Production Planning for Distributed District Heating Networks with JModelica.org

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Abstract

The short term production planning optimization problem for a district heating system is solved in two steps by integrating physics-based models into the standard approach. In the first step the unit commitment problem (UCP) is solved using mixed integer linear models and standard mixed-integer solvers. In the second step the economic dispatch problem is solved, utilizing the unit statuses from the UCP. This step involves dynamic optimization of non-linear physics-based models. Both optimizations aim at maximizing the production profit.

The modeling has focused on distributed consumption and production. Optimization results show that modeling of the district heating net impacts the production planning in several ways, with results such as reduction of production peaks and delay of costly unit start-ups.

The physics-based modeling and dynamic optimization techniques provide a flexible way to formulate the optimization problem and include constraints of physically important variables such as supply temperature, pressures and mass flows.

Keywords: district heating, physical modeling, distribution, optimization

1 Introduction

1.1 Background

The goal of production planning is to determine the most profitable scheduling of the different production units in a network, without violating operational constraints. It can be viewed as an optimization problem, which contains both continuous and discrete variables.

The operational statuses (on or off) of the different production units form the discrete decision variables of the optimization problem. The continuous decision variables are production unit loads and pump speeds.

The formulation also includes non-linear parts, such as turbine characteristics and steam properties. This results in an optimization problem referred to as a mixed integer non-linear problem (MINLP). Currently, there are no known algorithms with predictable and robust performance for solving this kind of problem.

The predicted customer heat load during the optimization interval is the main input to the production planning problem. The prediction is often generated from weather forecasts and cannot be known exactly in advance. In this paper manually generated predictions are used, mostly assuming perfect predictions, but formulations where uncertainties are included are also investigated. The implemented optimization model is based on the units and network distribution of the Uppsala district heating network, with special emphasis on the modeling of the cogeneration plant KVV.

The standard method to circumvent the difficulties of solving a MINLP problem in a production planning formulation is to simplify the modeling considerably. By linearizing plant models and reducing the network model to only contain energy flows, a linear optimization formulation is obtained instead. This kind of problem is called a Mixed Integer Linear Problem (MILP) and can be solved using standard techniques. Previous work based on linear plant models include (Arroyo and Conejo, 2004), where a method to formulate start and stop trajectories is presented and (Rolfsman, 2004), where a heat storage strategy based on the variations in electricity price is presented. In (Rong, *et al*, 2008) an improved algorithm for the unit commitment problem is presented.

1.2 Proposed Approach

The separation of the optimization problem into the Unit Commitment Problem (UCP) and the Economic Dispatch Problem (EDP) part presents an alternative solution to the problem of creating a robust optimization formulation of the production planning problem. The two optimization problems are solved in series, a method previously implemented in (Velut *et* *al,* 2013). The modeling and optimization efforts are conducted in the following manner:

- UCP: A linear optimization formulation is obtained by approximating the district heating network using piecewise linear models. The problem is solved using a MILP solver with the status signal for each production unit being the main result.
- EDP: A representation of the district heating network is created using physical modeling. Smoothened versions of the status signals from the UCP are implemented in the model, so that only continuous variables are present in the optimization formulation. By solving the optimization problem, the load for each unit is decided.

There are several benefits with including physical modeling in the optimization formulation. The optimization model becomes highly accurate when physical laws such as mass and energy balances are used to describe the units of the network. It also makes it possible to optimize physically relevant variables that effect the plant economics such as supply temperatures and mass flows. The possibility to impose constraints on these variables, based on the physical and operational limitations of the real system is another advantage.

In order to solve the EDP, the optimization problem is discretized into a Non-Linear Programming (NLP) problem using the so-called collocation method (Magnusson, 2012). Different solvers for NLP problems exist, in this work the open-source solver IPOPT (Interior Point Optimizer), see (Wächter and Biegler, 2006), was used. In previous projects the authors have used this method for dynamic optimization of a carbon capture plant (Åkesson *et al,* 2011) and, more notably, for short-term production planning of district heating (Velut *et al,* 2013).

2 Modeling

2.1 Uppsala District Heating Network

The production units and network distribution of the Uppsala district heating network were used as models when the production planning setup was created in this work. The main production unit in this network is the cogeneration plant KVV located at the production site Boländerna. The KVV has a production capacity of approximately 250 MW heat and 130 MW electricity. Other important units in the system include several oil boilers, a waste incineration plant, and an accumulator.

2.2 Discrete Optimization Model

The models used in the UCP are formulated in Python using the Pyomo modeling language. The models are linear and coarse and are mainly describing energy and energy flows.

2.2.1 Cogeneration Plant KVV

The KVV is modeled using a polytope in the space of electricity, heat and return temperature, which is displayed in Figure 1. This means that for each return temperature the polytope provides an area in the electricity-heat plane which the electricity and heat production is confined to. The KVV model in the EDP, which is summarized in section 2.3.1, was used to generate the polytope. The fuel consumption U_{KVV} for a certain electricity production P_{el} and heat production Q_{KVV} is calculated using the efficiency η_{KVV} according to

$$U_{KVV} = \frac{Q_{KVV} + P_{el}}{\eta_{KVV}} \tag{1}$$

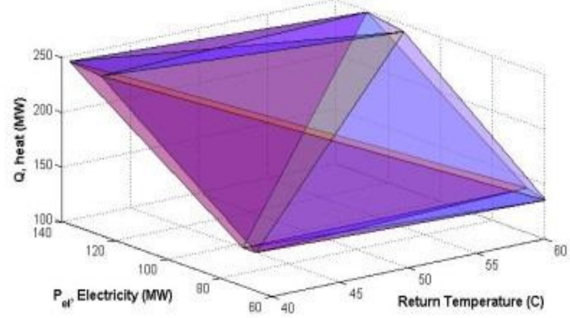

Figure 1. Polyhedron representing the operating regions of the cogeneration plant.

2.2.2 Other Production Units

For units that only produce heat, the relation between produced heat Q_{unit} and fuel consumption U_{unit} is given by

$$U_{unit} = \frac{Q_{unit}}{\eta_{unit}} \tag{2}$$

2.2.3 Accumulator

The accumulator works as an integrator, where the stored energy E_{acc} is determined by

$$E_{acc}[t] = E_{acc}[t-1] - hQ_{acc}[t-1] \tag{3}$$

where $Q_{acc}[t-1]$ is the energy flow to or from the accumulator and h is the sampling period.

2.2.4 Pipe Model

In order to represent the influence of the transportation of the district heating water, a pipe model containing a fixed time delay and a heat loss model is used. The heat loss from a pipe section, $\dot{Q}$, is determined using the outdoor temperature and is based on the following formula, describing the heat transferred from an underground cylinder with temperature t_0, when the ground temperature is t_s (Sundén, 2006).

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$$\dot{Q} = \frac{2\pi\lambda L(t_0 - t_s)}{ln\left(\frac{2N}{D} + \sqrt{4\left(\frac{N}{D}\right)^2 - 1}\right)} \qquad (4)$$

The other parameters of this equation is summarized in Table 1.

Table 1. Heat transfer parameters.

Parameter	*Interpretation*
L	Pipe length
D	Pipe diameter
N	Pipe depth
λ	Soil heat transfer coefficient

2.3 Continuous Optimization Models

The EDP modeling was performed in Dymola, where Modelica models representing the different units and components of the district heating network, were created.

Two different water media models are implemented, an advanced model using polynomials to approximate IF97 reference functions, and a simple model where the specific heat capacity and density of the water are constant. The advanced medium model is used in the vapor cycle of the KVV, while the simple medium model is used to represent the district heating water.

2.3.1 Cogeneration Plant KVV

The goal of the modeling of the KVV is to capture how the produced heat and electricity depends on the plant load, return water temperature and mass flow. For this reason the modeling efforts have been directed towards the vapor cycle. The entire cycle is however not included in the model, instead boundary conditions have been implemented using the following assumptions:

- The boiler outlet vapor characteristics (pressure and enthalpy) are constant and the mass flow is proportional to the plant load.
- The condensate leaving the condensers is at saturation pressure.
- Bleed streams from low pressure turbines are represented by a lumped pressure drop and a fixed pressure boundary.

A schematic illustration of the model of the KVV is displayed in Figure 2. A summary of the main components used in this model is presented below.

- Turbine: An isentropic efficiency parameter is used to calculate the outlet enthalpy and the mechanical work, while Stodola's law determines the relation between mass flow and pressure drop. The electrical output is calculated using mechanical and electrical efficiencies.
- Condenser: By considering the difference between incoming water temperature and the saturation temperature a heat flow rate to the district heating water is calculated. This heat flow rate determines the condensation rate and consequently the bleeding flow from the turbine stages.
- Control volume: Dynamic mass and energy balances are used to model a control volume. The equations are formulated using pressure and enthalpy as states, which requires partial derivatives of density with respect to enthalpy and pressure.
- Pressure loss: A quadratic loss function is used to relate the mass flow to the pressure drop.
- Reheater: An ideal representation of the reheating

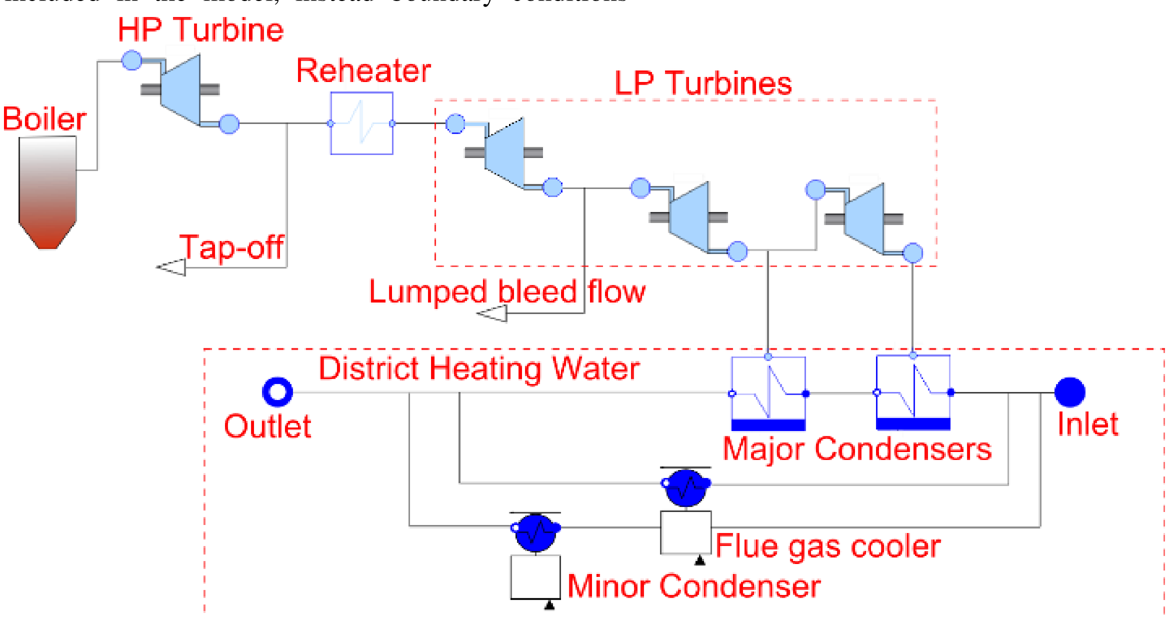

Figure 2. Schematic overview of the cogeneration plant model.

in the plant, as the outlet temperature is constant and determined by a parameter value.

2.3.2 District Heating Network Models

The models used to represent all units in the district heating network, except for the KVV, are summarized below.

- Heat production unit: The heat production from other units than the KVV is modeled empirically, adding heat to the district heating water proportionally to the firing power.
- Customer model: The mass flow through each customer is determined by the customer load model. The difference between the supply temperature and the predefined return temperature, which is based on the outdoor temperature, provides the mass flow based on the heat demand.
- Accumulator: A finite volume approximation is used where buoyance effects are neglected, i.e. no mixing is assumed when the accumulator is not charging or discharging. Heat losses are also neglected.

2.3.3 Pipe model

The production units and the customers are connected using pipe models. These are modeled using a combination of a standard finite volume implementation and a fixed delay of the temperature profile. The two components are connected in series, together with a heat loss component using the same heat dissipation equation as in the UCP pipe.

The goal of combining a fixed delay with a finite volume model is to capture the main characteristics of the pipe without having to use a model with very many pipe segments, something that would increase the complexity of the optimization problem considerably. It is a compromise between using only a fixed delay, which would result in incorrect delay times when the mass flow is varying, and using a fixed volume implementation with few volume segments, which would result in numerical dissipation. The ratio between the fixed delay and the finite volume pipe volume is decided based on the range of mass flows that will occur in each pipe and the accepted delay time error for the boundaries of this range.

2.4 Network Representation

The distribution of the customers and production units in the Uppsala district heating network is modeled using a one-dimensional approach. The network description is based on the setup presented in (Saarinen and Boman, 2012), where the customer distribution as a function of the delay time is determined. Compared to that model the setup in the optimization models is simplified further and only includes three customers. In Figure 3 a schematic representation of the implemented network structure is displayed.

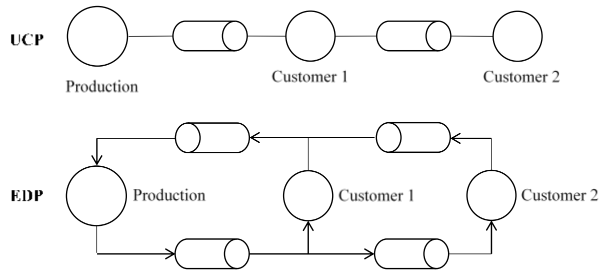

Figure 3. Schematic representation of network structure used in the discrete (upper structure) and the continuous optimization (lower structure).

3 Optimization Tools

3.1 Discrete Optimization

The UCP problem was formulated in Python using the Pyomo modeling language. Two different solvers were used for solving the UCP, the commercial solver Gurobi (Gurobi Optimization, 2015) and the open source package GLPK (Makhorin 2012).

3.2 Continuous Optimization

The optimization problem for the EDP was formulated using the Optimica language, extending the Modelica models describing the system. The open-source JModelica.org platform (Modelon AB, 2014) was used to translate the formulation into an NLP and this problem was solved using the Interior Point Optimizer (IPOPT), see (Wächter and Biegler, 2006). FMUs were used for initial trajectory simulations.

4 Optimization Formulation

4.1 Cost Function

In both the EDP and the UCP the goal is to maximize the economical profit. Incomes from selling heat and electricity, fuel costs and maintenance costs are therefore the main parts of the cost functions in the two optimization formulations. Only constant heat, electricity and fuel prices are considered and additional costs, such as pump costs are not considered in the model. In the UCP costs for starting and shutting down production units are also included in the cost function.

Additional terms must be added to the cost functions for numerical reasons. In the UCP one can easily obtain multiple solutions. To avoid this problem a small cost penalizing production unit load changes have been added. In the EDP a minor cost on input derivatives must be implemented for regularity reasons.

4.2 Degrees of Freedom

In the UCP the heat production and the status of each unit are decision variables, as well as the KVV electricity production and the energy flow to or from the accumulator.

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The decision variables for the EDP are similar to those in the UCP, but with a few key differences. Firstly, the status of each unit is fixed in the EDP. Secondly, it is not the heat production of each unit that is the decision variable, but the load change. This is achieved by introducing equations of the form

$$U_{unit}(t) = \int_t \dot{U}_{unit}(t)dt \quad (5)$$

The same formulation is used for the accumulator, but here another difference is also preset, as it is not the energy flow, but rather the district heating water mass flow that is controlled.

4.3 Constraints

Constraints represent an important part of the optimization formulation. In this section the most important constraints in the UCP and EDP formulations are presented.

All production units in the UCP and the EDP have constraints on their productions and their production change rates, corresponding to the limitations of the real plants. For the accumulator there are similar constraints defining the minimal and maximal amount of energy that can be stored, and how fast the energy level can change. To prevent emptying of the accumulator at the end of the optimization interval, an additional constraint of the form

$$E_{acc}[t_f] \geq E_{acc}[t_0] \quad (6)$$

is used in the UCP. Here t_0 and t_f represents the endpoints of the optimization interval. In the EDP an accumulator constraint based on the UCP accumulator energy at the end of each optimization interval is used.

When a production unit changes status the heat production must follow specific start and stop trajectories, denoted $Q_{unit,start}[t]$ and $Q_{unit,stop}[t]$, respectively. In the UCP this is implemented using constraints of the form

$$Q_{unit}[t] = Q_{unit,start}[t], \quad t \in [t_{start}, t_{start} + t_{startdelay}] \quad (7)$$

$$Q_{unit}[t] = Q_{unit,stop}[t], \quad t \in [t_{stop}, t_{stop} + t_{stopdelay}] \quad (8)$$

where $t_{startdelay}$ and $t_{stopdelay}$ are the durations of the constraints.

In the EDP the trajectories must not be followed exactly. Instead upper and lower constraints are used to confine the production to be close to the trajectory are used.

In the EDP more constraints are present, limiting e.g. mass flows, temperatures and pressures in different components. For a more detailed description, see (Larsson *et al,* 2014).

5 Optimization Example

Several test cases of varying complexity were developed to evaluate the production planning strategy. In this paper the main results from the most realistic case are presented.

5.1 Optimization Settings

A sampling interval of 30 minutes for UCP optimization and 20 minutes for EDP optimization is used in all optimization cases. The optimization interval is between one and four days in the UCP and between 20 and 24 hours in the EDP. The difference in optimization horizon is a result of the different objectives of the optimization problems; the UCP results determine long term plans while the EDP handles faster dynamics.

The customer load profile consist of a base load with two load peaks per day, representing the typical heat demand of a residential area.

5.2 Test Case

In this test case, the heat load profile is increasing linearly, with load peaks superimposed. The load profile during the first day of the scenario is displayed in Figure 4. The problem setup involves three production units, the accumulator, and customers. One of the production units, the waste incineration plant AFA is running with maximal load throughout the optimization. The KVV is also running at all times, but the load is a decision variable. The final producer is the Husbyborg oil boiler. This unit is initially turned off, but must eventually be started as the customer heat demand is increasing.

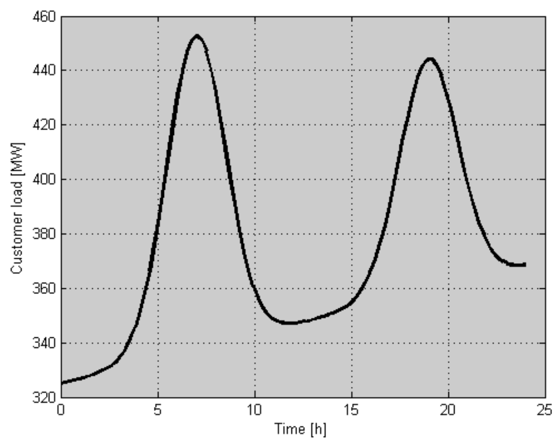

Figure 4. Customer load profile during day one.

Two subcases are considered, in the first one a point-wise network representation with one customer is implemented and in the second one a distributed network is used. The optimization interval is four days for the UCP. For the EDP, this period is divided into five separate optimizations for the first subcase, and six optimizations in the second subcase.

5.2.1 Optimization Results

The results from the test case are displayed in Figure 5 to Figure 8. The most important result is the difference in start-up time for the oil boiler, depending on which network topology that is considered. By including the distribution of the customers in the optimization formulation it is possible to delay the start-up with nine hours, from hour 30.5 to hour 39.5. The difference is explained by the reduced production peaks caused by the difference in time delay between the different customers.

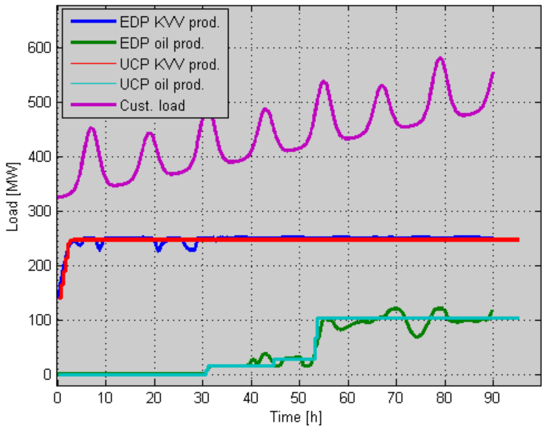

Figure 5. Customer load and heat production for different units using a point-wise network. Results from the discrete (UCP) and the continuous (EDP) optimizations are compared.

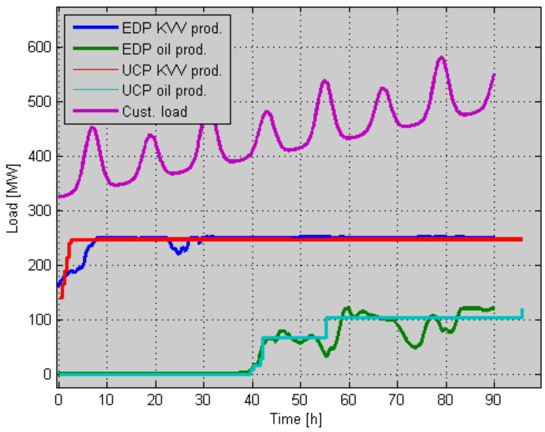

Figure 6. Customer load and heat production using a distributed network. Results from the discrete (UCP) and the continuous (EDP) optimizations are compared.

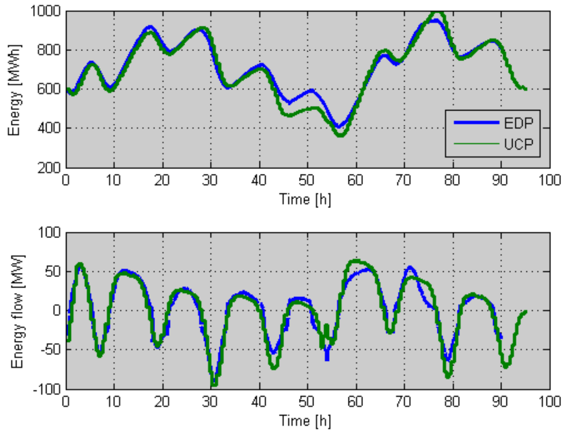

Figure 7. Accumulator usage in the point-wise network case. Results from the discrete (UCP) and the continuous (EDP) optimizations are compared.

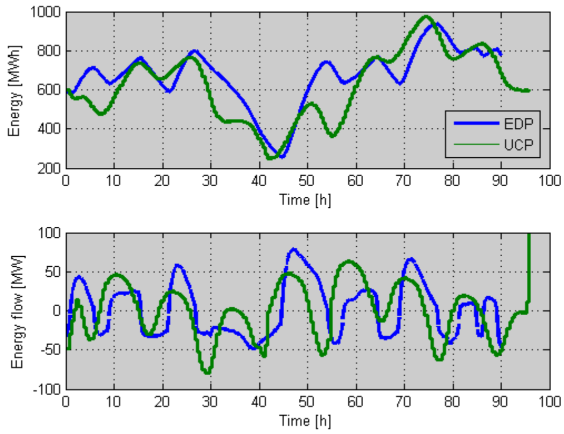

Figure 8. Accumulator usage in the distributed network case. Results from the discrete (UCP) and the continuous (EDP) optimizations are compared.

One can also see that there are some differences in the behavior of the EDP results compared to the UCP. Especially the signal describing the heat production of the oil boiler contains oscillations in the EDP results, which are not present in the UCP results. The oscillations are a result of the more detailed optimization model used in the EDP, which includes faster dynamics, and the shorter optimization horizon used for the EDP. The more detailed modeling makes it possible to utilize effects such as heat storage in the pipes and mass flow dependent delay times. This results in an optimal strategy that contains faster load variations.

The shorter optimization horizon introduces some transient behavior at the end of each optimization interval for the EDP, as the optimization attempts to use the free heat stored in the network. To counteract this, the final part of each optimization was disregarded, but nonetheless some transient behavior based on this effect can be observed. By implementing

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the EDP as an MPC, disregarding more of the optimization results, this unwanted effect would be removed. However, the EDP results are in general of higher quality than the UCP results due to the more detailed modeling. This means that they are more physically relevant, and also more optimal for the actual structure of the district heating network.

Another notable feature of the optimization results is that the accumulator is used to compensate for the load variations, while the production plants are mostly running at constant load.

The continuous formulation of the problem above contains 307 variables and 33 states, while the transcribed NLP formulation contains approximately 70 000 variables. Using a standard laptop with 8 GB RAM and four 2.6 GHz CPUs, the optimization problem was solved in less than ten minutes.

5.3 Conclusions from Other Test Cases

- The district heating water mass flow is typically maximized and the supply temperature is correspondingly minimized. This results in a maximization of the KVV electricity production.
- Pump limitations, customer supply temperature and condenser pressure can all be limiting the district heating highlighting the benefits of thorough physical modeling of the system.
- By introducing a pipe model to represent the customer distribution the mass flow dependency of the delay time can be captured.
- The importance of the delay time between customer and producer is highly depending on whether temperature or mass flow changes are used to compensate for heat load variations. When only the mass flow changes the delay time is irrelevant as water is incompressible.
- The possibility to use the network as an accumulator follows from physical modeling of the distribution network.

6 Conclusions

In this paper an extension of the approach for short-term production planning presented in (Velut *et al,* 2013) has been proposed. The economic dispatch problem is solved with JModelica.org, using non-linear optimization of physical models. The method have been investigated using data from the district heating network in Uppsala, Sweden.

The derived optimization strategy involves minimization of the district heating water supply temperature and, correspondingly, maximization of the mass flow. By considering constraints on variables such as pump speed, condenser pressure and customer temperature the limitations of the real system have been included in the formulation and the effect of these constraints can be seen in the optimization results.

The network distribution is included in the optimization model using physical pipe models and a simplified topology. By using this network model the different time delays for different customer groups is included in the model. In computation experiments, the distributed customer increased the economic profit by lowering production peaks and utilizing heat accumulation in the network.

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