Controller tuning of district heating networks using experiment design techniques

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Abstract

There are various governmental policies aimed at reducing the dependence on fossil fuels for space heating and the reduction in its associated emission of greenhouse gases. District heating networks (DHNs) could provide an efficient method for house and space heating by utilizing residual industrial waste heat. In such systems, heat is produced and/or thermally upgraded in a central plant and then distributed to the end users through a pipeline network. The control strategies of these networks are rather difficult thanks to the non-linearity of the system and the strong interconnection between the controlled variables. That is why a non-linear model predictive controller (NMPC) could be applied to be able to fulfill the heat demand of the consumers. The main objective of this paper is to propose a tuning method for the applied NMPC to fulfill the control goal as soon as possible. The performance of the controller is characterized by an economic cost function based on pre-defined operation ranges. A methodology from the field of experiment design is applied to tune the model predictive controller to reach the best performance. The efficiency of the proposed methodology is proven throughout a case study of a simulated NMPC controlled DHN.

Key words: model predictive control, district heating network, controller tuning, experiment design

Nomenclature

α	tuning parameters of MPC
β	tuning parameters of MPC
$\Delta\mathbf{u}$	change in manipulated variables
γ	tuning parameters of MPC
λ	extension or contraction coefficient
ρ	density of the heat transfer fluid ($\frac{kg}{m^3}$)
$\mathbf{u}$	manipulated variables

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$\mathbf{w}$	setpoint signals
$\mathbf{x}_m$	parameter vector of the simplex with the worst value of objective function
$\mathbf{y}$	controlled signals
ξ	mechanical loss coefficient
A	area for heat transfer in a cell (m^2)
c	value of control horizon
c_p	heat capacity of the heat transfer fluid ($\frac{kJ}{kgK}$)
E	length of modeling error vector
K	constant for trigger of IMC
L	length of the pipe (m)
M	number of optimized variables in simplex method
m	mass flow in the pipe ($\frac{kg}{sec}$)
ME	modeling error vector
N	number of cells in the heat production unit
N_o	number of consumers
p	value of prediction horizon
P_i^{on}	income when the consumed heat in the i^{th} consumer is inside the specification limits
Q	transferred heat in the heat production unit (kW)
Q_i^{on}	indicator in fulfilling the specification limits
R	radius of the pipe (m)
T	temperature in the pipe (K)
T_0	ambient temperature (K)
$T_c(i)$	temperature on the cold side in the i^{th} cell (K)
$T_h(i)$	temperature on the hot side in the i^{th} cell (K)
T_{in}	inlet temperature in the pipe (K)
U	heat transfer coefficient ($\frac{kJ}{m^2K}$)
v	velocity of the fluid in the pipe ($\frac{m}{sec}$)
V_c	the volume of a cell on the cold side of the heat exchanger
V_h	the volume of a cell on the hot side of the heat exchanger (m^3)

1. Introduction

District heating was promoted in Europe in the 1950s. Nowadays EU-CHP Directive could assure the legal framework for applying district heating for member states of the European Union. District heating network is implemented to utilize the heat generated by the combustion of city waste or industrial waste heat. Thanks to the efficiency and environmental friendly characteristics, the role of the district heating is still increasing ([1]). The main advantages of district heating systems are the following:

1. Energy efficiency thanks to the simultaneous generation of heat and electricity in combined heat and power plants (CHPs).
2. Environment friendly by implementing renewable energy sources and utilizing industrial waste heat.

Several variations exist for district heating networks: in [2] the district heating network includes several consumers located in different areas, but there is no energy storage and just one heat production unit. In [3], a storage tank is added to the network. In [4], a storage tank is also considered, but there is no thermal energy supply network. In some cases not just the local DHNs should be analyzed but the whole national DHN system, to investigate the sensitivity of the network to e.g. policy or even fuel price changes [5].

Modern optimal control and operation of a thermal plant and district heating network shall be a great project, especially if environmental aspects taken into consideration ([6] and [7]). To reach this goal a proper and detailed description of the process is clearly needed like in [8] and [9]. Optimal operation means to meet the consumers' and environmental requirements and at the same time fulfill the restrictions to make the operation of the plant safe. Optimal control strategies meet these restrictions and at the same time minimize the operational costs or the environmental effects like in [10]. Model predictive control (MPC) methods are highly applicable for these purposes since the formulation of the objective function might imply every aspects. As MPCs require proper process model, the whole network has to be modeled.

The models of a district heating network in the literature can be a physical description of the heat and mass transfer in the network, like [11] and [12], and utilize node method like in [13]. There can be another approach, based on a statistical description of the transfer function from the supply point to the critical point considered. The forecast methodology proposed in [14] and [15] is to set an ensemble of ARMAX (Auto-Regressive Moving Average with Exogenous input) models with different fixed time delays, and to switch between models depending on some estimated current time. In [16] the grey-box modeling approach combines physical knowledge with data-based, statistical modeling. Physical knowledge provides the main structure and statistical modeling provides details on structure and the actual coefficients/ estimates. This is advantageous since the physical knowledge reduces the model-space which must be searched, whereby the validity of the statistical methods is better preserved.

The aim of this work is to reduce the transition time in a non-linear model predictive controlled DHN presented in [17] by tuning the parameters of the non-linear MPC. The efficiency of the controller is measured by a cost function considering the limits of desired operation regime. To maximize this cost function the simplex method is applied, which is a well-known method in field of experiment design. This optimization method is able to handle mixed-integer optimization problems, which is needed because of the integer values of prediction and control horizon. Since there are periodic characteristics of heat demand, the proposed methodology can be easily inserted into an iterative learning control scheme ([18]).

The paper is organized as follows: in Section 2 the topology of the applied district heating network will be introduced. In the second part of Section 2 the applied MPC solution and the tuning method are introduced and then in Section 3 the control and optimization results will be examined.

2. Modeling and control approach of a district heating network

2.1. The applied topology and modeling approach

In this section the topology of the examined district heating network is presented. The topology depicted in Figure 1 is chosen to represent the main characteristics of a district heating network. The network contains two heat production units, three consumers, two pumps and a valve. The production unit, called Producer 1, is the base load boiler, which may represent e.g. a waste incineration plant. The other production unit, called Producer 2, is the peak load boiler station, which has to satisfy the increased heat demand in the network, especially in case of Consumer 3. HX1 and HX2 heat exchangers are for transfer the produced heat from the primary circles to the secondary circle, which distributes the heat to the consumers directly.

The model of this network is developed using the method of [11], which applies the physical description of the heat and mass transfer in the network. Structural approach is used to obtain a convenient global model: considering the complexity of the system, local models of the components of the network are established and then brought together.

2.1.1. Heat exchangers

In order to get the proper dynamic behavior of the heat exchangers an approach using a cell model with ordinary differential equations was chosen [10]. The heat exchanger was divided into perfectly and instantly mixed tanks, each featuring a hot side and a cold side element (Figure 2). As the number of cells increases the logarithmic mean temperature difference of the heat exchanger is approximated more accurately. It is assumed that each cell is perfectly homogenous, and no back-mixing occurred. Also, the mixing is instantaneous. In our model five cells were used on the hot side and five cells on the cold side.

The differential equations for the cells are shown in Eq(1) and Eq(2).

Hot side cell model:

$$\begin{aligned} \frac{dV_h \rho c_p T_h(i)}{dt} &= V_h \rho c_p (T_h(i-1) - T_h(i)) \\ &\quad - UA(T_h(i) - T_c(i)) \end{aligned} \tag{1}$$

where V_h is the volume of a cell on the hot side of the heat exchanger, ρ and c_p are the density and the heat capacity of the fluid, respectively, $T_h(i)$ and $T_c(i)$ are the temperature on the hot and cold side in the i^{th} cell of the heat exchanger, A is the area for heat transfer in a cell. To avoid the excessive complexity of the network the resistance of the wall is included to the heat transfer coefficient (U).

The cold side cell model is the following:

$$\begin{aligned} \frac{dV_c \rho c_p T_c(i)}{dt} &= V_c \rho c_p (T_c(i+1) - T_c(i)) \\ &\quad + UA(T_h(i) - T_c(i)) \end{aligned} \tag{2}$$

where V_c is the volume of a cell on the cold side of the heat exchanger, any further notations means the same as in the previous case.

2.1.2. Heat production units

The heat production units have been similarly modeled to the heat exchangers; the only difference is that only the cold side has been divided into cells.

Eq(3) represents the model of a cell (N is number of the cells, Q is the transferred heat):

$$\frac{dV_c \rho c_p T_c(i)}{dt} = V_c \rho c_p (T_c(i-1) - T_c(i)) + \frac{Q}{N} \tag{3}$$

This simplification is applied because since in the considered network it is not important how the heat has been produced, just the quantity and distribution of the invested heat is significant. Detailed description of modeling approach a heat producer e.g. a CHP could be found in [19].

2.1.3. Pipelines

Pipeline network has significant effect on the operation of the considered DHN. This effect must be taken into account already in the piping network design ([20]). In order to model the pipelines of a DHN, two crucial effects have to be taken into consideration: the heat loss on the pipes could not be neglected. A more important factor, the dead time between the ends of the pipe must also be taken into consideration. The thermal energy propagation in pipes can then be modeled by a partial differential equation ([11]).

$$\frac{\partial T}{\partial t}(x,t) + \frac{m(t)}{\pi \rho R^2}\frac{\partial T}{\partial t}(x,t) + \frac{2U}{c_p \rho R^2}(T(x,t) - T_0) = 0 \tag{4}$$

where T is the temperature, m is the mass flow in the pipe, ρ is the density of the fluid in the pipe, R is the radius of the pipe, U is heat transfer coefficient on the wall and T_0 is the ambient temperature. This equation leads to the solution presented in Eq(5) ([11]):

$$T_{out}(t) = T_0 + (T_{in}(t - t_0(t)) - T_0) \cdot e^{-\frac{2U}{c_p \rho R^2}(t - t_0(t))} \tag{5}$$

As the thermal losses on pipes are assumed very low, the previous equation is approximated by the following expression:

$$\begin{aligned} T_{out} &\approx T_0 + (T_{in}(t - t_0(t)) - T_0) \cdot \left(1 - \frac{2U}{c_p \rho R^2}\right) \\ &\approx T_{in}(t - t_0(t)) \cdot \left(1 - \frac{2U}{c_p \rho R^2}\right) \end{aligned} \tag{6}$$

The computation of variable time delays is time consuming. That is why constant (and for instance nominal) time delays have been considered. This approach allows modeling thermal propagation as a simple non-linear dynamic system, which can be quickly solved.

The mechanical losses in pipes are modeled by:

$$\Delta p = \xi \frac{\rho v^2}{2} \frac{L}{2R} \tag{7}$$

where L is the length of the pipe. Detailed modeling approach and description of the topology can be found in [17].

2.2. *Multilayer optimization for DHNs*

The main goal is to minimize the transition time between two operation points. For that purpose there is a need to formalize the problem first. To do that, the certain operation regime shall be specified by defining the upper and lower limits. The goal is to reduce the out-of-limits operation, which usually occurs during transitions. If the considered operation limits are not violated, then the operation can be called appropriate. The linear cost function presented in Eq(8) is applied for measuring the appropriate operation time.

$$E = \sum_{i=1}^{N_o} P_i^{on} \cdot Q_i^{on} \tag{8}$$

where N_o is the number of consumers, P_i^{on} is the income when the consumed heat at the i^{th} consumer is inside the specification limits. Q_i^{on} means the amount of consumed heat that is between the pre-determined limits (the value of it is 1 when inside 0 when outside the limits). This objective function shall be maximized by optimizing the tuning parameters of the applied model predictive controller. That is why there is a need to find a methodology which could handle mixed-integer optimization problems. The objective function (Eq(8)) represents the upper layer of the multilayer optimization problem. The MPC in the lower layer also formulates an optimization problem, hence the whole process optimization approach could be considered as a multilayer optimization problem.

2.3. *Model predictive control of the DHN*

2.3.1. *Manipulated variables*

In this section, the particular DHN described in Section 2.1 is considered. The possible manipulated variables are: the invested heat in Production unit 1 and 2, pump duty of P1 and P2 pumps and the valve opening. Since the P1 pump is chosen to compensate the pressure drop of the heat exchangers and pipelines, the P1 pump does not take part in satisfying the heat demand of consumers, so it was considered to be controlled by a local regulator.

The pressure drop in the direction of the Consumer 2 and in the direction of Consumer 3 must be the same. To reach this goal two manipulated variables can be used: the valve opening and the pump duty of the P2 pump. These manipulated variables are for determining the split ratio on the splitter and through this control the flow in the two directions to be able to transfer enough heat to the consumers.

2.3.2. *Analysis of applied models*

The similarity of the model and the controlled system is assumed because the parameters of the model is estimated based on the ”measurements” of the controlled system. The difference is caused by approximating the variable time delay (in the pipes, see Eq(6)) with a constant one. Since in the case study a non-linear model with constant time delay is applied as controlled system, the proposed similarities and differences are assumed to be realized by applying the same model with different time delays.

Creating a mathematical model for control purposes is a challenging task in every MPC ([21]). In this case, since there were no real available operating plant, the process was replaced by the process model. This is based on the physical description of the DHN (called ”A” model). ”A” model is implemented in Simulink. In the examinations, a process model without time delays is going to be utilized for prediction ($t_0 = 0$ in Eq(5)-(6), but also based on the physical description of the DHN). This model is implemented in Matlab and called ”B” model. In commercial MPCs, usually linear models have been applied for prediction (such as Dynamic Matrix Controllers, see [22]). Since the controlled systems are mostly non-linear, it is necessary to update the model parameters regularly to keep the model valid in every operation range.

The application of two different models has an important advantage: it is possible to simulate the situation when the model is not able to describe the operating process perfectly. A non-linear model, based on the physical description of the system is created to reduce the necessity of updating the model parameters and extend the validity of the model in the whole operation range. The prediction ability of the model is based on the ”measurements” of the controlled system, which are applied for parameter estimation purposes. The difference of the ”operating network” and the process model for prediction is caused by assuming a different time delays as described previously.

To demonstrate the differences between the ”operating network” and the process model used in the MPC an examination has been carried out. The results of the comparison shown in Figure 5 with respect to the same input signals.

2.3.3. Objective function and constraints of the model predictive controller

When creating the model predictive control system of a district heating network, the first task is to define the possible manipulated variables, which can be continuous ([23]) or integer variables (e.g. boiler status ([24])). In case of optimization this leads to a mixed integer optimization problem. Solving an optimization problem like this is rather difficult, time consuming and computationally demanding. In this paper a simple non-linear sequential quadratic programming (SQP) method with soft constraints will be applied to avoid the difficulty of mixed integer non-linear programming (for more details see [17]). The solution to avoid the problem of mixed-integer optimization is to augment the conventional objective function of MPC with the absolute values of manipulated variables. To differentiate the importance of the manipulated variables different weights shall be applied for them in the extended objective function (e.g. utilizing heat invested from the base load boiler rather than applying the peak load boiler). The objective function of the utilized MPC is formalized in Eq(9).

$$\min_{\mathbf{u}(k+j)} \beta \sum_{j=1}^{p} (\mathbf{w}(k+j) - \mathbf{y}(k+j))^2 + \\ \alpha \sum_{j=1}^{p} \mathbf{u}(k+j)^2 + \gamma \sum_{j=1}^{c} \Delta\mathbf{u}^2(k+j-1) \tag{9}$$

where $\mathbf{w}$ is the setpoint signal, $\mathbf{y}$ is the controlled variable, $\mathbf{u}$ and $\Delta\mathbf{u}$ is the absolute value and the change of the manipulated variable, $p, c, \alpha, \beta, \gamma$ are the tuning parameters of the MPC. The aim of the controller to fulfill the heat demand of consumers. $\mathbf{y}$ means the transferred heat in the consumers, calculated based on the difference of the outlet and inlet temperature of consumers on the cold side, Eq(2). The control goal is reached by varying the implemented heat in the production units. The transferred heat in the production units are symbolized by $\mathbf{u}$ the same as denoted with Q in Eq(3). The performance of the controller highly depends on its’ tuning parameters and the forecast of the heat demands. So the determination of values of tuning parameters is crucial project in reduction of transition time.

In the case study, α is a vector with four elements: the weight for Producer 1 is 0, since it is not necessary to punish the control actions of Producer 1. On the contrary the weight of the control action for Producer 2 is non-zero, since it is important to punish its' control action, utilizing the heat sources in Producer 1 instead. The situation is the same in case of the valve and the P2 pump since the control action of the valve is preferred to the control action of P2 pump. γ is a constant for punishing the change of valve position.

In the created MPC framework SQP optimization method has been utilized to minimize the objective function presented in Eq(9). The optimization in the MPC has to be realized taking into account the constraints of the process. These constraints express that the actuators have a limited field of action as well as determined slew rate, as in the case of valves. The input constraints in this study are formalized as in Eq(10).

$$\begin{aligned} \mathbf{u}(k+j-1) - \Delta\mathbf{u}_{max} \leq \mathbf{u} \leq \mathbf{u}(k+j-1) - \Delta\mathbf{u}_{max} \\ j = 1 \ldots c \end{aligned} \tag{10}$$

where c is the length of the control horizon.

2.3.4. Application of Internal Model Control scheme

The obvious model mismatch, shown in Figure 5, motivated us to apply the Internal Model Control (IMC) scheme ([25]), depicted in Figure 4. The IMC scheme is used in a modified form as follows. Since the IMC structure modifies the set point signals during transitions significantly, leading to huge overshoot, it is not advantageous to apply this scheme during the transitions. At the same time it is very useful to apply the IMC scheme to eliminate the steady state offset. So a trigger is implemented in the optimization box to switch on and switch off the IMC scheme. The trigger is formulated with the following expression:

$$\frac{\sum_{k=1}^{E} ME_k(i) - ME_k(i-1)}{E} \leq K \tag{11}$$

where ME is the modeling error vector in i^{th} and $(i-1)^{th}$ sample time, E is length of the modeling error vector, K is constant. When the change of the model error is smaller than a previously determined constant, the controlled variable is relatively close to the set point. If this condition is fulfilled the IMC scheme will be expected to switch on and eliminate the steady state offset.

2.4. Methodology for tuning parameter optimization

In the field of MPC tuning there are no common practices to determine the parameters especially in case of punishment factors. In [26] a methodology has been introduced to solve this problem based on the first order and dead time models of the controlled object but this method is valid only for linear MPCs.

A well-known simplex methodology was employed to maximize the objective function of Eq(8) with varying the tuning parameters of model predictive controller. This methodology is widely applied in field of experiment design ([27]). The simplex method consist of the following steps:

1. In case of M pieces of variables, $M+1$ pieces of experiments are necessary to be carried out to create the initial simplex. In this paper $M = 6$ since the following tuning parameters shall be adjusted: α (except the weight of control action of Producer 1), γ, p and c.

2. Evaluation of objective function at the peaks of the simplex. With reflecting the peak with the lowest value (since maximizing Eq(10)) to the opposite hyperplane defined by the residuary peaks, the parameters of the new experiment is found.
3. The obtained parameters is used instead of the reflected peak.
4. Carrying out the experiment with the new parameters.
5. Continue the reflection (Step 2 and Step 3) and determine the value of extension or contraction coefficient. Stop if the value of the objective function reach the desired value.

The equation for the procedure of reflection can be written:

$$\mathbf{x}_m^{new} = \frac{1+\lambda}{M} \cdot \sum_{i=1}^{M+1} \mathbf{x}_i - (\lambda + \frac{1+\lambda}{M}) \cdot \mathbf{x}_m \tag{12}$$

Where M is the number of optimized variables (the length of $\mathbf{x}$), $\mathbf{x}_i$ stands for the coordinates of the simplex before reflection, $\mathbf{x}_m$ is the parameters of the simplex with the worst value of objective function and λ is the extension or contraction coefficient.

3. Results and discussion

In the case study the main goal is to maximize the income (formulated in Eq(8)) by tuning the MPC. The tuning parameters are the values of the prediction and control horizons and the values of α and γ in Eq(9). These parameters represents the search space where the simplex methodology is applied.

To show the advantaged of the presented methodology, the performance of the controller with initial and tuned parameters have been compared, see Figure 6 and Figure 7.

As these figures show, the time demand of the transition is shortened. Although a badly tuned MPC is also capable of performing the transition, the optimization of tuning parameters is necessary. The parameters of the MPC determine how effective the de-coupling of the process variables is, which is presented throughout the example of Consumer 2. In this case the regulator could not eliminate the effect if there is a transition at Consumer 1. In the optimized case the heating network fulfills the requirement of Consumer 1, 2 and 3 more than 63 %, 52% and 57% of the examined time horizon in contrast to the initial guess where these ratios were 50%, 45% and 52%, respectively. It has another advantage as well, because the MPC tuned with the proposed method eliminates the effect of changes in the heat demand of other consumers, quite effectively. In the optimization scenario 7 simulation have been executed to initialize the simplex, and 5 more to improve the control performance. 4 more experiments were evaluated to prove that the optimum solution was reached. During these experiments the simplex seemed to rotate around, which indicates that the maximal value of objective function (Eq(8)) was reached.

4. Conclusion

In this study a multilevel optimization approach of a district heating network has been presented. The main goal was to fulfill the heat demand of consumers as soon as possible in a non-linear model predictive controlled DHN. To reach the goal of shortening the length of transients the first task is to create a cost function for measuring the efficiency of control. This cost function is based on the income if the consumers' heat demands are fulfilled. The next step is installation of the non-linear model predictive controller (NMPC). The model applied for prediction is based on the physical description of heat and mass transfer. To take the possible model error into consideration the internal model control (IMC) scheme has been utilized. The optimal tuning parameter combination of the NMPC provides the shortest transient time and the maximal income. To find these parameters the simplex method can be a good choice as this method involves reduced number of experimental runs to localize the optimal value of tuning parameters. The efficiency of the proposed methodology has been shown by a case study where the efficiency of the transition is increased by 10% .

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Figures

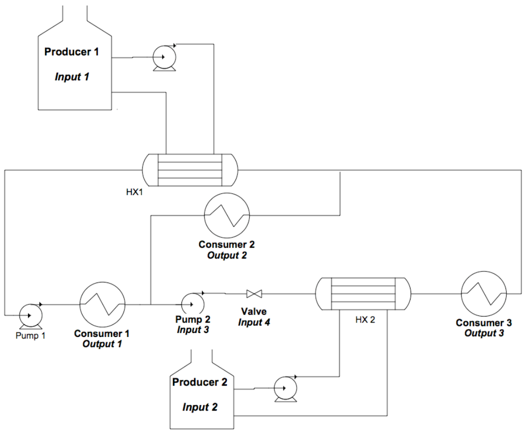

Figure 1: Topology of the examined district heating network

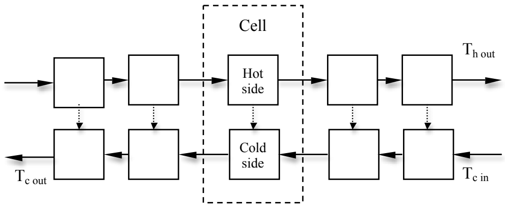

Figure 2: Cell model of the heat exchanger

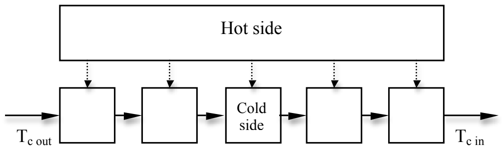

Figure 3: Cell model of the production unit

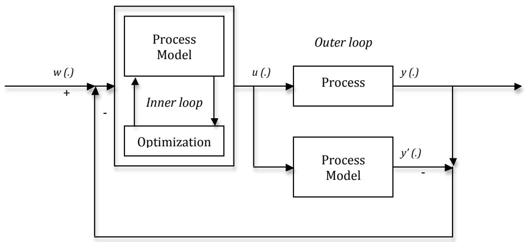

Figure 4: The scheme of the implemented non-linear model predictive controller

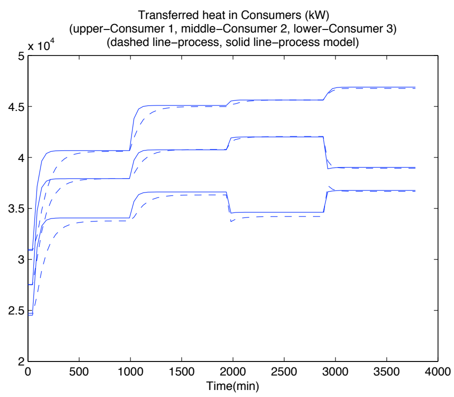

Figure 5: The outputs of the ”operating process” and process model to the same input signal

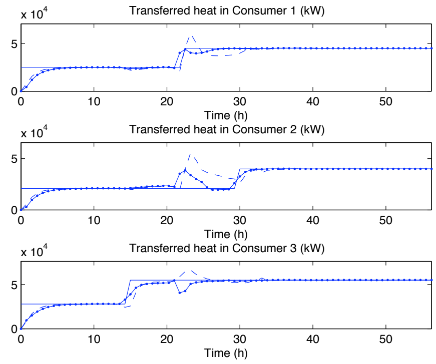

Figure 6: Comparison of the transitions in outputs with initial parameters (dashed line) and with the experimentally determined parameters (dotted line)

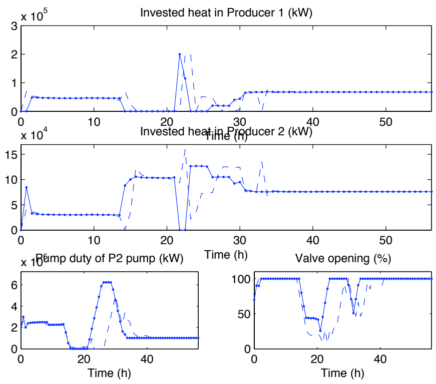

Figure 7: Comparison of the transitions in inputs with initial parameters (dashed line) and with the experimentally determined parameters (dotted line)