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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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Keywords: District Heating; Flexibility; Supply Temperature; Optimization

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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]

$$\phi_c = \dot{m}_c c_p (T_{s,c} - T_{r,c}), \tag{1}$$

where customer heat load ϕ_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]