Predictive Supply Temperature Optimization of District Heating Networks Using Delay Distributions

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Abstract

Fluctuating power production in combined heat and power (CHP) plants may cause unwanted disturbances in district heating (DH) systems. DH-systems are often automated, however, supply temperature (ST) is still primarily chosen manually by the operator because of uncertain heat demand in near future and uncertain delay from heat supplier to consumers. In this work, future heat demand and return water temperature are predicted based on outdoor temperature forecast and process data history using neural network estimators. Consumers in network are presumed to be similar, but their distances from production site vary thus creating a distribution of range. Delay is modelled as a distribution function based on the distances between heat consumers and the suppliers, which weights the ST from last few hours calculating the average ST received by the consumers. The derived function models how the temperatures develop along the network. A brute force optimizer was developed to minimize pumping costs and heat losses and to smooth temperature gradient originated thermal stresses. System delays are fixed during an optimization cycle, and after each iteration, the delays are updated according to new system flowing rates. The resulting ST curve is a discrete curve that cuts the heat load peaks by charging and discharging the energy content of the DH network. Optimization keeps the ST and flow rates in control and stabilizes the network smoothly and efficiently after disturbances. Optimization is demonstrated by using case data of one year from a district heating system in Finland.

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Peer-review under responsibility of the Scientific Committee of The 15th International Symposium on District Heating and Cooling.

Keywords: District Heating; Flexibility; Supply Temperature; Optimization

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10.1016/j.egypro.2017.05.076
1. Introduction

Control of district heating systems (DHS) consists of pressure controls and temperature controls. Pressure controls regulate the pump stations to produce desired mass flow and pressure difference for DH customers. Dynamics of pressure transients are relatively rapid enabling the utilization of basic control methods. Transient dynamics of temperature behaviour along the network is related with the flow rate of DH water typically resulting to delays of several hours. Varying transport delay behaviour, estimation of heat consumption, and definition of optimal supply temperature are issues that have contributed for the current situation of low level of automation in temperature controls. For those reasons, the supply temperature is usually set manually by operator according to the time of the day and the outdoor temperature.

With functional supply temperature controls the heat losses and pumping costs can be balanced to provide minimum running costs of the system. It also enables the utilization of DH network energy storage capacity to avoid temporary starts of supporting heat stations with significantly higher running costs. According to [1-5], the supply temperature is usually set too high if it is ran manually.

There are not many DHS applying advanced control methods to control supply temperature even though the subject has been studied a lot. Production optimization has been studied already in 1980s and [6] studied supply temperature optimization in early 90s. Temperature optimization is usually connected with the solution of the unit commitment and economic dispatch problems [5]. Other optimization methods are presented in [7-9]. Supply temperature can also be controlled by model based control methods [2], [10], [3] and [11]. However, most of the methods do not consider pressure dynamics but assume that mass flows can be produced within certain boundaries. Including pressure dynamics to the system model improves the results slightly, but complicates the calculations significantly.

The result of optimization can be at its best as good as the forecast used for heat consumption and customer return temperature estimation. Consumption and return temperature can be determined by stochastic black box and grey box models as ARX [2], neural network [12], and soft computing [13].

District heating network (DHN) can be modelled from one generalized customer to all real customers. There is a significant potential to create exact models of pipe networks, as there usually exist a lot of measured data from the network. The challenge is the decision of the level of generalization. Whole DHN of Uppsala in Sweden was modelled in [3] by TERMIS, but the simulation was too slow to be used for control purposes. Hereby the model should be simple. However, the heat delivery distribution can be modelled as a distribution function based on real DHN dimensions, which is presented in this paper.

2. Heat load and return temperature models

The heat consumption depends on customer behaviour affected by weather and daily routines. Process model, such as neural network model can be trained to model that behaviour. In this work, the heat load and return water temperature are both modelled by a neural network. Inputs to neural network presented in Figure 1 are heat loads from 24, 48, 72 hours and 7 days ago. In addition, the average heat load from last 24h, outdoor temperature forecast and day of the week as a binary variable are used as model inputs. There are 10 neurons in the hidden layer that are trained using Levenberg-Marquardt algorithm.

It is assumed that all heat consumers behave similarly according to the average consumption. When the whole DHN is reduced into one consumer, the consumption can be presented as [14]

\[ \phi_c = \dot{m}_c c_p (T_{s,c} - T_{r,c}). \]  

where customer heat load \( \phi_c \), is calculated from mass flow \( \dot{m}_c \) at the customer, supply water temperature \( T_{s,c} \), return water temperature \( T_{r,c} \) and heat capacity \( c_p \) of water. Heat consumption can be determined by data collected from consumer substations. However, online data from customer substations is not usually available and so the heat consumption has to be calculated from production plant data as [2]
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Figure 1. Neural network model for heat load predictor

Figure 2. Delay distribution model

\[ \phi_c(t) \approx \dot{m}_c(t)c_p(T_{ss}(t - \tau_s) - T_{rs}(t + \tau_r)). \]

where \( T_{ss} \) is the supply water temperature and \( T_{rs} \) the return water temperature at heat supplier. \( \tau_s \) is the delay from supplier to customer and \( \tau_r \) the delay from customer back to supplier.

Return water temperature depends on weather and similar to heat load follows a daily pattern. Therefore, it is modelled according to the same principle except the heat loads are replaced with return water temperature measurements.

3. Delay distribution model

Delay distribution is a function to model the different transport delays to customer around the DHN. According to Figure 2, there are \( d \) customers that have similar delays. Each consumer is fixed such that 1\(^{st}\) consumer has delay of 1 time step, 2\(^{nd}\) consumer delay of 2 time steps etc. The current heat load is distributed to the consumers based on mass flow rate such that during high flow rate the heat load is weighted on consumers with short delays.

In the example case, the distribution function is based on the real distances from production plant to customer along with DH delivery pipes. It is assumed that the water flows to the customers along the shortest route.

All the real individual customers have reference consumptions \( \phi_{c,r} \) and certain distance from presumed production plant, that is dependent on current production plan. With the exact network data, it is possible to calculate how much consumption exists within certain range from suppliers.
\[
\phi_p = \sum_{r=p-1}^{p} \phi_{c,r},
\]  
(3)

where \( p \in \mathbb{Z} \) is the range interval between suppliers and customers, \( r \) is the distance of customer to presumed supplier and \( \phi_p \) is the total heat load within certain range. Histogram of heat load is formed using (3) and placed into

\[
f_{\text{range}} = \frac{1}{\sum_{p=1}^{d} \phi_p} \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_d \end{bmatrix},
\]  
(4)

where unscaled probability vector \( f_{\text{range}} \) is based on predetermined heat load distribution on range axis. The distribution is scaled according to reference mass flow of the network \( \dot{m}_j \) to fit into time scale \( j = 32 \) time steps. The probability function is scaled into time axis by scaling function \( f \) with following inputs. The discrete moment of time \( k \in \mathbb{Z} \) and the discrete time step of optimization \( \Delta t \) is a constant, such that \( \Delta t \in \mathbb{R}, \Delta t > 0 \).

\[
f_{\text{time}}(k\Delta t) = f \left( f_{\text{range}}, \dot{m}_j(k\Delta t) \right).
\]  
(5)

Function \( f \) scales \( f_{\text{range}} \) according to scaling parameter \( \dot{m}_j \) such that low value spreads the function in time scale. Finally \( f \) fits the scaled probability function into vector of \( j \) time steps. Theoretical customer temperature \( T_{s,c,\text{th}} \) without disturbances is

\[
T_{s,c,\text{th}}(k\Delta t) = [T_{s,s}(k\Delta t) \ T_{s,s}((k-1)\Delta t) \cdots T_{s,s}((k-j)\Delta t)]f_{\text{time}}(k\Delta t).
\]  
(6)

Delay distribution model also considers heat losses and pumping energy, which are considered with network-specific parameters in equation

\[
T_{s,c}(k\Delta t) = T_{s,c,\text{th}}(k\Delta t) - K_1 \hat{\tau}(k\Delta t) (T_{s,c,\text{th}}(k\Delta t) - T_g(k\Delta t)) + K_2 \dot{m}_c(k\Delta t)^x,
\]  
(7)

where \( K_1 \) is heat loss factor, \( \hat{\tau} \) the average delay, \( K_2 \) pumping energy factor, \( T_g \) temperature of ground surrounding the pipes and \( x \) the parameter to determine the relation between pressure difference and mass flow.

4. Brute force optimizer

Because of the process nonlinearity with varying distributed delay, derivation of a linearized process model is a complex task. Instead, brute force search will calculate all the possible trajectories of supply water temperature within prediction horizon. There might be restrictions in gradients, upper and lower boundaries, fixed initial and final values, which must be included in the calculation. The optimizer calculates the mass flow presented in Eq. (1), according to supply temperature \( T_{s,c} \) by Eq. (7), estimated return temperature and heat demand.

Trajectories are formed within certain constraints to exclude the unreasonable ones before the calculation.

- Optimization is discrete with time step \( \Delta t = 0.5 \) hour. The dynamics of DHN is slow and rapid fluctuations in temperatures stress the network. Therefore shorter time step would not give any advantage.
- Trajectories have 7 possible gradients. \( 0 \ ^\circ\text{C/}\Delta t, \pm1 \ ^\circ\text{C/}\Delta t \) for minor changes, \( \pm2 \ ^\circ\text{C/}\Delta t \) for moderate changes and \( \pm5 \ ^\circ\text{C/}\Delta t \) for extreme changes.
- Only the first 6 time steps are optimized, while next 18 steps are fixed during optimization of one time step. Fixed time steps ensure that the final accumulation level of the network is same in all of the trajectories.

Thus the optimization of 24 hours horizon is formed by 48 stepwise optimizations. The cost function of optimizer is based on total production and delivery costs and penalty cost for rapid control changes

\[
J(k\Delta t) = C_{\text{pump}}(k\Delta t) + C_{\text{heatloss}}(k\Delta t) + C_{\text{penalty}}(k\Delta t).
\]  
(8)
which consists of simplified cost functions

\[ C_{\text{pump}}(k\Delta t) = a_1 E_{\text{el}}(k\Delta t) \Delta p(k\Delta t) \dot{m}_c(k\Delta t), \quad (9) \]

\[ C_{\text{heat loss}}(k\Delta t) = a_2 E_{\text{fuel}}(k\Delta t) \frac{T_{s,s}(k\Delta t) - T_g(k\Delta t)}{m(k\Delta t)}, \quad (10) \]

\[ C_{\text{penalty}}(k\Delta t) = a_3 [T_{s,s}(k\Delta t) - T_{s,s}((k-1)\Delta t)]^2, \quad (11) \]

where \( a_1 \) and \( a_2 \) and are constant parameters depending on system dimensions, \( a_3 \) is adapted according to other parameters, \( \Delta p \) is the reference pressure difference over the pumps, \( T_g \) the ground temperature around the DH pipes. \( E_{\text{fuel}} \) is the average price of fuels used hourly and \( E_{\text{el}} \) the total price of electricity based on hourly spot price.

5. Case study

Optimization was applied in a municipal case study using DHN of Kuopio located in Eastern Finland. The DHN is operated by Kuopion Energia Oy, which has 5778 customers with total annual consumption of 865 GWh. There are two CHP plants at the same location near the city centre, which produce 97% (2015) of the annual heat demand. The plants use peat and biomass as main fuels and one of them is equipped with a flue gas condenser. Rest of the heat is produced by a small biogas CHP engine and eight oil-fired heat-only stations. The electricity production is maximized in CHP plants, because the electricity price is most of the time high enough to make it profitable. Hereby DHN should support electricity production by being operated with as low DH supply water temperature level and high flow rate of DH water as possible. Low return water temperature is also targeted as it increases the efficiency of flue gas condenser. Currently the supply water temperature is controlled manually in order to accumulate network before peak loads. The baseline is good, but without predictive controls, the future events are difficult to calculate.

[15]

6. Results

Results are based on consumption data from customer substations and production data from automation system of power plants and DHN.

6.1. Heat load and return water temperature predictors

Neural network prediction error to target value depends on the quality of input data. Heat consumption and customer return water temperature predictions can be calculated from production data, but not accurately. The challenge may be that consumer substation data cannot be gathered online. In that case the consumption has to be estimated by using Eq. (2) Standard deviations (SD) and variances (VAR) of prediction errors are presented in Table I. Histogram of the heat load and return temperature predictors accuracies are presented in Figure 3.

<table>
<thead>
<tr>
<th>Substation data as input</th>
<th>Production data as input</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \phi_c ) SD (MW)</td>
<td>5.69</td>
</tr>
<tr>
<td>( \phi_c ) SD (%)</td>
<td>7.82</td>
</tr>
<tr>
<td>( \phi_c ) VAR (MW2)</td>
<td>56.5</td>
</tr>
<tr>
<td>( T_{r,c} ) SD (°C)</td>
<td>0.59</td>
</tr>
<tr>
<td>( T_{r,c} ) VAR (°C2)</td>
<td>0.67</td>
</tr>
</tbody>
</table>
It can be seen that real substation consumption data provides better prediction results than the production data. However, in this optimization case the production data is used as input data as the substation measurements are not available for distributed control system.

6.2. Customer supply water temperature modelling

To model customer supply water temperature, customers’ distances from heat producers at certain heat loads are noteworthy. In Figure 4, heat production is distributed into three generation plants, Haapaniemi CHP plant (red, 258 MW), Bio heat station (green, 2 MW) and Saarijärvi Heat station (blue, 40 MW). On the right, there is a histogram of distances from the supplier to consumers. The shape of heat distribution function is the same as the histogram.

During a medium or high load, the delay responses are almost linear to mass flow, but on low demand, the delay is shorter than modelled. This phenomenon was corrected by weighting more the temperature difference.
Figure 5. The first graph shows the customer supply temperature model response according to Eq. (7). Second graph is fitted to match measurements by the correction factor.

There were problems on modelling the summer temperature as can be seen in first graph of Figure 5. By multiplying the heat loss term in (7) with correction factor $T_{S, c}(t) - T_g(t)\frac{0.55}{12.5}$, the model was able to match the real customer temperature accurately enough. The correction factor parameters were solved by data fitting to match the measured and modelled supply water temperatures. With the correction term, the $T_{S, c}$ could be modelled more accurately with SD=0.35 °C. Modelled and measured customer supply temperatures with correction term are presented in lower graph of Figure 5.

6.3. Optimization

The optimized supply temperature is compared with the measured supply temperature (Meas) during observed period. Figure 6 introduces an instructional control curve proposed by Energiateollisuus ry (ET, Finnish Energy Association) to Finnish district heating operators to operate their networks as a function of outdoor temperature [16]. This curve is used as the second baseline in the simulations.

Time period 2.1. – 30.12.2015 was optimized using predicted heat load and return water temperature. Delay distribution was used to determine supply temperature at customer $T_{S, c}$ and return temperature at the plant $T_{r, s}$.

The actual electricity consumption of DH pumps was not available in the measurement data. Therefore, exact balance between pumping cost and heat loss cost was not able to be determined. However, there is a tuning parameter for that and the optimization was performed with three different values giving three optimization results (Opt1, Opt2 & Opt3). The effect of parameter links straight to mean supply temperature by raising the cost of pumping. For optimizations, the parameters were chosen such that the mean supply temperature is around the mean value of ET -curve. Opt3 was chosen for inspection in Figures 7-9, because the daily variations can best be compared with measured values, as the mean supply water temperature of Opt3 is highest of the optimizations and closest to the measured.
There is a comparison between three $T_s$ -control methods in Figure 7. Measured supply temperature ‘Meas’ is quite noisy, whereas outdoor temperature and instruction curve based ‘ET’ is smooth because of the smooth behaviour of the outdoor temperature. The optimized supply temperature curve is quite conservative because of the penalty for unnecessary fluctuations and steep gradients. The upper limit of the supply water temperature in DHN is 110 °C, which was reached in some conditions. Additionally, Figure 7 shows the three different strategies and their impact on flow rate and heat production.
Figure 8 shows optimized supply temperature at the supplier $T_{SS}$ and the modelled supply temperature at customer $T_{SC}$ in another case example. In addition, the predicted consumption and production are shown on top of the figure in addition to measured values as comparison. There are extremely high electricity price peaks during Wed – Fri.

According to Figure 8, the peaks in heat consumption and electricity price lead to a raise of the supply temperature. Therefore, optimization works very well minimizing pumping during high electricity price and maximizing during low price.

Supply temperatures of the three methods (Meas, ET and Opt3) are plotted into same graph as a function of outdoor temperature in Figure 9. Even though the mean temperature of optimization is only 0.88 °C higher than ET, it diverges from the ET more than Meas on cold temperatures. This is partly based on anticipation of delay in optimization and partly because of the electricity price variation.

To compare the benefits of the three optimizations, they are compared to two baselines: measured $T_s$ (Meas) and ET –curve (ET). Optimization period is 2.1. – 30.12.2015. Results are presented in Table II and III, such that (-) is for decrease and (+) increase because of optimization. The differences between the optimizations are based on the different level of supply water temperature caused by a different pumping cost term.

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**Figure 8.** Opt3 at medium heat load at 5.10. – 11.10.2015. There is time and day on x-axis.
Figure 9. Meas (red), ET (green) and Opt3 (blue) in function of outdoor temperature 2.1.-30.12.2015.

According to Table II and III, the mean supply temperature of Opt1 is below Meas and ET such that heat loss is smallest and pumping costs highest of all. The supply temperatures of Opt2 and Opt3 are between ET and Meas. Heat production is clearly proportional to supply water temperature as heat losses increase along with increased supply water temperature. Respectively pumping power reduces along with increased supply temperature. However, pumping costs are dominating in optimizations compared to pumping power as optimizer increases pumping during low electricity price and vice versa. Pumping power measurements should be done to determine which of the three optimizations fit best for the real set-up.

**Table II.** Optimization results compared to measured supply temperature. Values are differences of optimization and the baseline (Opt - Meas).

<table>
<thead>
<tr>
<th></th>
<th>Opt1</th>
<th>Opt2</th>
<th>Opt3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cost (%)</td>
<td>-1.52</td>
<td>-1.33</td>
<td>-1.18</td>
</tr>
<tr>
<td>Heat production (GWh)</td>
<td>-14.00</td>
<td>-9.22</td>
<td>-5.72</td>
</tr>
<tr>
<td>Heat production (%)</td>
<td>-1.63</td>
<td>-1.07</td>
<td>-0.66</td>
</tr>
<tr>
<td>Return temperature (°C)</td>
<td>-0.32</td>
<td>-0.22</td>
<td>-0.15</td>
</tr>
<tr>
<td>Supply temperature (°C)</td>
<td>-2.75</td>
<td>-1.82</td>
<td>-1.13</td>
</tr>
<tr>
<td>Pumping energy (%)</td>
<td>+11.17</td>
<td>+6.88</td>
<td>+3.92</td>
</tr>
<tr>
<td>Pumping cost (%)</td>
<td>+9.12</td>
<td>+4.52</td>
<td>+1.42</td>
</tr>
</tbody>
</table>

**Table III.** Optimization results compared to supply temperature by ET-curve. Values are differences of optimization and the baseline (Opt - ET).

<table>
<thead>
<tr>
<th></th>
<th>Opt1</th>
<th>Opt2</th>
<th>Opt3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cost (%)</td>
<td>-1.52</td>
<td>-1.33</td>
<td>-1.18</td>
</tr>
<tr>
<td>Heat production (GWh)</td>
<td>-14.00</td>
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<td>-5.72</td>
</tr>
<tr>
<td>Heat production (%)</td>
<td>-1.63</td>
<td>-1.07</td>
<td>-0.66</td>
</tr>
<tr>
<td>Return temperature (°C)</td>
<td>-0.32</td>
<td>-0.22</td>
<td>-0.15</td>
</tr>
<tr>
<td>Supply temperature (°C)</td>
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</tr>
<tr>
<td>Pumping energy (%)</td>
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<td>+6.88</td>
<td>+3.92</td>
</tr>
<tr>
<td>Pumping cost (%)</td>
<td>+9.12</td>
<td>+4.52</td>
<td>+1.42</td>
</tr>
</tbody>
</table>
6.4. Impact of prediction error on flow rate and heat production

Prediction error in heat load and return water temperature predictions may lead to false optimization. Error in the supply temperature will result an error in flow rate if the real consumption and return temperature do not match with the estimates. Error in flow rate is directly reflected into current heat production. Table IV presents error mean (EM) and error standard deviation (SD) of error caused by neural network prediction error. As the prediction error SD of heat load is 9.71 %, and return temperature is 0.83 °C, the 11 % of SD in heat production is only a little bit higher.

Table IV. Prediction errors’ reflection to flow rate and heat production.

<table>
<thead>
<tr>
<th>Meas</th>
<th>ET</th>
<th>Opt1</th>
<th>Opt2</th>
<th>Opt3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi_{prod}$ EM (MW)</td>
<td>0.010</td>
<td>0.019</td>
<td>0.026</td>
<td>0.029</td>
</tr>
<tr>
<td>$\phi_{prod}$ SD (MW)</td>
<td>5.37</td>
<td>5.36</td>
<td>5.36</td>
<td>5.36</td>
</tr>
<tr>
<td>$\phi_{prod}$ SD (%)</td>
<td>10.9</td>
<td>11.0</td>
<td>11.0</td>
<td>11.0</td>
</tr>
<tr>
<td>$\dot{m}$ EM (kg/s)</td>
<td>1.20</td>
<td>1.11</td>
<td>1.11</td>
<td>0.80</td>
</tr>
<tr>
<td>$\dot{m}$ SD (kg/s)</td>
<td>36.2</td>
<td>37.9</td>
<td>38.6</td>
<td>37.7</td>
</tr>
<tr>
<td>$\dot{m}$ SD (%)</td>
<td>6.56</td>
<td>6.55</td>
<td>6.52</td>
<td>6.52</td>
</tr>
</tbody>
</table>

7. Discussion

The role of the CHP production together with DHNs exploited as an energy storage will increase significantly in the future. This is because the more alternating renewable power generation will be connected in the power systems, the more flexible generation will be needed to balance the systems. The total thermal efficiency of CHP-generation is about twice as good as that of the conventional condensing power generation. For this reason, it is reasonable to utilize CHP-generation as much as possible.

The storage capacity of DHN can be utilized to decouple the power generation in a CHP plant from temporary heat load. However, utilization of the storage capacity of the DHN requires that the dynamic behaviour of the DHN can be monitored/estimated reliably. The primary function of the CHP-generation is to produce the required heat load to customers together with the production units in the DH network during every moment of the year. Thus, the utilization of the heat storage capacity of the DHN is constrained by the customers’ heat demand. Another important issue in using the DHN as an energy storage is thermal stresses caused by temperature gradients in the system. Charging and discharging rates of the stored energy in the system must be constrained according to the maximum temperature change rates determined for the DHN structures. Hot water accumulators connected with the DHN will increase the degree of freedom when planning the operation of the system.

The level of optimization in the operation of DHNs has traditionally been pretty low. The reasons for that come from the complex dynamics of the DHN and the lack of measurement information from geographically extensive systems. Thus, the operation strategy of these systems is mostly based on empirical result and the results may be far from optimal regarding to fuel consumption and other operation costs, e.g. pumping costs. However, progress in computation capacity and IT-technology has made it possible to apply more sophisticated control methods also to DH-systems, which is a fundamental requirement to be able to utilize the flexibility potential of CHP and DH-systems.

The neural network predictors act as they are trained. They are tools that process the input data providing some result. It is good tool for this application, if the data has some repetitive cyclic behaviour and strong connections to target data. The success of prediction is dependent on choosing and processing the input data and choosing the time scale such that the DHS functions similarly whole time period.

As neural network predictor, also the optimizer is a tool that provides a solution according to defined cost functions and delay distribution model. In this study, the cost functions were created to serve DHS, such that power production was excluded. Optimization minimizes the flow rate during high electricity price to avoid expensive pumping. However, to maximize the production of CHP the condensing heat load of steam turbine should be as high as possible to enhance the power output of turbine and boiler. Thus, the flow rate should be high to provide a
maximum cooling load. Pumping costs and condensing load are partly in contradiction. Therefore, condensing load should be in cost function to provide an optimization that fully satisfies the requirements of CHP suppliers.

8. Conclusions

This research was carried out because of the low level of supply water temperature controls in district heating systems (DHS). The aim was to find some solution to control the supply temperature such that there would be more flexibility and predictability in perspective of heat and power co-generation. Also, improved cost and energy efficiencies were objectives. Heat load demand and return water temperature of district heating (DH) customers were predicted by neural network predictors. The dynamic response of supply temperature was modelled through delay distribution model. The supply water temperature was optimized by brute force optimizer that minimizes the total costs of heat loss and pumping. The research was carried out by modelling the DHN of Kuopio by scaling and validating the models with the system data and measurements.

The optimization was performed for period of one year with three different values of cost tuning parameters. Optimizations were compared with measured supply temperature and instructional supply temperature curve. Compared with measured values, supply water temperature reduced in range 1.1–2.8 °C, reducing the total operating costs 1.2 – 1.5 %. Cumulative error caused by prediction error was rather small as the standard deviation of heat production was only 11 %. However, better accuracy would be achieved if neural network predictor was trained for each season separately.

The results of optimization are good and in accordance with the definitions. The most remarkable factor determining the supply water temperature was the rapidly fluctuating electricity price that sets the pumping costs. The results did not give remarkably high savings in total operating costs, as the supply temperature could not be lowered that much, as measured supply water temperature was fitted near to the instructional green line presented in Figure 8. However, the results can be tuned with other weight factors in cost function case specifically.

In the future, the optimization should be extended to CHP-production, such that DHN could support electricity production by supply temperature control.

Additionally, to improve the optimization algorithm, linear parameter varying (LPV) state-space model could enhance the speed and accuracy of the optimization. The varying delay is challenging for basic state-space models. LPV model of DHS would be similar to marine cooling systems, which is modelled in [17]. LPV model is also formulated for DHS, but was failed to implement due to numerical difficulties [18].

Acknowledgements

This work has been carried out in research program Flexible Energy Systems (FLEXe, grant no. 2532/31/2014) and supported Tekes - Finnish Funding Agency of Innovation. This work aims to increase flexibility of controlling district heating networks in cogeneration power plants. District heating system time series for the research was provided by Kuopion Energia Oy, who is gratefully acknowledged.

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