similar results were obtained for the five other houses, with the same conclusions.

Any missing data in the forecasts was ignored by setting it to zero. This means that some periods in the annual simulation have no solar input or no consumption at all. For the six different houses the total missing number of samples in the consumption data sets was around 510 (~21 days) for all houses except house 1, where 1800 samples were missing (~78 days). For the solar data that were used for every house, 351 samples were missing (~14 days). An example of the missing data in the consumption forecast can easily be seen in Fig. 3.

Computation times for solving the individual open loop MPC problem are in the millisecond range. Simulating a whole year takes around 5-10 seconds for a prediction horizon of 24 hours running Matlab on an Intel i7 2.67 GHz laptop.

6. Conclusion

The heat dynamics of a smart solar storage tank were modelled and its parameters were found from maximum likelihood estimation procedures. An Economic MPC was designed to control the power consumption of the auxiliary heating elements in the storage tank. The MPC minimizes electricity costs given the price and forecasts of the solar radiation and consumption. Electricity cost savings of 25-30% compared to current thermostat control strategy were found for six different houses.

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