László Csaba Dobos

DYNAMIC MODEL AND CONTROL OF HEAT EXCHANGER NETWORKS FOR DISTRICT HEATING

Master Thesis

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The Master Thesis Project

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In Trondheim there is a district heating network for hot water based on the Tiller incineration plant for burning waste, and in Oslo there are similar plants. It is possible to save energy by improving the operation and control of such systems. This will be a continuation of a successful ongoing project in cooperation with Helge Mordt at Prediktor (Fredrikstad) who has been working with the Oslo plant.

Depending on the interest of the student, three possible projects are suggested

1 Modelling of district heating network

- Literature research on modelling district heating systems for cities
- Develop a simple model
- Combine this model with an existing model of an incineration plant
- Propose a simple control structure and simulate the plant

2 Model predictive control of district heating network.

The project is to develop a (possibly non-linear) model predictive controller for a district heating system.

- Literature study on non-linear MPC and model reduction
- Dynamic model reduction of heat exchangers
- Implementing a non-linear model predictive controller

3 Self-optimizing control of polynomial systems

To obtain optimal operation, it is important to identify “self-optimizing” controlled variables. In this project the objective is to find higher-order self-optimizing variables

- Literature study on polynomial systems
- Deriving a polynomial model approximation
- Finding polynomial self-optimizing control variables using elimination techniques
- Implementing the control structure in Simulink

In this thesis the modeling and the model predictive control parts will be discussed in details.

Alulírott Dobos László Csaba diplomázó hallgató, kijelentem, hogy a diplomadolgozatot a Pannon Egyetem Vegyészmérnöki Intézet, Folyamatmérnöki Intézeti Tanszéken készítettem vegyészmérnök diploma megszerzése érdekében.
Kijelentem, hogy a szakdolgozatban/diplomadolgozatban foglaltak saját munkám eredményei, és csak a megadott forrásokat (szakirodalom, eszközök, stb.) használtam fel.
Tudomásul veszem, hogy a diplomadolgozatban foglalt eredményeket a Pannon Egyetem, valamint a feladatot kiíró szervezeti egység saját céljaira szabadon felhasználhatja.

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Abstract

The various governmental policies aimed at reducing the dependence on fossil fuels for space heating and the reduction in its associated emission of greenhouse gases such as CO_2 demands innovative measures. District heating systems using residual industrial waste heats could provide such an efficient method for house and space heating. In such systems, heat is produced and/or thermally upgraded in a central plant and then distributed to the final consumers through a pipeline network.

In this work two main objectives will be considered: the first is to create a dynamic model which can represent the main characteristics of a district heating network and the second one is to design a non-linear model predictive controller (NLMPC) to satisfy the heat demands of the consumers in the heat exchanger network. As the model predictive controller is based on minimizing an objective function, it is totally perfect to find the way to reduce the superfluous energy consumption and make the best of using the freely applicable industrial waste heats. Beside this environmental aspect, reducing the invested energy consumption can reduce the operational costs.

Keywords: district heating network, modeling, non-linear model predictive control, MPC

Table of Contents

Introduction

It became obvious for people today to have a network for the distribution of the electricity from the power plants to the consumers, the picture is much different when it comes to heating. Today the majority of the buildings in western Europe are heated with individual boilers that are fed either with city gas or with oil. It is only in some cases, when the recycling of heat generated by the combustion of city waste allows it for instance, that a district heating network is implemented to use this heat. However, because of the different advantages of district heating systems, it would be beneficial to implement them not only in areas for which there is a specific opportunity like the recycling of heat released by the combustion of waste or the process of a near-by situated industry, but also in other areas. The main advantages of district heating systems are [25]:

1. Fewer sources of emission in densely populated areas.
2. Less individual boilers, thus increasing the available space in the buildings that can be used for other purposes.
3. A professional and on-going operating and maintenance of the centralised heating technology.

So it can be stated that energy becomes a more and more competitive market nowadays, thus optimization of the energetic systems became a crucial project for energetic companies. The district heating facility can provide higher economic and environmental efficiency compared to localized boilers, that is why the importance of these networks are increasing in the countries which use localized heat suppliers to satisfy the heat demand, such as the Nordic countries.

District heating networks are for distributing heat generated in a centralized location for residential and commercial heating requirements. The heat can be obtained from cogeneration plants or waste incineration plants although to satisfy the periodically increased heat demand so-called heat-only/peak load boiler stations are also used. These stations can be suppliers of residential and commercial consumers for space heating and for hot tap water and if necessary it can provide heat for industrial consumers for a certain level.

Several variations exist for district heating networks: in [1] the district heating network includes several consumers located in different areas, but there is no energy storage and just one production unit. In [26], a storage tank is added to the network. In [18], a storage tank is also considered, but there is no thermal energy supply network. So the variety of the district heating networks are numerous.

In order to meet the consumers requirements the suppliers have to pay significant attention to find the optimal control strategies that have some restrictions e.g. assure the minimum inlet temperature of consumers this way satisfying their heat demand. The aim of the control strategies to meet these restrictions and at the same time minimizing the operational costs of the heat supplier. The model predictive control methods are highly applicable for meet these demands since the formulation of the objective function can assure the possibility to take every aspect into consideration.

Managing a district heating network implies to assign values to integer variables (status of production units, status of pumps…) and to continuous variables (amounts of energy to produce). As a result, the optimization of the production and energy supply planning appears to be a huge, mixed and non linear optimization issue. Consequently, most studies use a simplified model, leaving aside some of the district heating network aspects. This modeling approach allows the use of one of the classical optimization methods listed in [24], but the solution can be strongly suboptimal when applied to the whole district heating network.

The thesis is organized as follows: in the Modeling section the topology of the applied district heating network will be introduced and the applied model equations will be defined. In the Control section first the general non-linear model predictive controllers will be described, then defining the purposes, introducing the applied MPCs and examining the control results.

Modeling section

The models of a district heating network in the literature either can be a physical description of the heat and mass transfer in the network [20] or they are based on a statistical description of the transfer function from the supply point to the critical point considered. The proposed forecast methodology in [23] 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 [13] the grey-box approach for modeling 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.

In this section a modeling of a district heating network is presented. The model is developed with using the method of [19] so applying the physical description of the heat and mass transfer in the network. Structural approach is used to obtain a convenient global model: considering complexity of the system, local models of the components of the network are established and then brought together.

Topology

The following topology was chosen to represent the main characteristics of a district heating network:

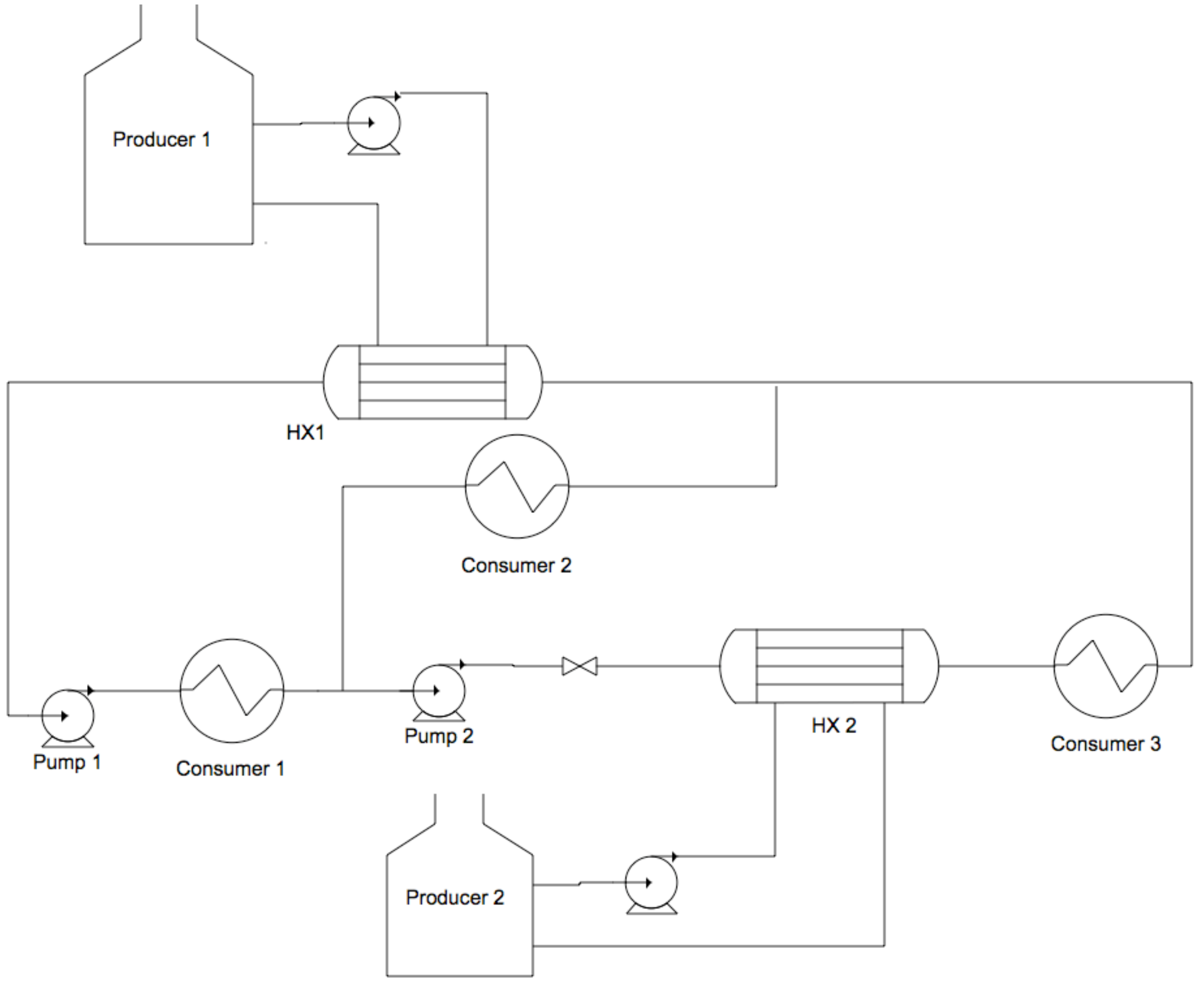

Figure 1. - the topology of the examined district heating network

As it can be seen 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 can represent 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 the Consumer 3. HX1 and HX2 heat exchangers are for transfer the produced heat from the primary circles to the secondary circle that is practically for distributing the heat for the consumers.

During the modeling procedure the following simplifications and assumptions were made to avoid the excessive complexity of modeled network:

- Since the system contained only pressurized water a thermodynamical and material properties like heat capacities and densities were assumed constant. Average values for the respective temperature intervals were used.
- Isothermal flow was assumed through the pumps and valve. This was done due to the low pressure differences in the system.
- The pressure profile of the system can change much faster than the temperature profile, so it was modeled with steady-state equations, while the heat exchangers are modeled with dynamical assumption.

The following model equations were applied to describe the network:

Valves

The valve is modeled using the following equation:

$$p_{out} = p_{in} - \xi \cdot \frac{\rho \cdot v^2}{2} \qquad (1.)$$

where ξ means the valve coefficient that is calculated by the expression below:

$$\xi = \frac{\xi_{(totalopened)}}{valveopening_{\%}/100} \qquad (2.)$$

As it was mentioned previously, there is no difference in the inlet and outlet temperature.

Pumps

By neglecting any temperature rise in the water during the travel through the pumps, they could be described using the Bernoulli equation. The elevation difference was set to zero, and the pipe diameter was assumed equal before and after the pump, the following expression can be set to characterize the pump:

$$p_{out} = p_{in} + \frac{\rho \cdot P \cdot \eta}{w} \qquad (3.)$$

where P means the pump duty, η means the efficiency of the pump, w means the mass flow.

If there were an operating system (a real plant) to fit the model there would be the chance to use a polynomial model for describing the pumps as [19].

Mixers

The mixing unit was modeled using the following simple expressions, under the assumption of instant and homogeneous mixing:

$$w_{out} = \sum_{i=1}^{N} w_i \tag{4.}$$

$$T_{out} = \frac{\sum_{i=1}^{N} w_i \cdot T_i}{w_{out}} \tag{5.}$$

In modeling the mixers' pressure profile the further assumption was followed:

$$P_{in,i} = P_{out} \tag{6.}$$

Pipes

In modeling the district heating networks taking the effects of pipelines into consideration is an important factor. The heat loss on the pipes can not be neglected, but the more important factor is the dead time that can happen between the ends of the pipe. The thermal energy propagation in pipes can then be modeled by a partial differential equation ([19]):

$$\frac{\partial T}{\partial t}(x,t) + \frac{m(t)}{\pi \cdot \rho \cdot R^2}\frac{\partial T}{\partial x}(x,t) + \frac{2 \cdot \mu}{c_p \cdot \rho \cdot R^2}(T(x,t) - T_0) = 0 \tag{7.}$$

Where:

T – temperature

m – the mass flow in the pipe

ρ - the density of the fluid in the pipe

R – the radius of the pipe

μ - heat transfer coefficient on the wall

T_0 – the ambient temperature

This equation leads to the following solution ([8]):

$$T_{out}(t) = T_0 + (T_{in}(t - t_0(t)) - T_0) \cdot e^{\left(-\frac{2 \cdot \mu}{c_p \cdot R \cdot \rho}(t - t_0(t))\right)} \tag{8.}$$

where the varying time delay $t - t_0(t)$ is defined by:

$$\int_{t_0}^{t} \frac{m(\tau)}{\pi \cdot R^2 \cdot \rho} d\tau = L \tag{9.}$$

Where L is the length of the pipe (m).

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

$$\begin{aligned} T_{out}(t) &= T_0 + (T_{in}(t - t_0(t)) - T_0) \cdot \left(1 - \frac{2 \cdot \mu}{c_p \cdot R \cdot \rho}(t - t_0(t))\right) \\ &= T_{in}(t - t_0(t)) \cdot \left(1 - \frac{2 \cdot \mu}{c_p \cdot R \cdot \rho}(t - t_0(t))\right) \end{aligned} \tag{10.}$$

The computation of varying time delays is time consuming. That is why constant (and for instance nominal) time delays have been considered in the previous equation. This approach allows to model thermal propagation as a simple non linear dynamic system, which can be quickly solved.

The mechanical losses in pipes are modeled by:

$$\Delta p = \xi \cdot \frac{\rho \cdot v^2}{2} \frac{L}{D} \tag{11.}$$

Heat exchangers

In order to get the proper dynamic behavior from the heat exchangers an approach using a cell model with ordinary differential equations was chosen [10]. This means that the heat exchanger was divided into perfectly and instantly mixed tanks, each featuring a hot side, a wall side, and a cold side element (Figure 2.). The idea is that this will approximate the logarithmic mean temperature difference of the heat exchanger as the number of cells increases. In our model five cells were used on the hot side and five cells on the cold side.

It is assumed that each cell was perfectly homogenous, and that no back-mixing occurred. Also, the mixing is instantaneous.

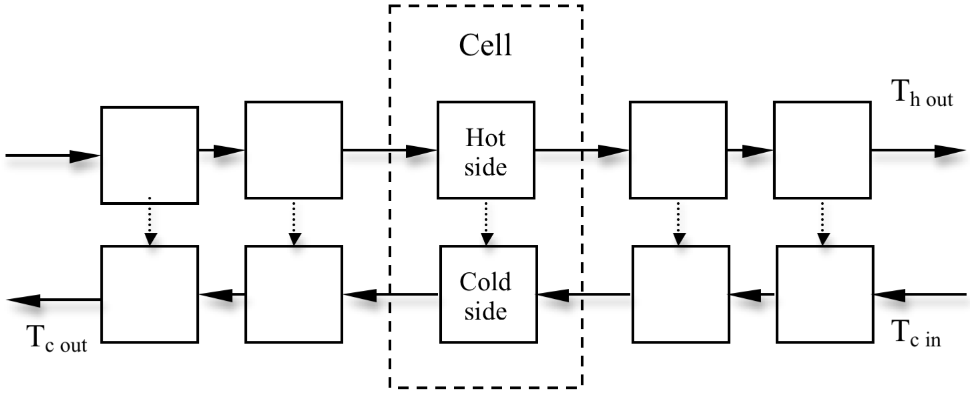

Figure 2. - cell model of the heat exchanger

The following equation are applied for a cell:

Hot side:

$$\frac{dV_h \cdot \rho \cdot c_p \cdot T_h(i)}{dt} = \dot{V}_h \cdot \rho \cdot c_p \cdot (T_h(i-1) - T_h(i)) - U \cdot A \cdot (T_h(i) - T_c(i)) \tag{12.}$$

Cold side:

$$\frac{dV_c \cdot \rho \cdot c_p \cdot T_c(i)}{dt} = \dot{V}_c \cdot \rho \cdot c_p \cdot (T_c(i+1) - T_h(i)) + U \cdot A \cdot (T_h(i) - T_c(i)) \tag{13.}$$

To avoid the excessive complexity of the network the resistance of the wall is included to the heat transfer coefficient (U).

The pressure drop of the heat exchanger is usually consist of the following parts:

- Pressure drop of the inlet nozzle
- Pressure drop caused by the friction on the sell and on the tubes
- Pressure drop of the outlet nozzle

To model these areas separately it would be necessary to use complex equations (Volverine heat transfer data book).

To reduce the number of the expressions (and because we do not have an operating system to fit the model) the pressure drop of a heat exchanger is approximated with the model equation of a valve. This way it was possible to model the pressure drop as the function of the flow rate and at the same time keep the model as simple as possible.

Heat production units

The approach of modeling the heat production units are very similar to the model of the heat exchangers, however in this case just the cold side was divided into cells, following the scheme below:

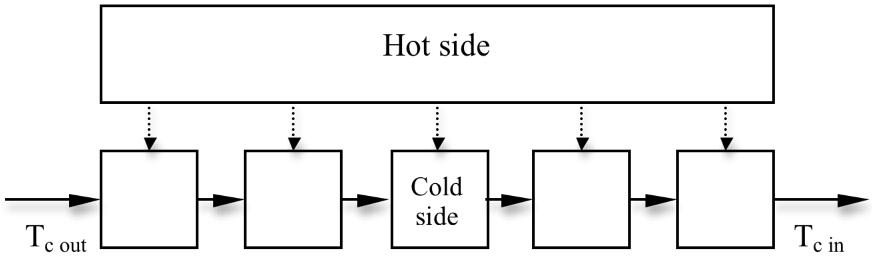

Figure 3. - cell model of the production unit

The following equation is for representing the model of a cell (*N* – number of the cells):

$$\frac{dV_c \cdot \rho \cdot c_p \cdot T_c(i)}{dt} = \dot{V}_c \cdot \rho \cdot c_p \cdot (T_c(i-1) - T_c(i)) + \frac{Q}{N} \tag{14.}$$

This simplification is applied because in the aspect of the heating network it is not important how the heat was produced, just the quantity of the invested heat is significant.

The introduced topology was built up from the parts that were introduced previously. This network was implemented in Simulink. An other model of this network is implemented in Matlab with the approximation of neglecting the time delay of the pipelines (in Eq. 8.). This approach was necessary because this way reduction of computational demand was expected.

Control section

Model based control concepts

The development of modern model based control concepts can be traced back to the early 1960s, designing the linear quadratic regulator (LQR), which is to minimize an unconstrained quadratic objective function of states and inputs. This concept can assure the basics of model predictive control. However the concept of minimizing an objective function is very simple, the complexity of the controlled systems require different algorithms to solve the problem. At the early stage of designing model predictive controllers there was no sufficient computation background to realize complex algorithms which require numerical solutions, so linear control algorithms were preferred [9, 22], like DMC, because of the analytical solution to the objective function. When modern computers could meet the computational requirements, more complex methods could be applied to develop the accuracy and stability of the control algorithms, and this way the non-linear model predictive algorithms could be born.

The numerical solution of an optimal control problem

Optimal control deals with the problem of finding a control law for a given system such that a certain optimality criterion is achieved. A control problem includes a cost functional that is a function of state and control variables. An optimal control is a set of differential and occasionally algebraic equations describing the paths of the control variables that minimize the cost functional. The model predictive control is typically an optimal control problem since the previously mentioned set of equations are the model of an operating plant.

In this section two powerful methods will be introduced that are applicable to optimize complex non-linear dynamic problems:

The single-shooting method is used for problems with many state variables, few control (optimization) variables and few control intervals. In this technique time-varying controls are defined as simple functions of time over a number of control intervals. In this thesis this method will be applied, since the model contains more than 60 states and just a few control variables, so the previously described method is suitable in this case.

The multiple-shooting method is used for problems with few state variables, many control (optimization) variables and many control intervals. The technique optimizes control intervals individually while then manipulating control variables to obtain a consistent solution at the interval boundaries. In more details:

Single shooting method

Single shooting also known as initial value approach has been introduced for optimal control of ODEs by [6] and of DAEs by [3]. [21] employs the single shooting approach for the estimation of parameters in dynamical systems. In single shooting the dynamical system is solved by a numerical integrator. The solution is directly computed by numerically solving an initial value problem and the vector parameters is the only degree of freedom for the non-linear optimizer. The advantage of single shooting is that standard DAE solvers with sensitivity analysis capabilities and standard NLP solvers can be applied. Due to the use of standard DAE solvers the grid of the state discretization can be adapted automatically such that the error of the states is below a prescribed error tolerance. The disadvantage is that unstable systems are difficult or even impossible to converge even if a good initial guess for the optimization variables is available. Also, single shooting can converge to several local minima due to the usually high nonlinearity of the resulting NLP. For the treatment of unstable systems, multiple shooting or full discretization seem to be more favorable [15].

Direct multiple shooting method

Multiple shooting for the direct optimization of optimal control problems[1] has been introduced by [2]. Roughly spoken, multiple shooting for direct optimization is an adaption of the multiple shooting method for the solution of multipoint boundary value problems to optimization. Multiple shooting for the solution of boundary value problems has firstly been investigated by [14]. A state-of-the-art direct multiple shooting implementation is MUSCOD of [7, 8]. The basic idea of multiple shooting is to divide the time horizon into a number of intervals. For simplicity we assume that the edges of the intervals coincide with the grid $t_0<t_1<<tl$. If the dynamical system is described by a set of ordinary differential

equations just the initial values of the state variables, are adjoint as additional degrees of freedom to the optimizer. To ensure the continuity of the trajectories, junction conditions are added as equality constraints to the overall non-linear program. We use the denotation

$$\hat{Z} := \begin{pmatrix} \hat{x}_1 \\ \vdots \\ \hat{x}_l \end{pmatrix} \in R^{l-n_z} \tag{15.}$$

and let $x_i(t;p)$, i=1,…,l, be the solution of the initial value problem

$$\dot{x}_i(t) = f(x_i(t), u(t), p) \quad t \in [t_{i-1}, t_i] \tag{16.}$$

$$\dot{x}_i(t_{i-1}) = \hat{x}_{i-1} \tag{17.}$$

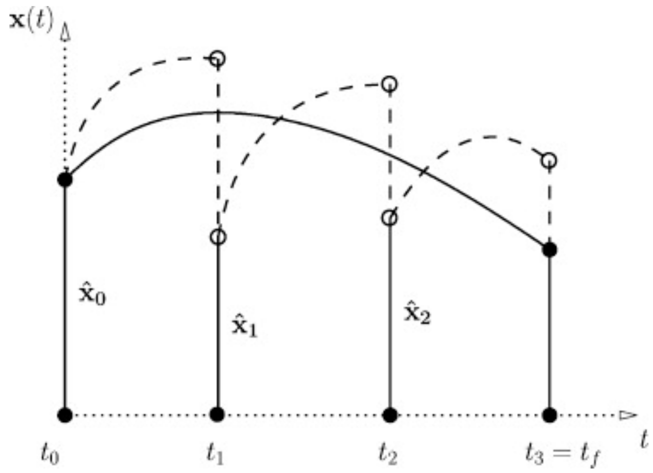

Figure 4. - Illustration of multiple shooting, the dashed lines show the initial trajectory, the solid line shows the trajectory if the junction conditions Eq. 17. are satisfied.

where for notational convenience we set $\hat{x}_0 := x_0$. Then, the non-linear program in multiple shooting is given by

$$\min_{p \in P, \hat{x}_i, i=1,\ldots,l} (\tilde{Z} - \hat{Z})^T V_M^{-1} (\tilde{Z} - \hat{Z}) \tag{18.}$$

s.t. $$x_i(t_i;p) - \hat{x}_i = 0 \tag{19.}$$

In the beginning of the optimization, the junction conditions (Eq. 17.) do not have to be satisfied, allowing for discontinuous trajectories to avoid instabilities. At the optimal solution, the junction conditions are satisfied yielding a continuous trajectory (see also Figure 4).

If DAEs instead of ODEs describe the dynamical system, several strategies can be applied. For example, the initial values of the algebraic variables at each shooting interval can be computed by a consistent initialization. Or, the initial values of the DAEs can be added as additional degrees of freedom if for each free initial value the algebraic equations are adjoint as equality constraints to the non-linear program. Then, relaxation techniques to conserve consistency of the algebraic equations have to be applied [7]. The advantage of the multiple shooting method is that a standard DAE solver for stiff systems with stepsize control can be employed and the computer code can be parallelized in a natural way. As in single shooting the use of stepsize control guarantees that the error of the state variables is less than a prescribed error tolerance. On the other hand, due to the introduction of the additional degrees of freedom the size of the NLP is enlarged, especially if the dimension of the parameter vector is rather small compared to the dimension of the differential states.

Model Predictive Controllers– theoretical basis

MPC is a model based control algorithm where models are used to predict the behavior of dependent variables (i.e. outputs) of a dynamical system with respect to changes in the process independent variables (i.e. inputs). In chemical processes, independent variables are most often setpoints of regulatory controllers that govern valve movement (e.g. valve positioners with or without flow, temperature or pressure controller cascades), while dependent variables are most often constraints in the process (e.g. product purity, equipment safe operating limits). The MPC uses the models and current plant measurements to calculate future moves in the independent variables that will result in operation that satisfies all independent and dependent variable constraints. The MPC then sends this set of independent variable moves to the corresponding regulatory controller setpoints to be implemented in the process. With the help of the Figure 5. the essence of the model predictive control is easily understandable.

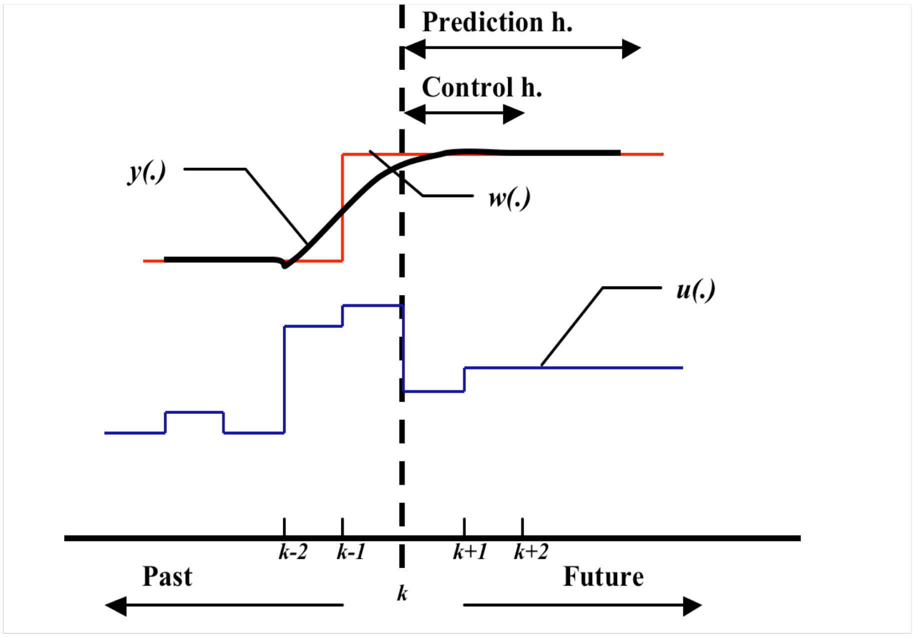

Figure 5. - The essence of model predictive control

Formulating the aim of the method, an objective function is the result, which is:

$$\min_{\Delta u(k+j)} \sum_{j=H_{p1}}^{H_{p2}} (w(k+j)-y(k+j))^2 + \lambda \sum_{j=1}^{H_c} \Delta u^2(k+j-1) \qquad (20.)$$

where $\Delta u(k)$ denotes the change of the control signal, the H_{p1} and H_{p2} parameters are the minimum and maximum cost horizons and H_c is the control horizon, which does not necessarily have to coincide with the maximum horizon. λ is a weighting factor, it is a sequence that considers future behaviors, usually constant values or exponential sequences are used. *w* is the set point signal following the notation of Figure 5.

Predictive control uses the receding horizon principle. This means that after the computation of the optimal control sequence, only the first control action will be implemented, subsequently the horizon is shifted one sample and the optimization is restarted with new information about the measurements.

In the presence of unmeasured disturbances and modeling errors the MPC controller can exhibit steady-state offset. One way of handling this it to design a disturbance estimator which gives the controller implicit integral action. The simplest method for incorporating integral action is to shift the setpoints with the disturbance estimates as depicted in Figure 6., where the corrected setpoints $w'(k) = w(k) - d(k)$ are modified based on differences between the output of the system and its estimated value $d(k) = y(k) - y'(k)$

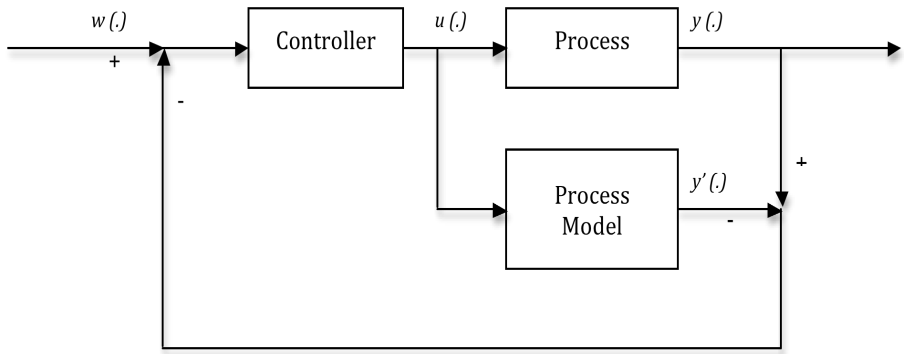

Figure 6. - The IMC (Internal Model Control) scheme

The scheme shown in Figure 6. is often referred as internal model control (IMC) strategy. This disturbance model assumes that plant/model mismatch is attributable to a step disturbance in the output and that the disturbance remains constant over the prediction horizon. While these assumptions rarely hold in practice, the disturbance model does eliminate offset for asymptotically constant setpoints under most conditions.

Non-linear model based predictive controller

Non-linear model-based predictive control (NLMPC) algorithms should be applied in situations where the controlled process is inherently nonlinear, or where large changes in the operating conditions can be anticipated during routine operation, such as in batch processes, or during the start-up and shut-down of continuous processes.

The advantages of non-linear predictive control include the following.

• Manipulated and state variable constraints are explicitly handled.

• Nonminimum-phase processes are easily handled. (if the prediction horizon is chosen adequately)

• Knowledge of future setpoint changes is included that is useful for scheduled, coordinated operational changes.

The main problem in real-time NLMPC is that a non-linear often (non-convex) optimization problem must be solved at each sampling period. This hampers the application to fast processes where computationally expensive optimization techniques cannot be properly used, due to short sampling time. Several methods can be used to solve such constrained non-linear optimization problems. The most widely studied algorithms are based on [4].

When the non-linear model is used directly in the NLMPC calculations, the name of the resulting solution is sequential technique. The algorithm involves the optimization of the objective function using the model equations as an “inner loop” to reach the value of the control signal.

Using sequential quadratic program (SQP) method it is possible to minimize the value of the objective function, in each sampling period, varying the control signal values ($u=[u(i)\ldots u(i+H_c)]$) on the control horizon. Hence the solution of the optimization problem is a control signal trajectory, and it has the ability to determine the value of the control signal of “outer loop” (which can mean the operating process or the model equations of the process) in the next sequent, since this is the first member of the previously determined control signal trajectories.

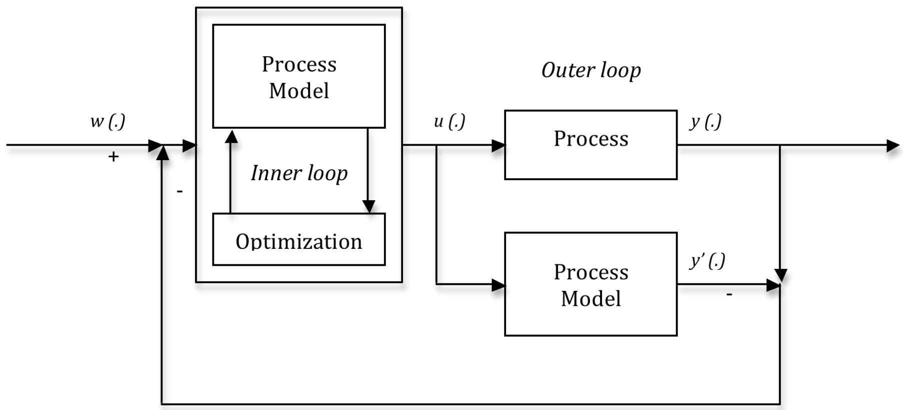

Figure 7. - The scheme of the non-linear model predictive controller

In practice all processes are subject to constraints. The actuators have a limited field of action as well as determined slew rate, as in the case of valves. Constructive reasons, safety or environmental ones or even sensor slopes themselves, can cause limits in the process variables such as levels in tanks, flows in piping of maximum temperatures and pressures. All of this leads to the introduction of constraints in the MPC problem. Usually, input constraints like

$$u_{\min} \le u(k+j) \le u_{\max}\ ,\ j = 1, \ldots, H_c \qquad (21.)$$

$$\Delta u_{\min} \le \Delta u(k+j) \le \Delta u_{\max}\ ,\ j = 1, \ldots, H_c \qquad (22.)$$

are hard constraints in the sense that they must be satisfied. Coversely, output constraints can be often viewed as soft constraints because their violation may be necessary to obtain a feasible optimization problem:

$$y_{\min} \le y(k+j) \le y_{\max} \quad j = j_1, \ldots, H_p \qquad (23.)$$

where j_1 represents the lower limit for output constraint enforcement.

Model predictive control of a district heating network

Energy markets have become more and more competitive. Producers and network managers have to drive their power systems, which are more and more complicated, to fulfill consumers power demands with the lowest global costs. Producers are also aware of environmental issues by environmental laws. They are compelled to reduce their rate of polluting emissions. Thus, technical, economical and environmental constraints have to be simultaneously dealt with.

The optimization problem stated from this multi field area can hardly be solved as it is a non-linear programming problem, consists of numerous variables. The optimal control of district heating networks, for which propagation delays can not be neglected and mechanical and thermal losses have non linear expressions, picks up all these harsh difficulties. Managing a district heating network implies to assign values to integer variables (status of production units, status of pumps…) and to continuous variables (amounts of energy to produce). As a result, the optimization of the production and energy supply planning appears to be a huge, mixed and non linear optimization issue.

However solving a non-linear mixed integer optimization problem might have the ability to provide a control signal that may provide better performance than solving a simple non-linear optimization problem in this thesis a simple non linear SQP method with soft constraints will be introduced to avoid the complexity of mixed integer non linear programming. To take the different weights of the control variables into consideration the objective function is augmented with the absolute value of the control variables:

$$\min_{\Delta u(k+j)} \beta \sum_{j=H_{p1}}^{H_{p2}} (w(k+j) - y(k+j))^2 + \lambda \sum_{j=1}^{H_c} \Delta u^2(k+j-1) + \alpha \sum_{j=1}^{H_{p2}} u^2(k+j) \tag{24.}$$

It can also be important to define weights (β) for the error the set points and manipulated variables, because the main task – keeping the manipulated variable equal to the set point – can be easily assured. This approach of the objective function will be applied in this thesis.

The MPC algorithms can be used in the local control level, but they are also suitable in the advanced control level. In this thesis these algorithms are applied in the local control level, so there have been no exactly defined optimization problem in the advanced control level, such as minimize the cost transitions.

The developed MPC toolbox

During this study our main purpose is to design a framework for non-linear model predictive control of a district heating network. In the other aspect the modular set up of the framework was also very important while designing it. Hence MATLAB/Simulink environment was chosen to develop the non-linear MPC toolbox, which is based on the previously introduced scheme (Figure 7.). The control box, so called “inner loop” is composed of the process model/tendency model and a optimization algorithm. The optimization algorithm is to minimize the objective function in the “inner loop”. Using the advantages of MATLAB the Optimization Toolbox was used to fulfill this expectation. In this case sequential quadratic programming method is applied, but other methods, like an evolutionary algorithm, may also be appropriate for reach this goal. Using the Optimization Toolbox we have the ability to provide the opportunity of implementing the constraints (Eq. 21-23) easily.

While designing the NLMPC toolbox it was very important to keep the modularity of the framework, which means to keep the ability to change either the optimization algorithm or the process model. In this case, since there were no real available operating plant, the process was replaced by the process model. The process model in the control box can be the same which is used in replacing the process, but it is not necessary. During the examinations there will be to separated case. In the first case a model without time delay ('B' model) will be used during the optimization while the "operating network" contains time delays. In the second case the process model ('A' model) and the "operating network" are the same.

In case of B model there is no model mismatch and there were no applied disturbances, so the scheme of non-linear model predictive controller, on Figure 7. can be simplified as the scheme depicted on Figure 8.

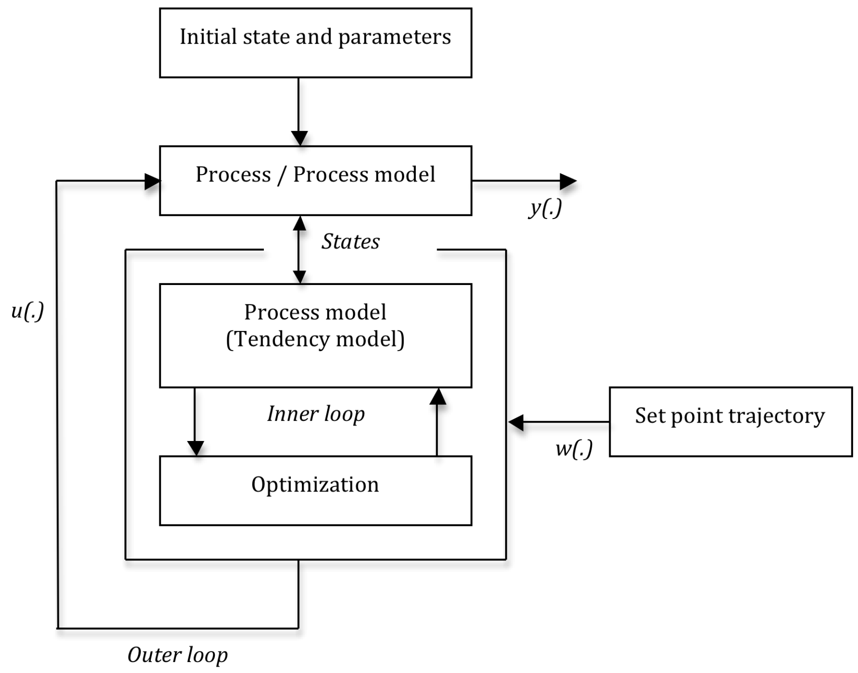

Figure 8. - The scheme of applied non-linear model predictive algorithm without the IMC structure

Differences of the model without time delay ('A model') and the model with time delay ('B model')

To fulfill the requirements of the consumers, to make the possibility of controllability the control variables of the system is needed to be defined. In the case of the depicted (Figure 1) district heating network the possible control variables are:

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 the Consumer 3 must be the same. To reach this goal two control variables can be used: the valve opening and the pump duty of the P2 pump (as the pressure increase on the pump is the function of the pump duty (Eq 3.)). These control 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.

In order to use the model without time delay it was inevitable to examine what kind of differences can cause this neglect. The following pictures show the difference between the two models (full line means the model without time delay, dot line means the model with time delay):

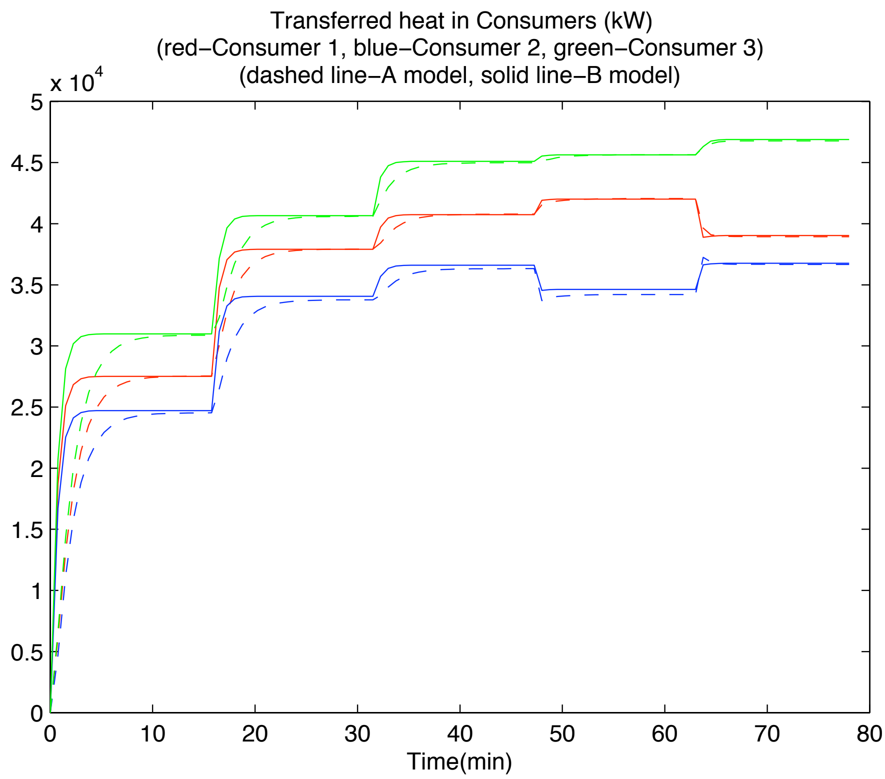

Figure 9. – Comparing the outputs of 'A' model (dashed line) and 'B' model to the same input depicted on Figure 10.

Naturally both simulations were run with the same inputs. In the initial moment there is no temperature profile in the network so the first 15 minutes are for show the temperature startup of the network. After 15 minutes there is a step in the invested heat in Producer 1. When the network is in steady state, there is a step in the invested heat in the Producer 2. In the 50th minute there is a step in the pump duty of Pump 2 The last change in the inputs is changing the value of the valve opening in 63rd minute. These changes can be seen on the figure below:

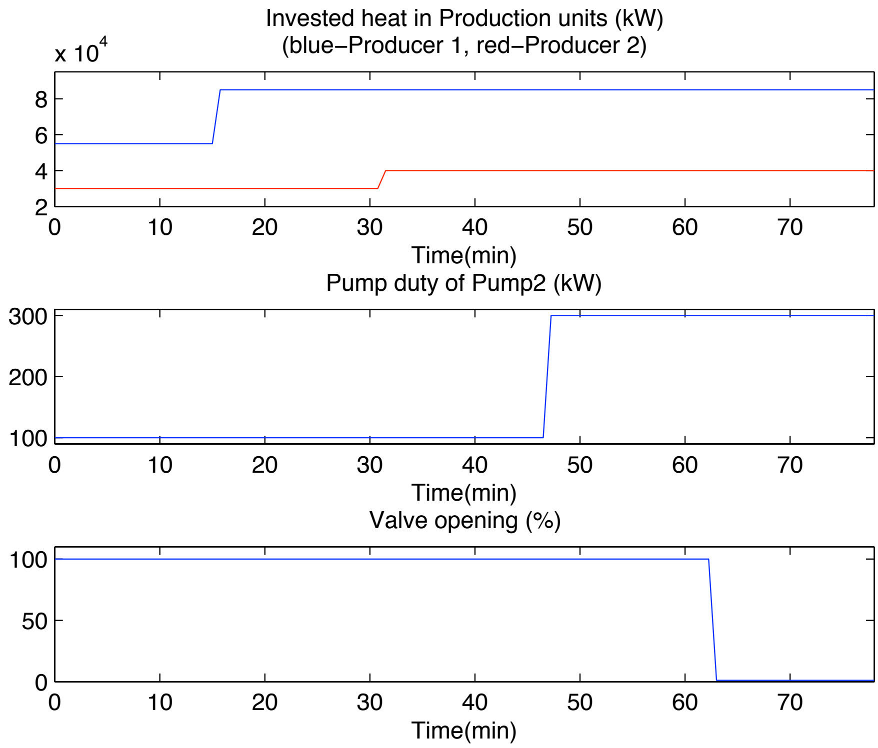

Figure 10. - The input parameters of the district heating network related to Figure 9

Due to the Figure 9. it can be stated that the model without time delay can provide almost the same steady state than the model with time delay. The main difference is in the dynamical behavior.

Problem description

The main goal is to satisfy the heat demand of the consumers. During the examinations heat demand of the consumers is assumed to be known. That is why it can be handled as the set points of the district heating network. To test the performance of the DHN the following set point trajectories were chosen:

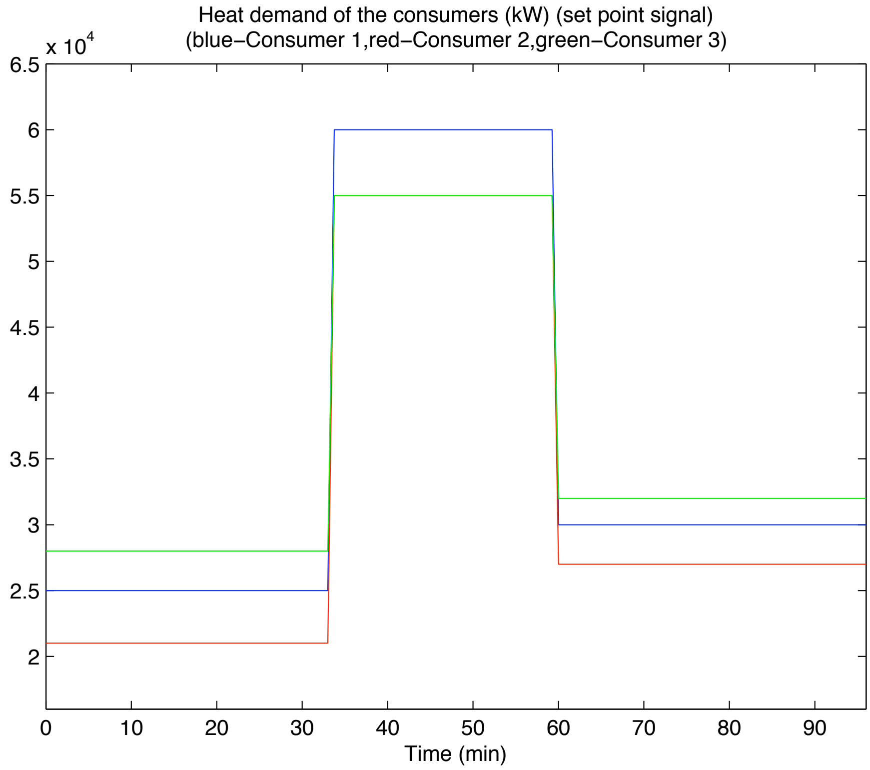

Figure 11. – the set point of the transitions during the examinations

The set point changes are at the same time: at around 33rd minute and 60th minute. In order:

- Consumer 1 (blue line) has 25000 kW - 60000 kW - 30000 kW heat demand
- Consumer 2 (red line) has 21000 kW – 55000 kW – 27000 kW heat demand
- Consumer 3 (green line) has 28000 kW – 55000 kW - 32000 kW.

The main goal is to minimize the transition time as possible and at the same time fulfill the requirements of the consumers considering to minimize of the use of the Production unit 2 and the pump duty of P2 pump.

Models during the optimization

As it was mentioned previously during the optimization two different models were used:

- Model contains time delays ('A model'): practically, the model and, the process were the same, in this case. So it was not necessary to use the IMC control scheme, because there were no mismatch, and because of our purpose, the optimization of the transition, there were not any disturbances during the simulations.
- Model without time delays ('B model'): in this case the model does not contain any time delays. That is why differences can be seen in the dynamic of the model with time delay and without time delay as depicted on Figure 9. This model was programmed in Matlab, because it was expected to have less computational demand.

Because of this obvious model mismatch experiments will be carried out to test the performance of the MPC with IMC scheme and without IMC scheme. Since the steady states of the two models should be equal the MPC was expected to reach the set point trajectories in both cases, but the dynamical behavior can not be predictable without simulations.

Control results

Control performance of MPC with A and B model

It is necessary to qualify the controllers and to realize it a performance index was needed, and due to this it was possible to compare them with each other. The ISE (Integral Square of Error) criteria was chosen to satisfy this demand, but as it does not provide further information about the performance of the controllers, plots are used to compare quality of control. The set point is the same in all case, because of the comperableness.

The tuning parameters of model predicitve controllers are the lenght of the prediction horizon, control horizon, and the value of α, ß and λ parameters (Eq 24.). To keep the comparebleness of the cases the same tuning parameters were chosen (prediction horizon: 4, control horizon: 1, sample time: 45 sec). The computation demand of the NLMPC controller is very high, since the objective function is solved with SQP in each sequent (recending horizon strategy), and this solving method is very time-consuming. This is the reason why the tuning parameters of the NLMPC controller have not been optimized.

Because of the SQP solving method, some constraints can be implemented while solving the optimization problem. These constraints are for taking into consideration for example actual physical states of actuators or valves. These constraints can be defined as input constraints, like Eq. 21-22.

In this study the input constraint were introduced in the following form:

$$u(k+j-1) - \Delta u \leq u(k+j) \leq u(k+j-1) + \Delta u \quad , \mathrm{j} = 1, \ldots, \mathrm{H_c} \qquad (25.)$$

using the fact that the value of Δu is maximized.

Control results using the ‘A’ model

‘A’ model means that the applied model during the optimization is the same as the model used as the operation process. Thus there is no model mismatch is expected so there is no need to apply the IMC scheme. This yields that the applied scheme of the controller is equal the scheme depicted in Figure 8.

During the experiments the constrained and unconstrained case were also examined. The constraints are formulated like Eq 25. These constraints are mainly for the change of the valve opening and the change of the pump duty. This fact might have serious effects on the computed control signal, in some cases it might have influence on transition. This phenomenon can be seen the following figures, using the same value of control horizon, and prediction horizon in all NLMPC examinations.

With this approach the following control performance can be assured:

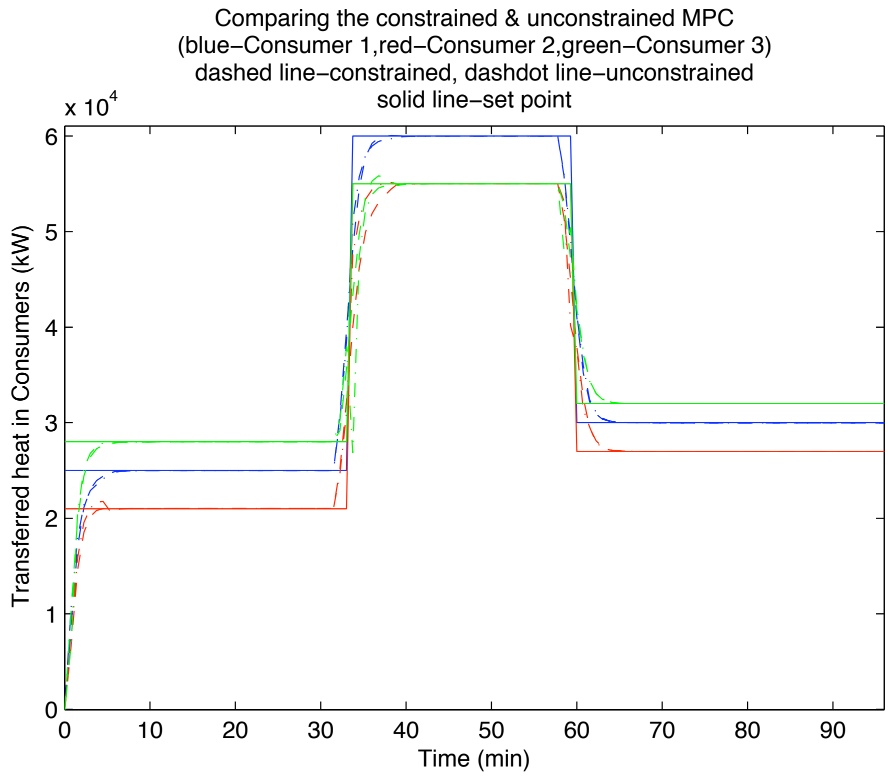

Figure 12. - comparing the control performance of the unconstrained (dashdot line) and constrained (dot line) MPC

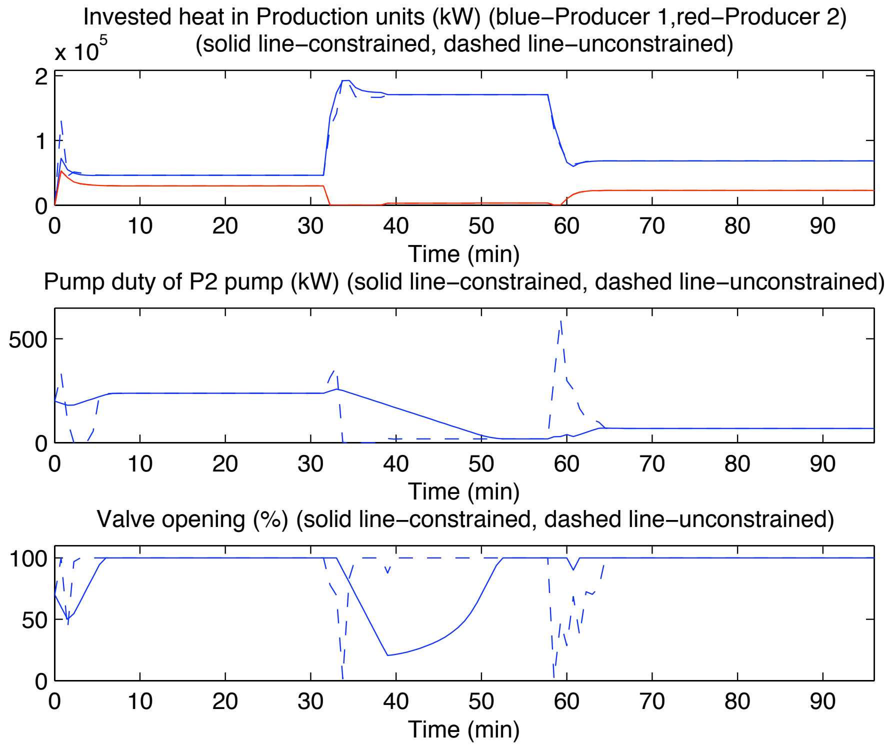

Figure 13. - the manipulated variables regarding to the previous figure full line – constrained, dashed line – unconstrained MPC

In the Figure 12. the controller can be seen to be able to keep the set point trajectories accurately with only a little overshoot in transitions in both cases. Since the input constraints for the input actions of production units were not too strict and the production units have the most influence on changing the transferred heat in the consumers the control performance is almost the same. The value of the other two manipulated variables are also varied as expected: since the flow control in direction of Consumer 2 and direction of Consumer 3 can be influenced by the pump duty of P2 and the valve opening, it was expected to find a valve opening – pump duty pair that is for minimizes the pump duty as much as possible. Since stricter input constraint were implemented for these inputs it is not possible to reduce the pump duty arbitrary in contrary to the unconstrained case. The most significant difference can be detected on Fig 13. during the first transitions.

Analyzing the first transition: to assure a lower flow rate in direction of Consumer 3 it was necessary to set the higher pressure drop of that section. To reach this goal infinite variations of valve opening-pump duty value pairs exist.

By formulating the objective function in a proper way the biggest valve opening – the lowest pump duty pair should be applied. In the steady state of the system this condition is obviously determined. In the unconstrained case pump duty is decrease quickly to increase the pressure drop if that direction of flow, but the at the same time the valve opening is set as high as possible – 100%. In the constrained case the controller handles the changes of these manipulated variables differently since it is not permitted to change them arbitrary. The increasing of that direction is handled by closing the valve and at the same time reduce the pump duty. Closing the valve is a necessary action since the change of the pump duty is constrained.

The quick and accurate control actions are not surprising since the most precise model was applied during the optimization, but at the same time this accuracy has enormous computational demand: simulation needs almost 8 - 10 hours to be finished.

In the further cases only constrained MPCs will be described using the assumption that in unconstrained cases they would provide similar control action as it was recently shown.

Control results using the 'B' model

'B' model means that the applied model in the optimization section is not the same as the model used in as an operation process. This model is applied because it was expected to speed up the optimization process as it does not contain any time delay so the internal states of the process are not necessary to be saved and used during the optimization.

In this section 3 different cases will be introduced:

- Case 1: MPC without IMC scheme
- Case 2: MPC with IMC scheme
- Case 3: MPC, combination of the previous cases.

Case 1 – MPC without IMC scheme

In this case also the scheme, depicted in Figure 8., was applied. This means that the control algorithm does not have any pieces of information about the contingent model mismatch and any changes in characteristics of operation system. The accuracy on the control scenario mainly depends on the punctuality of the model. In the previous case it did not cause any problem since the model was 100% accurate, but in this case this requirement is not fulfilled.

The control performance can be illustrated by the following figure:

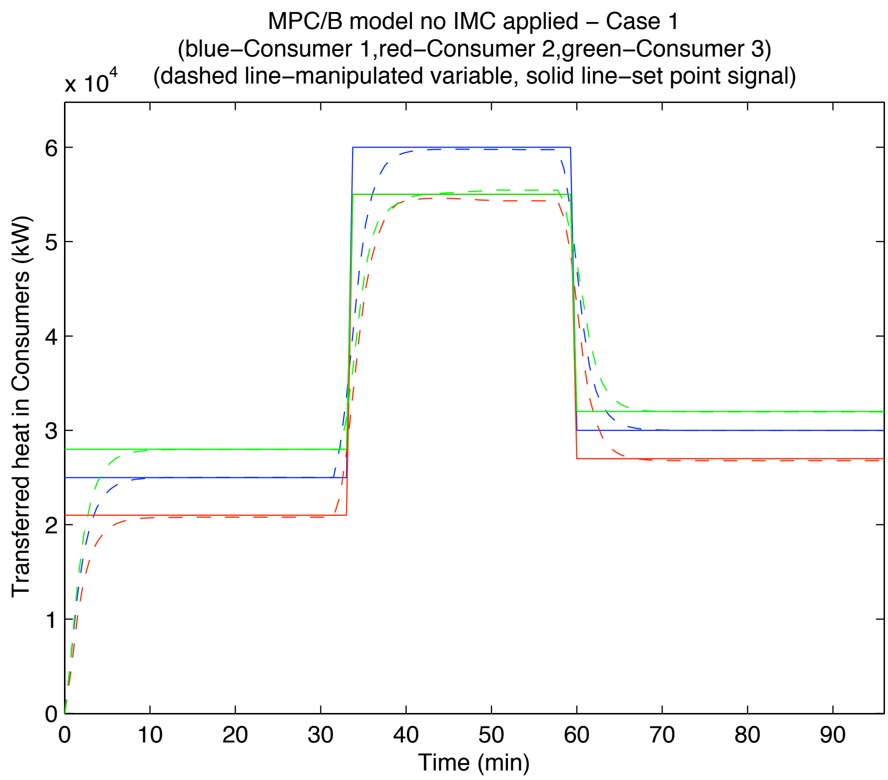

Figure 14. – The control performance of the model predictive controller in Case 1

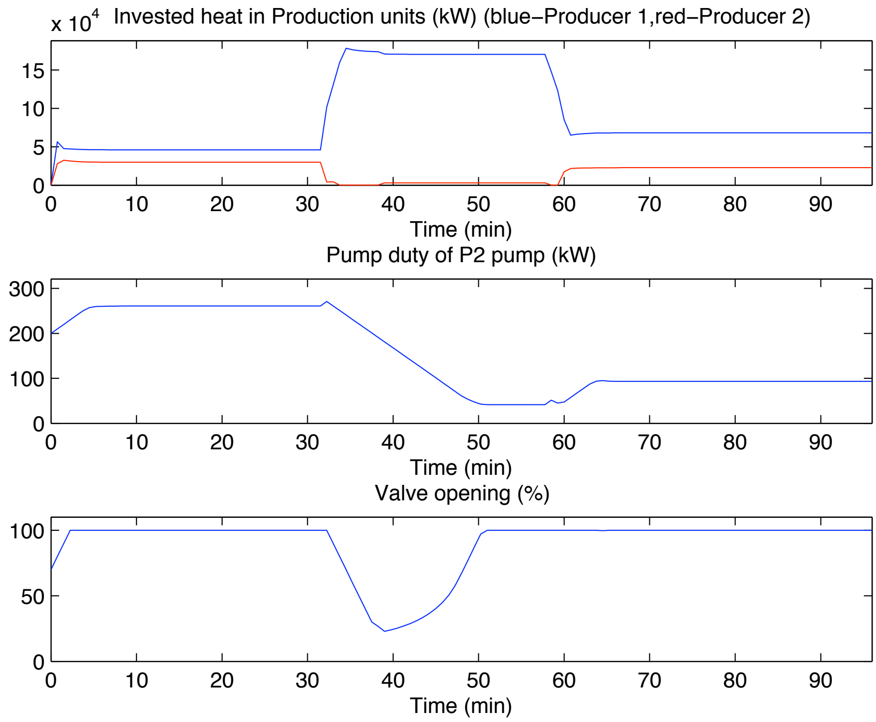

Figure 15. – The computed control signal regarded to the control scenario depicted on Fig. 14.

As the Fig 14. shows, the existing model mismatch causes steady state offset, mainly detectable after the first transient, however this MPC still has the advantage of avoiding any overshoot. The steady state offset – if it is converted to temperature difference - means 2-3 °C difference.

Since the same objective function was used in the optimization section in all cases, the control variable trajectories kept all the characteristics that were introduced in the case of using constrained MPC using ‘A’ model.

The expectation of reducing the computational demand was fulfilled: the computational demand was reduced to the half of the previous simulation, it needs almost 3-4 hours to be accomplished.

Case 2 – MPC with IMC scheme

The attempt for eliminating the steady state offset has a theoretical importance in this thesis. In the industrial practice the strictest limit of the prescribed accuracy is mainly the measurement accuracy. During the simulations the measurement accuracy is extremely high so such as big steady state offset as was observed in the previous case is not permited. Because of the steady state offset of Case 1 the internal model control scheme (depicted on Fig. 7.) is necessary to be applied. The dynamic behavior of the controller is difficult to predict, because of the significant difference in the dynamic behavior of the models (depicted on Fig 9.), but in steady state the IMC scheme is expected to eliminate the offset that occurred in Case 1.

After running a simulation using IMC scheme, the following control result can be observed:

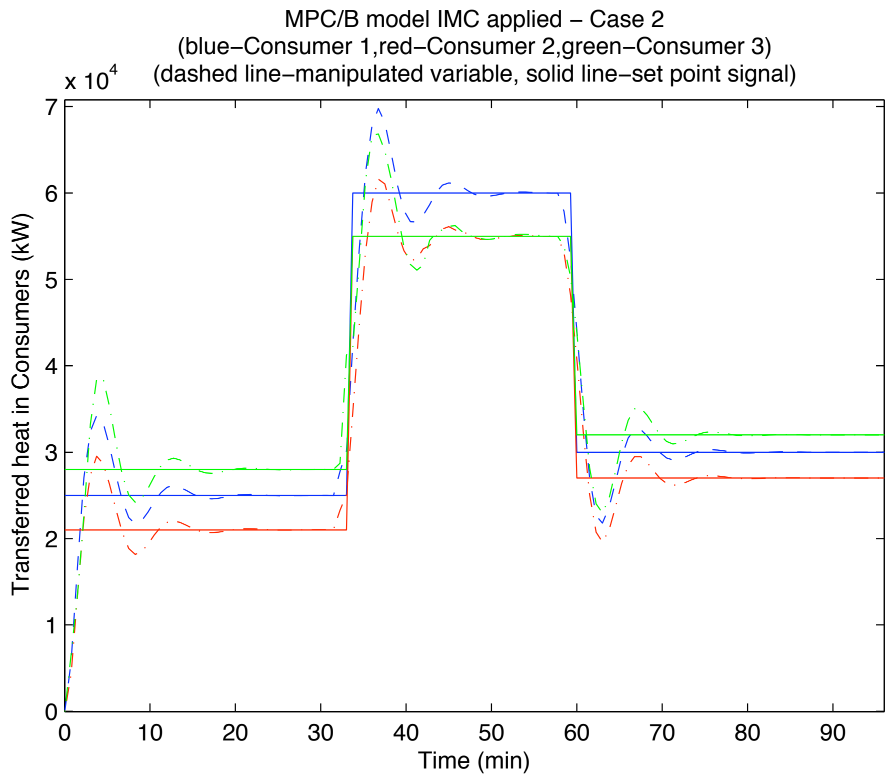

Figure 16. – The control performance of the model predictive controller in Case 2

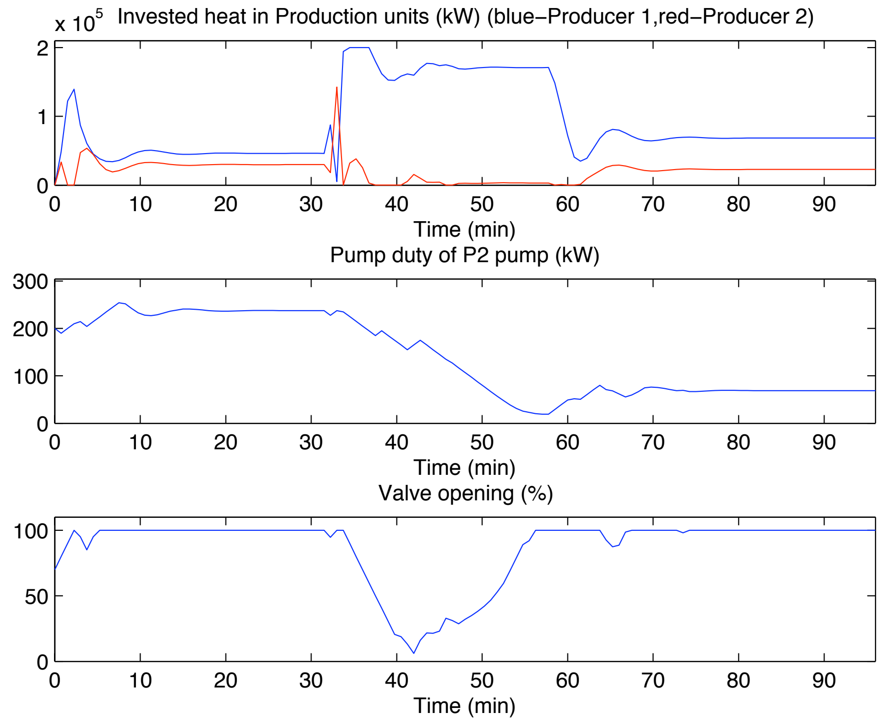

Figure 17. – The computed control signal regarded to the control scenario depicted on Fig. 16.

In contrast to Case 1 and simulation using 'A' model in this case some overshoot and oscillation occurred. It could happen just because of the IMC structure, since it modifies the set point signals with the error of the model and operational system , so set point signals are modified with a significant model error. That is why the input of the optimization section is also changed as the following figure shows:

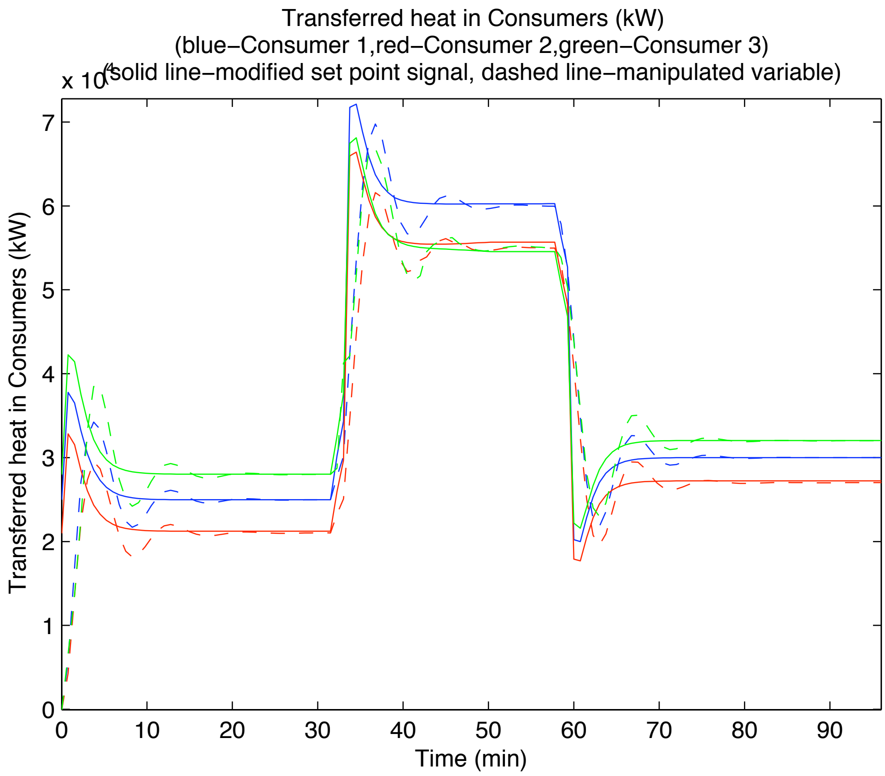

Figure 18. – the modified set point signal (by IMC scheme) (full line) and the output of the network (dashed line)

On the previous figure the outputs of the operating system are shown. This figure has the ability to explain the reason of the occurring overshoot: since the error of model and the operating system is mainly detectable in dynamic actions, the IMC modifies the set point signals with a significant model error. The modified set point signal is the input of the optimization section and used in computing the minimum of the objective function.

Case 3 – combination on Case 1 and Case 2

In this case an attempt will be made to combine the advantages of Case 1 and Case 2, so avoiding the overshoot and eliminating the steady state offset. To reach this goal the following strategy is applied: since the IMC structure modifies the set point signals significantly during transitions – this way causing significant 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 in this case 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:

$$\frac{(ME(i)-ME(i-1))^2}{N} \le K \qquad (26.)$$

where:

ME – the model error vector in i^{th} and $(i-1)^{th}$ sample time

N – length of the model error vector

K – constant

So if the change of the model error is smaller than a previously determined constant, it means that the manipulated variable is relatively close to the set point. If this condition is fulfilled the IMC scheme is expected to switch on and eliminate the steady state offset.

By applying this method the following control result can be yielded:

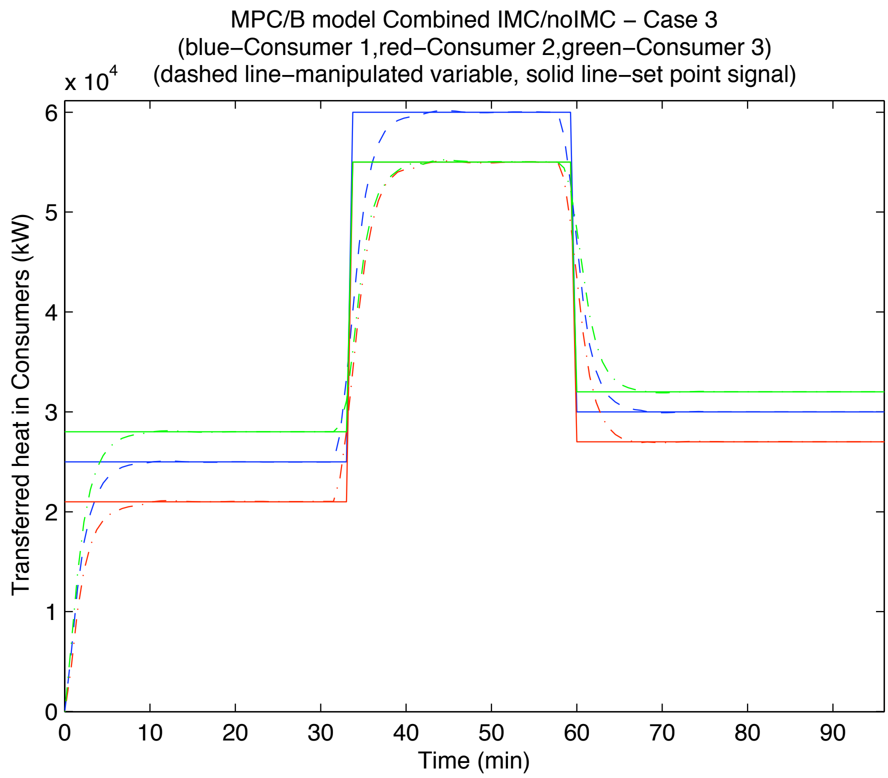

Figure 19. – The control performance of the model predictive controller in Case 3

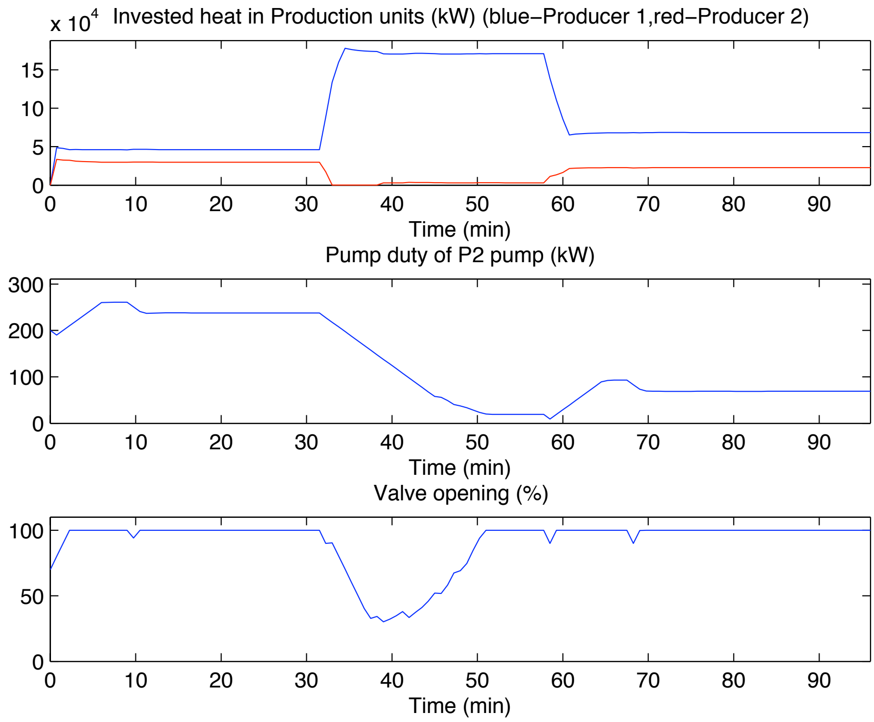

Figure 20. – The computed control signal regarded to the control scenario depicted on Fig. 19.

As the figures show, this method can extract the advantage of IMC – set the manipulated variable equal to the set point signal - and at the same time this method is able to exclude the disadvantage – exaggerated modification in the set point signal which can cause overshoot.

Comparison of the applied MPCs

In this section the comparison of the applied MPCs will be introduced using a performance index, Integral of Square Error (ISE), and using visual comparison. Furthermore some explanation will be introduced to explain the occurring differences.

General comparison

In this short section the controllers will be compared in some general aspects:

- Performance index
- Settling time and overshoot
- Computation demand

Performance index

The performance index is suitable to represent the performance of the controller numerically. The integral of square error (ISE) is a measure of the performance of the controller formed by integrating the square error of set point signal and controlled variable over the time interval of the simulation. As the values of the controlled variables are known not at every moment, but at every sample time, the ISE can be approximated with the following expression:

$$ISE = \sum_{i=1}^{N} (w_i - y_i)^2 \qquad (27.)$$

Where w_i means the value of the set point in ith moment, y_i is the output of the system, N is the number of time steps.

The following table contains the ISE value of the previously introduced simulations:

	ISE (*10^9)				
	Consumer 1	***Consumer 2***	***Consumer 3***	***Mean***	***%***
Case 'A' model	1.7	1.45	1.6	1.58	100%
Case 1	2.54	2.31	2.72	2.52	159%
Case 2	2.52	2.12	3.14	2.59	164%
Case 3	2.56	2.27	2.74	2.52	159%

Table 1. – comparing the performance of the applied MPCs by ISE value

Table 1. shows that the constrained MPC with 'A' model has the ability to provide the best performance. This is not surprising, since the controller use the most accurate model to predict the reaction of the plant to a certain input. In cases that use 'B' model the controllers have worse performance caused by having less capability to predict the dynamic behaviour of the DHN because of the less accurate model. Case 1 and Case 3 has equal ISE value, despite the combination of IMC/noIMC scheme. This might happen because Case 3 might be different in

dynamics than Case 1.

Settling time and overshoot

This performance index has the ability to represent the control performance numerically, this way provide a way of comperableness, but it can not be the single aspect, however a lower value of the performance index can indicate a more accurate control action. In this case accuracy means as least overshoot as possible hand in hand with the lack of steady state offset. The following tables are for introducing other, occasionally numerically not representable characteristics of the controllers:

	Overshoot		
	Startup	***Transient 1***	***Transient 2***
Case 'A' model	no	yes	no
Case 1	no	no	no
Case 2	yes	yes	yes
Case 3	no	no	no

Table 2. – comparing the applied MPCs by the existing of overshoot

	Settling time (min)		
	Startup	***Transient 1***	***Transient 2***
Case 'A' model	7	7	9
Case 1	11	12	13
Case 2	25	28	24
Case 3	15	15	13

Table 3. – comparing the applied MPCs by settling time

Computation demand

Since the non-linear optimization problems usually does not possess analytical solutions but numerical solutions so they have enormous computational demand. In case of infrequently sampled processes it might not cause problem, since the optimization algorithm can find the optimal solution in a sample time. In case of frequently sampled processes the increase computational demand (compared to the linear MPCs or PID controllers) might mean the optimization algorithm can not find the solution of the objective function, so the control system can not make a feasible control action in time.

The following table summerizes the computation time of the 1.5 h long simulation horizon in case of the examined MPCs:

	Simulation time (h)
Case 'A' model	8
Case 1	3.5
Case 2	3.5
Case 3	3.5

Table 4. – comparing the applied MPCs by simulation time

Using the accurate ‘A’ model during the optimization needed 8 hours to finish the simulation. Although this controller can provide the best performance, the long computational time is not acceptable. This reason has led us to implement a simplified model - ‘B’ model, that not contains any time delays – that is expected to provide less simulation time. This goal has been finally reached as the computational time reduced 3.5 hours, however it caused a slower control action.

Model simplification is not the only way to reduce the computational demand. Calculating the gradients of the objective function respect to the input signals has the capability to speed up the optimization process. There are traditionally 3 method to calculate the gradients for optimization:

- Finite differences method
- Sensitivity equations [11]
- Adjoint approach [16]

Detailed comparison of the examined MPCs

In the previous section general comparison of the applied MPCs was made. In this section some detailed comparison will be introduced to examine the different behavior of the controllers.

Comparison of the ‘B’ model used MPCs

In this section a brief comparison of the ‘B’ model used MPC will be made. Since the main advantage of these controllers – reduced computational demand - was introduced in the general comparison, in this section some important characteristics are highlighted.

Because of the less accurate model and the lack of IMC scheme the MPC in

Case 1 can not reach the set point signal as it can be seen on Figure 14. To eliminate this phenomenon the IMC scheme was applied. The following figure shows the result (highlighted to Transient 1):

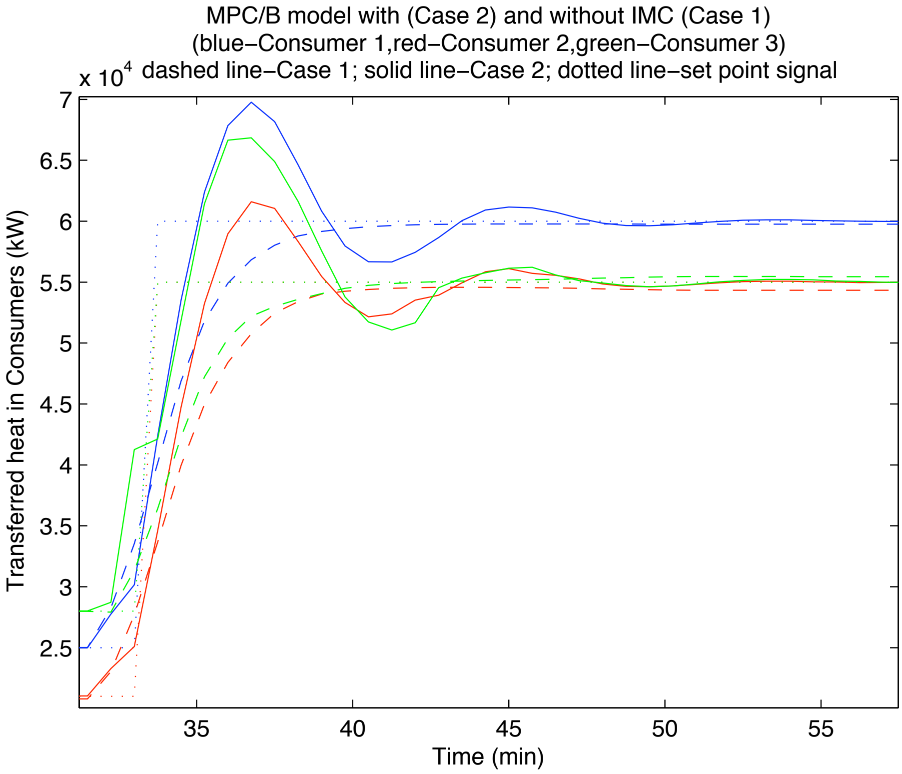

Figure 21. – graphical comparison of control performance of Case 1 and Case 2 controller

The overshoot of IMC-MPC has been caused by the significant model error in the transients (depicted on Fig. 9.)

To combine the lack of steady state offset and the lack of overshoot the Case 3 can be applicable. However Table 1. shows the same performance for Case 1 and Case 3, the latter has the advantage of taking the model error into consideration in a certain level in contrast of Case 1. This is not a negligible fact since the performance of the model predictive control is a function of the model parameters, and model parameters can be the function of the time (eg. fouling in the heat exchangers can change the heat transfer coefficient).

Comparing the Case A model and Case 3

As the benefit of Case 3 is stated in the previous section, it might be interesting to define the relative performance in regard to the most accurate applied MPC. Table 1. contains a brief relative comparison of MPCs. The following figure might explain the difference of these two controllers:

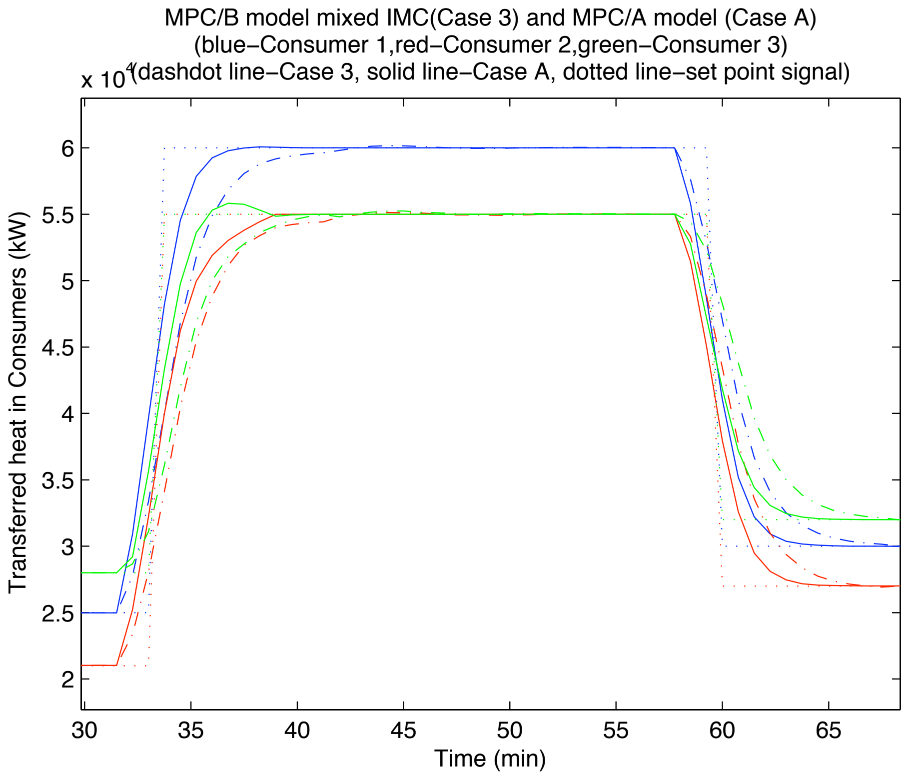

Figure 22. – graphical comparison of control performance of Case 'A' model and Case 2 controller

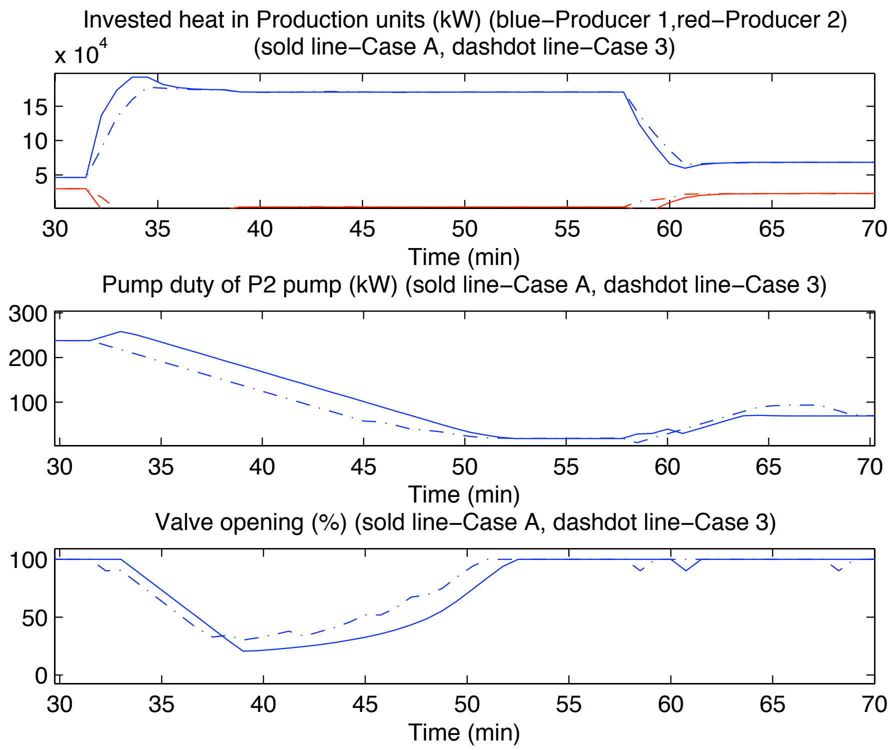

Figure 23. – control variables of Case 'A' model and Case 3

The main difference is the settling time. The Case 3 controller can reach the set point slower than controller which uses the 'A' model. This can happen because 'A' model and 'B' model have different dynamics ('B' model has no time delay). Thus the 'B' model can reach the set point signals faster by the effect of the same input signal than 'A' model. That is why the 'B' model considers the transient finished sooner than it is realized by the operating process ('A' model).

In steady state both models response almost the same output (for the same input). Finally the operating system also with almost reaches the set point. To reach the set point signal without steady state offset the IMC scheme switches on and eliminates the offset.

Discussion

In the previous sections detailed and general comparisons of the applied controllers was performed. The Case ‘A’ model was the most accurate model during the optimization. This model was able to provide the highest accuracy that was confirmed by the lowest ISE value and settling time. The most significant disadvantage of Case ‘A’ model was the enormous computational demand that was reduced by using the ‘B’ model in the optimization section.

In Case 1 it was observed, that a less accurate model was also useful for control purposes, however the accuracy was not as high as in Case A, since there was a steady state offset and the settling time was higher than in the previous case. The Case 1 controller had the drawback of the lack of the feedback that contains the difference of the model and the operating system. This feedback was installed in Case 2 by introducing IMC scheme.

It had the advantage of eliminating the steady state offset of Case 1, but unfortunately it accentuated the model mismatch in the dynamics. In Case 3 the beneficial characteristics – eliminating the steady state offset caused by the model mismatch and avoiding the overshoot - of Case 1 and Case 2 were combined. This kind of solution could provide the most attractive performance in controllers using ‘B’ model, but it has a relatively difficult set up. It can be more difficult to predict the behavior the controller and the controlled system, compared to the Case ‘A’ model.

Finally it can be stated that it is beneficial to use a model which is as accurate as possible but at the same time it is important to consider the fact that the computation demand is increasing with the increasing model accuracy. In case of real operating control systems the use of IMC scheme can be very useful since it can handle the occurrent model mismatch and the effect of unmeasured disturbances at the same time.

Conclusion

District heating is a system for distributing heat generated in a centralized location for residential and commercial heating requirements such as space heating and water heating. The heat is often obtained from a cogeneration plant burning fossil fuels but increasingly biomass, although heat-only boiler stations, geothermal heating and central solar heating are also used, as well as nuclear power. District heating plants can provide higher efficiencies and better pollution control than localized boilers. These reasons and the stricter and stricter governmental policies force the development of control system to reach the requirements. The modern, model based controllers are able to handle the MIMO (which has several inputs and outputs) systems easily and district heating networks are typically MIMO systems like that.

In the first chapter of the thesis as a first step a topology was chosen to represent the main characteristics of a district heating network. As a second step the parts of the heating network were modeled. The accurate model ('A' model) was implemented in Simulink and was used basically as the operating heating network. A less accurate model ('B' model, excluding all the time delays) was implemented in Matlab. Due to its lower computational demand this model was used mainly in the optimization section of the designed NLMPC.

The second chapter of the thesis dealt with designing a non-linear model control framework that was applicable for using the previously implemented models. Important aspect was the following during designing the controller: it should have been designed in a modular way so any other non-linear process model should have been implemented in it easily, without any hardship. Different cases were studied: as a first case, called Case 'A', the accurate model was applied in the optimization section of the MPC. In the analysis it was found that this system provided the best control performance, but had an important drawback: enormous computational demand. To handle this problem a less accurate model ('B' model) was used in the all further examinations. In Case 1 this model was applied without any information feedback loop about the performance of the control actions. The results were promising despite of the occurring steady state offset. To eliminate the steady state offset IMC scheme was introduced in Case 2. However this controller had the ability reach the set point signals accurately, but it also had drawbacks: the overshoot and the long settling time. Since the settling time in Case 1 was acceptably short (however longer than in Case 'A' model) and had the advantage of no overshoot, the beneficial properties of Case 1 and Case 2 were combined in Case 3. In Case 3 the IMC scheme was switched off during the transitions, but as the system approached steady state it was switched on to eliminate the occurring offset.

In the detailed analysis the differences between the previously examined cases were introduced and explained. In the final valuation it was stated that the accessible, most accurate model should be used during the optimization to keep the control scheme as simple as possible and at the same time reach the highest, possible accuracy.

The goal of this thesis was to model a district heating network and to introduce a non linear model predictive framework, and the usability of the NLMPC toolbox which can handle the transitions as an optimal control problem. The non-linear model predictive controller framework can assure the application of any nonlinear model without respect of the construction of the model. As the results show it is worth to apply this kind of non-linear model predictive method during transitions, however it is important to take the limits of the method into consideration.

Outlook and future work

While designing the previously introduced non-linear MPC framework it was very important to create a modular construction. This kind of construction can assure the ability of developing the framework. It is surely necessary to keep the toolbox applicable in the industrial practice. In this field the two most important characteristics of the control algorithms are:

- to have the opportunity to implement the control algorithm in the control system in a short time
- the ability of the control algorithm to provide a feasible control signal in a shorter time interval than the sampling time

The first reason is to obtain a competible and easily usable control algorithm, the second one is to assure the usability of the control algorithm in case of short sampling time. Applying non-linear model predictive algorithm it is very is very important requiring that the optimization algorithm can find the (global) minimum of the objective function in an certain time interval or at least a feasible solution. Considering that numerical optimization in each sequence can be very time consuming it is necessary to find the methods which can reduce the computational demand and speed up the optimization process:

- Model reduction, which can yield less states in the model
- Applying the gradient of the objective function during the optimization
- Using self-optimizing techniques, finding self-optimizing variables

When it can be realized, these kind of control algorithms can be used widespread in the industrial practice as a real time optimization algorithm, regarding that the MPC algorithms can be applied in the advanced control level.

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