

Forward temperatures and production planning in district heating systems

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Abstract. Subject of study: short-term planning in district heating systems. The major goal is to minimize the operation cost, subject to the condition of fulfilling the heat demand.

We propose a new concept for controlling the supply temperature in district heating systems using stochastic modeling, prediction and control. A district heating systems is a difficult system to control (optimally) as the dynamic relationship between supply temperature (the control variable) and key parameters such as network temperature and flow rate are time-varying and difficult to establish, which in both cases can be attributed to the time-varying heat load in the system.

Materials and methods: we have summarized results of many research papers on District heating systems and primary principles of heat exchange theory.

Results: describes a concept for controlling the supply temperature in district heating systems using stochastic modeling, prediction and control.

Conclusions: This document discusses how to consider distribution planning, with a focus on how to handle the forward temperature. Focus is on how to handle the forward temperature. Two alternative approaches are suggested. The first applies transformation of data before an ordinary load prediction algorithm is applied. The second models the district heating system as a network. As we all know the controlling parameter for modeling the heating system is temperature. However, the traditional model does not account for the change in load of the consumers in time. Temperature forward still needs to be predicted, or more correctly, to optimize. In that sense the load forecasting problem and the planning problem are linked.

1. Introduction

District heating is used to supply cities with heat from a common heating system. The heat is produced in units of different types. In Combined Heat and Power (CHP) plants, both heat and power are produced from biomass or fossil fuels. Heat only boilers produce heat from biomass or fossil fuels, and heat pumps and electric heaters produce heat from electricity. The heat is distributed to the consumers through a pipe system in which the distribution water circulates continuously.

Due to relatively high operation costs, it is necessary for the energy companies to optimize the production. Different approaches modeling the network can be found in the literature. However, many references focus on network simulation rather than on production planning. This paper discusses how to consider the distribution in the planning, with focus on how to handle the forward temperature.



2. Numerical simulation methods

The heat demand in a district heating system consists of three components: heat for warming buildings, heat for warming tapwater, and losses in the distribution network. Their respective contributions are about 70% for warming buildings, 25% for warming tapwater and 5% for losses. The outdoor temperature, together with the behavior of the consumers, referred to as the social component, have the greatest influence on the demand. Weather conditions like wind, global radiation (sunshine) and precipitation have less effect.

The heat, q_i , delivered from a production plant during hour i is

$$q_i = c_w G_i (t_i^f - t_i^r) \quad , \quad (1)$$

where c_w is the specific heat capacity of water, G_i is the water flow, t_i^f is the forward temperature and t_i^r is the return temperature.

The forward temperature is chosen in the range from 70 to 150 degrees Celsius, which implies that the return temperature becomes 30 to 70 degrees. In this paper we simplify the problem and assume that the return temperature is constant. This means that we only need to use the forward temperature when modelling the influence of the temperatures.

The forward temperature is controlled by the system operator. The choice of forward temperature is an optimization problem that has to be solved by the system operator.

Several methods for load prediction have been suggested and implemented, including e.g. time series models [1] and Artificial Neural Networks [2]. Both methods find an expression that describes the heat load as a function of weather and consumption patterns.

In the above mentioned methods, it is possible to also consider the forward temperature as an explaining variable. The drawback with the approach is that the forward temperature still needs to be predicted, or more correctly, be optimized. In that sense the load forecasting problem and the planning problem are linked. Thus, to find the global optimum, the two problems must be solved simultaneously.

Assume the district heating network consists of only one production plant and one large consumer. The distance between the plant (supply node) and the consumer (demand node) is defined as the energy weighted average distance between the real plants and demands. On this simple network model, it is easy to compute how a change in forward temperature moves from the supply node to the demand node. Used here is the knowledge that a change in water flow results in an immediate change in flow in the whole network. A change in water temperature, on the other hand, moves with the speed of the water. Measured flow and temperature at the supply node is transformed to the demand node. Then a load forecasting algorithm is applied to the transformed data. This results in a prediction of the demand (including losses in the distribution network). The predicted load serves as base for planning the forward temperature. Then, given the future forward temperature, the consumer load is transformed back to the supply node, which results in a prediction of the heat that shall be produced.

In a traditionally controlled district heating system the supply temperature is often determined as a function of the current air temperature, and it seems reasonable to let the minimum acceptable net temperature in the critical netpoints be governed by a similar function as illustrated in Figure 1. The reference curve determines the required netpoint temperature as a function of the low pass filtered air temperature. The increasing net temperature with decreasing air temperature reflects the limited capacity in the consumers room heating installations, whereas the minimum is determined by the hot tap water installations.

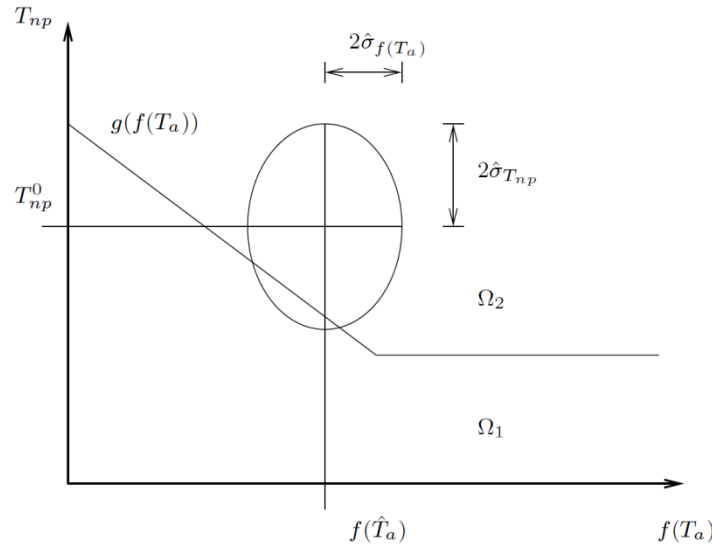


Figure 1. Reference net-point temperature curve

Given all of the above, it is necessary to create a controller that will maintain the output parameters of the system close to some given reference signal, the value of which can be either constant (the so-called set value of the adjustable quantity) or changing with time.

For a generalized control system with anticipation, these requirements are met in the following time-dependent optimization

$$\min_{\nabla u(t)} J(\Lambda; t, \nabla u(t)) = E_t \left[(y(t) - y^0(t))^T (y(t) - y^0(t)) + \nabla u(t)^T \Lambda \nabla u(t) \right], \quad (2)$$

where $y(t)$ is the vector of future output values, $y^0(t)$ is the vector of future values of control points, $\Delta u(t)$ is the vector of the future calculated difference of reference values, is the diagonal weight matrix of future control costs:

$$\begin{aligned} y(t) &= (y(t + N_1), \dots, y(t + N_2))^T \\ y^0(t) &= (y^0(t + N_1), \dots, y^0(t + N_2))^T \\ \nabla u(t) &= (\nabla u(t + N_1), \dots, \nabla u(t + N_u))^T \end{aligned}$$

$$\Lambda = \begin{pmatrix} \lambda_1 & 0 & \dots & 0 & 0 \\ 0 & \lambda_2 & \dots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \dots & 0 & \lambda_{N_u} \end{pmatrix}$$

where E_t - denotes the conditional mean value of its variable due to the data before the time t .

For advanced general proactive control, the strategy is based on minimizing a more general cost function than the cost function in standard proactive control:

$$\min_{u(t)} J(\Gamma(t), \Lambda(t), \omega(t); t, u(t)) = E_t \left[(y(t) - y^0(t))^T \Gamma(t) (y(t) - y^0(t)) + u(t)^T \Lambda(t) u(t) + 2\omega(t)^T u(t) \right] \quad (3)$$

where

$$y(t) = (y(t+1), \dots, y(t+N))^T$$

$$y^0(t) = (y^0(t+1), \dots, y^0(t+N))^T$$

$$u(t) = (u(t), \dots, u(t+N-1))^T$$

N - is the maximum predicted interval, $\Gamma(t)$ is a positive semidefinite and symmetric matrix that specifies the weighting factor for the errors of the control system, $\Lambda(t)$ is a positive semidefinite symmetric matrix that specifies the weighting factor for the control values squared, $\omega(t)$ is a vector that specifies the linear weighting factor to control values.

It should be noted that by selecting the appropriate values for the weight coefficients in the expression, you can calculate the controller's cost function

Optimization of production costs is carried out within the constraints imposed by the communication system and consumer installations [3,4]. Such limitations relate mainly to the maximum flow rate limit, as well as the minimum inlet temperature requirements for consumer installations. To fulfill both restrictions, it is necessary to maintain a sufficiently high delivery temperature.

The paper proposes a control scheme for the optimal functioning of a SC with a single heat source. Optimization of the system operation is realized in the form of a number of regulators controlling the system as close as possible to the minimum temperature of the coolant in the supply heat pipe without violating the boundary conditions. The flow rate is controlled by one regulator, while the temperature at the input of the consumer is controlled by regulators located at the critical points of the DHS. Critical points are selected in such a way that when the temperature requirements for the critical points are fulfilled, the temperature requirements for all consumers are also satisfied. Thus, as shown in Figure 2, the control system consists of a flow controller and temperature controllers for the critical points of the heat network. At certain times, the temperature of the coolant in the supply line at the outlet from the heat source is selected as the maximum recommended coolant temperature of the individual regulators. The secondary regulator, which determines the temperature of the coolant at a certain time, is called the active regulator.

The temperature regulator for network points depends on the model describing the dynamic relationship between the temperature of the coolant in the supply line and the temperatures of the network points. Due to the changing heat load, this ratio is demonstrated by daily, as well as annual changes. The regulator operation model is as follows[5,6]:

$$A_t(q^{-1})T_{np,t} = B_t^1(q^{-1})T_{s,t} + B_t^2(q^{-1})\cos\frac{2\pi t}{24}T_{s,t} + B_t^3(q^{-1})\sin\frac{2\pi t}{24}T_{s,t} + e_t \quad (4)$$

$$A_t(q^{-1}) = 1 + a_t^1 q^{-1} \quad (5)$$

$$B_t^i(q^{-1}) = q^{-\tau}(b_t^{0,i} + b_t^{1,i}q^{-1} + b_t^{2,i}q^{-2}) \quad (6)$$

where T_t^s and T_t^{np} are the supply temperature and the temperature of the network point at time t , respectively, q^{-1} is the inverse shift operator, a_t^1 and $b_t^{0,2,1,3}$ are the parameters models with temporal changes, and τ is the time delay.

The daily change in the dynamics of the system is directly included in the model, whereas the slow offsets in the model parameters due to annual changes are compensated by adaptive estimation of the model parameters using the recursive least-squares algorithm. This equation is a one-step prediction model, whereas the recursive use of the one-step prediction model will be required to obtain j -step forecasts.

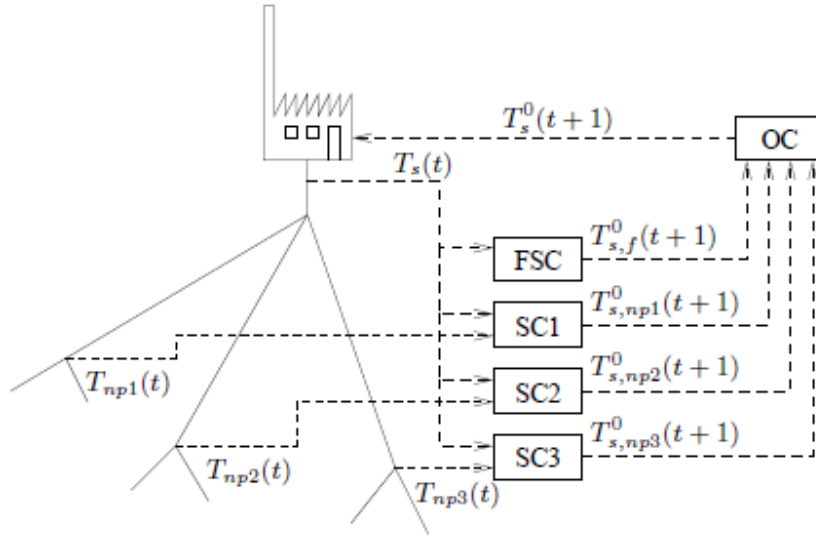


Figure 2. General view of a district heating network with 3 critical points and regulators. OC is a general controller, FSC is a secondary flow controller, SC # is secondary coolant temperature regulators, $T_{np\#}$ are the values of the heat carrier temperature in the supply pipeline in the network, T_s the value of the coolant temperature in the supply line from the installation, and T_s^0 are the temperatures of the coolant in the supply line, which are necessary for the secondary regulators

The time delay specified in the model varies with time and must be evaluated. Here, the time delay is determined by a scheme based on maximizing the cross-correlation between the time series of the network temperature temperature of the network point

The forecasting model that relates the future mass flow to the past and future coolant temperature in the supply pipeline must take into account the future heat load, i.e. it must depend on the predictions of the heat load.

A change in the temperature of the coolant in the supply line during time t will affect the mass flow in the system until the temperature changes reach the remotest (remotely) consumers, which takes several hours in a large district heating network. Thus, the flow control must be based on the heat load forecasts for the values that are most affected by the temperature change in the supply line as opposed to the equation that takes into account only the heat load forecast at time $t + 1$. For the values considered, the controller is based on the equation, , the calculation of the temperature in the supply pipeline is carried out in the form of a weighted sum of an individual quantity $T_{s,t+1}^{(j)}$

$$T_{s,t+1}^{(j)} = \hat{T}_{r,t+j|t} + \frac{\hat{P}_{t+j|t}}{c_w q_{t+j|t}^0} \quad (7)$$

$$\text{Where } T_{s,t+1} = \sum_{j=N_1}^{N_2} \gamma_j T_{s,t+1}^{(j)} \text{ and } \sum_{j=N_1}^{N_2} \gamma_j = 1$$

We find the weight γ_j as the fraction of the heat produced during the time t absorbed during the time $t + j$. In equation (7) $\hat{T}_{r,t+j|t} = T_{r,t}$, is used as a forecast of the return water temperature - this simplification looks logical in light of minor changes in $T_{r,t}$

Forecasts of the thermal load in equation (3) are calculated using the following model:

$$A_t^k(q^{-1})p_t = B_{1,t}^k(q^{-1})\nabla T_{s,t} + B_{2,t}^k(q^{-1})T_{a,t} + \mu_{1,t}^k + I_{a,t}\mu_{2,t}^k + l^k + e_t^k \quad (8)$$

when $A_t^k(q^{-1})$, $B_{1,t}^k(q^{-1})$ и $B_{2,t}^k(q^{-1})$ these changes with time polynomials of the inverse shift operator q^{-1} , ∇ is a difference operator, $I_{a,t}$ is an indicator function equal to 0 on working days and 1 on other days, $\mu_{1,t}^k$ and $\mu_{2,t}^k$ are the daily working and non-working days profiles, respectively, l^k is the average value, and e_t^k is the noise component.

3. The results of numerical simulation methods

The results of computer modeling for the microdistrict on Laukhina St of the village of Yablonovsky of the Republic of Adygea are shown in Figure 3

The dashed line represents the minimum control curve for the minimum temperature of the network water that was to be used in the microdistrict.

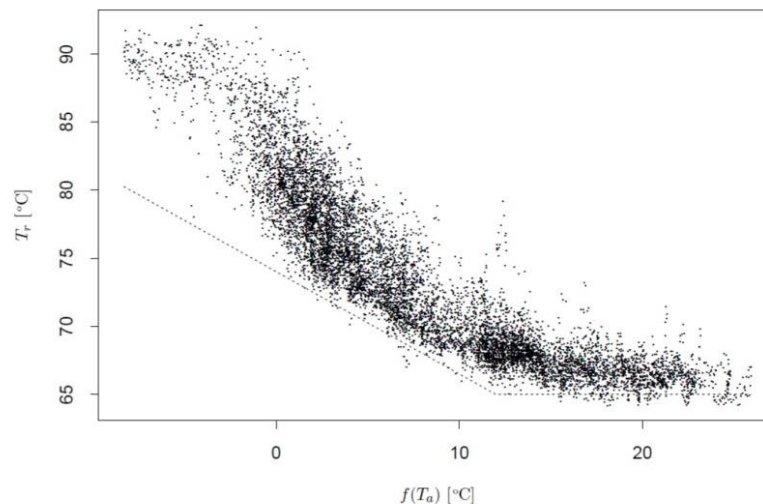


Figure 3. The average hourly values of the network water temperature

4. Conclusion

The points are the average hourly values of the temperature of the mains water, depending on the temperature of the outside air. The graph clearly shows that part of the observed temperatures are higher than the required temperatures (indicated by a dashed line) exceeding the indicated value of 95% with some reserve. Consequently, it was concluded that the software system complies with the imposed network temperature limits.

Thus, the regulator allows to optimize the costs of operation of the SC by minimizing the network temperature without harming the end user.

The function (2) penalizes the quadratic control errors, hence positive and negative control errors are weighted equally in the control criterion. This implies, that the controller will aim at minimizing the control errors, but not discriminate between realizations above or below the reference signal.

In many situations this is as intended, but in some applications the reference signal acts as an output restriction and the uncertainty in the predictions of system output and explanatory variable(s) must be taken into account, when the output reference values are determined. The reference values are determined so that the probability of future net-point temperature observations below a value given as a simple function of the future air temperature is fixed (and small).

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