EXAMINATION OF OPERATIONAL OPTIMIZATION AT KEMI DISTRICT HEATING NETWORK

by

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Model-based minimization of short term operational costs for energy distribution systems is examined. Based on the analogies between mass and energy distribution systems, a direct application of a stochastic optimal control approach was considered, previously developed and applied by the authors to water distribution systems. This paper examines the feasibility of the approach for district heating systems under certainty equivalence, i. e., the uncertain quantities are replaced by their nominal values. Simulations, based on a rough model of a part of the Kemi district heating network, are used to illustrate and validate the modeling and optimization approach. The outcomes show that optimal network loading can be designed with the considered tools.

Key words: *district heating, dynamic simulation, energy systems, optimization, sustainable urban energy*

Introduction

A seminal paper on operational optimization of district heating (DH) systems appeared in the mid 90's by Benonysson, *et al.* [1]. The paper focused on short term (say, from a few hours to few days) optimization of the DH network operation, based on a model of the system and its components, a scenario of consumer behavior, and a suitable optimization technique. The approach follows the well-known model predictive control (MPC) paradigm, which is an overwhelming methodology in process control community today. With the increasing power of cheap computers, more and more complicated models can be simulated online for the evaluation of control sequences, in order to find the most suitable ones. Also design of control policies based on excessive simulation of complex models of real-life network dynamics is becoming realistic today. Since the pioneering work of Benonysson, *et al.* [1] a variety of research work has been published on DH network operational optimization, focusing on topics such as: model aggregation [2-4] modeling and control tools [5] optimization methods [6, 7] prediction of heat consumption and temperature [8, 9] linear and fuzzy control [8, 10, 11]. Many of the papers report real small-scale applications, the main outcome being the optimization of DH supply temperature [3, 6, 7]. However, the pumping costs [6] or costs in networks of energy suppliers and storages have been considered also [12, 13].

A major restriction in the application of the proposed methods to real life full scale DH networks has been in the lack of dynamic models of DH networks, and the computational

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resources to provide the simulations required by the optimization methods. However, basic network information (*e. g.* network geometry and spatial distribution of consumers) is typically well documented, and measured information on the network temperatures and flows is available at the power plant and some critical points in the network. In modern DH systems the user consumptions and meteorological data are collected and stored on hourly basis. The main dynamics in the network are due to time delays between supply (at power plant), consumption (at spatially distributed users), and return (to power plant). Given the computational resources of today, dynamic simulations are becoming valid without a need for re-identification or excessive simplifications in the network structure. This holds despite the typical complications due to the existence of several peak plants, heat storages, *etc.* Loop structures in the network may require more detailed hydrodynamic considerations. Also, the heat capacity of the pipelines can be taken into account in the prediction of the propagation of the heat pulses.

The hypothesis taken by the authors is that the domain is mature enough for an efficient application of model-based operational optimization in full industrial scale DH applications. The research work reported in this paper aims at a general stochastic optimization framework for DH network operational optimization. The first milestone towards this goal is to provide a feasibility study of the optimization approach in the considered context. The results are evaluated using the settings from the DH network of the city of Kemi, in Finland.

There are a number of trends that point towards a significant increase in the need for DH network operational optimization in the near future. Putting together the rapid increase in the share of alternative energy sources (wind mills, solar energy, exploitation of waste heat from the industry) and problems to provide the necessary control power with water and fossil fuel plants, the storage capacity provided by the DH networks is an appealing alternative [14]. Developments towards possibilities for two-directional heat supply (a customer may occasionally become a supplier of heat to the network), and consideration of extended possibilities for dynamic heat storage and user flexibility (*e. g.* large buildings, street heating, *etc.*), introduction of three-pipe structures, *etc.*, all result in that the role and operation of DH networks may be at the edge of major changes. Proper control of DH networks is in the very focus of the future requirements.

Modeling of DH systems

From optimization point of view, modeling of DH network dynamics is of major importance. The power plant is usually capable of responding in a much faster time frame than the DH network is able to tolerate. Hence, detailed modeling of the power plant is not in the main focus. The modeling of consumers is a delicate issue, complicated by the problems in prediction of future load, such as prediction of meteorological conditions and depending on the type of the user: commercial, industrial, and residential. What's more, the DH network operator sets only some basic constraints on the customer (*e. g.* on minimum temperature drop, *etc.*), and within these limits the user is fairly free to operate on the temperature/flow from supply to return. Hence, also the users control system needs to be modeled in order to accurately simulate the effects to the primary network. Clearly, the behavior of the user always presents a significant uncertainty to the network operation, which needs to be tackled either via robustness, adaptivity and/or stochastic considerations in the operational optimization. The consumers determine the flows (hydrodynamics) in the DH network, which together dictate the main components of dynamics of DH network: the system delays. Given the network geometry and a model for heat losses along the pipeline, the propagation of temperature pulses in the network can be modeled.

Governing equations

The usual way to picture a DH network is to use the elements of graph theory and describe the network's topology by a set of vertices and edges. In this context, the edges represent active as well as passive hydrodynamic components such as pipes, pumps, valves, heat exchangers, *etc.*, and the vertices are the joints of distinct hydrodynamic elements.

Suppose the DH system is represented by a set of N vertices and E edges. The laws of mass, momentum, and energy conservation apply to each edge and vertex of the graph. This results in a system of $3NE$ joint partial differential equations which must be solved subject to the constitutive law of the work fluid used in the DH network (total $4NE$ equations). For example, a common form of the governing equations for a single pipe is [15]:

$$\frac{\partial}{\partial t}\rho + \frac{\partial}{\partial x}(\rho v) = 0 \tag{1}$$

$$\frac{\partial}{\partial t}(\rho v) + \frac{\partial}{\partial x}(\rho v^2 + p) + \frac{\lambda}{2D}\rho v\left|v\right| + \mathrm{g}\rho\frac{\partial}{\partial x}h = 0 \tag{2}$$

$$\frac{\partial}{\partial t}\left(c_v\rho T + \frac{\rho v^2}{2} + \rho g h\right) + \frac{\partial}{\partial x}\left[v\left(c_v\rho T + \frac{\rho v^2}{2} + \rho g h\right) + vp\right] + \frac{\mu}{D}(T - T_w) = 0 \tag{3}$$

where eqs. (1), (2), and (3) describe the conservation of mass, momentum, and energy, respectively. The unknown quantities ρ [kg/m^3], p [Pa], T [K], v [m/s] are fluid density, pressure, temperature, and velocity, respectively. Equations (1)-(3) provide a 1-D approximation, thus the unknown quantities are functions of (one dimensional1-D) space x [m] and time t [seconds]. Furthermore $h = h(x)$ [m] represents the elevation of the pipe, and $T_\mathrm{w} = T_\mathrm{w}(x)$ [K] is the pipe wall surface temperature. The constants λ [–], g [m/s^2], c_v [J/kgK], μ [W/m^{2}K], and D [m] are the Fanning friction coefficient, gravitational constant, the specific heat, the heat transfer coefficient, and pipe diameter, respectively. Equation (2) considers losses by friction while eq. (3) incorporates heat loss through the pipe wall due to heat conduction which is described by Fourirer's law.

The three previous equations include four unknowns. In order to be able to determine the unknowns a fourth equation is required which is the constitutive law of the work fluid. This can be expressed:

$$f(p, T, \rho) = 0 \tag{4}$$

Through the example of a single pipe, it is easy to see that, by applying conservation principles together with the constitutive law, the resulting system of four equations well defines the four unknowns for each element (edge and vertex) of the graph.

Numerical solution

The simultaneous solution of the governing equations results in the state of the fluid in the DH network including the evolution of flow velocity, pressure, temperature, and density at any location of the network. However the associated computational load becomes overwhelming when dynamic simulation is used together with optimization. In fact, simultaneous solution is typically avoided, and the coupled transient thermal and hydraulic models are rendered in a computationally more efficient form by means of approximation. In order to reduce the computational burden the most common considerations are: (a) the work fluid is incompressible. This assumption is based on the fact that the work fluid used for heat transfer in a DH network is in liquid phase, thus the change in fluid density induced by the increase/decrease of pressure and/or temperature in the operating range is negligible, (b) the friction factor is determined by the Reynolds number and the relative roughness of the pipe. However, in the operating range, $\mathrm{Re} > 10^6$, the friction factor for a steel pipe can be considered as constant, and (c) hydraulic transients are usually 2-3 magnitudes of order faster than thermal transients. Flow changes are driven by pressure waves which travel with the local speed of sound (approx. 1500 m/s for water) in the fluid. Thus, hydraulic steady-state conditions in the network are reached typically in seconds. The heat transfer on the other hand is solely determined by the speed of flow which is relatively small in relation to the speed of pressure pulses. In a usual DH network, temperature changes at the power plant may require hours to reach the consumer stations. This results in the fact, that, the dynamics of the hydraulic process are very fast compared to the dynamics of the energy distribution.

The outlined assumptions allow the reduction of the governing equations to the so called decoupled pseudo-steady-state model. Here, the energy equation is solved independently of the mass and momentum equations. The calculation of hydraulic transients is omitted and as a result the temperature transient behavior is calculated under hydraulic steady-state conditions.

Steady-state hydrodynamics

Steady-state hydraulic considerations are founded on pressures and flows in the network. Pumps provide the basic pressure difference, while pressure losses occur due to friction in pipes, elbows, valves, *etc.* The network pressure has to be sufficient enough to provide hot water to all consumers, irrespective of the head difference between supply and consumer.

Under steady-state framework, the corresponding hydraulic differential equations are discretized spatially, resulting in N unknown pressures (associated with vertices) and E unknown (mass) flows (associated with edges). The relation between pressures and flows is determined for each edge of the graph and is expressed:

$$p_i(t) - p_j(t) = f[\dot{m}_\mathrm{e}(t)] \tag{5}$$

where $i \neq j \in \{1,\dots, N\}$, are two distinct vertices connected by edge e, $e \in \{1,\dots, E\}$, and $\dot{m}_\mathrm{e}$ [kg per second] denotes the mass flow in the corresponding edge at time t. For edges of different types (*e. g.* pipes and pumps) a second order polynomial approximation of the right hand side of (5) is very common in practice.

The mass conservation law determines the mass-flow balance at each vertex:

$$[\mathrm{C}]\vec{\mathrm{m}}(t) = 0 \tag{6}$$

where $\vec{\mathrm{m}}(t) = [\dot{m}_1(t), ..., \dot{m}_E(t)]^T$ is the vector of mass flows, and [C] denotes an $N \times E$ connectivity matrix defining directed connections between the vertices: (a) $c_{i\mathrm{e}} = 1$, if edge e ends at vertex i (in), (b) $c_{i\mathrm{e}} = -1$, if edge e starts at vertex i (out), and (c) $c_{i\mathrm{e}} = 0$, if edge e is not connected to vertex i, where $i = 1,\dots, N$, and $e = 1,\dots, E$. The solution of the outlined steady-state hydrodynamic equations provides the unknown pressures and flows. In simple cases the equations can be solved analytically or graphically. In more complex hydrodynamic networks (including loops), iterative procedures are required.

It should be noted that the model of a real life DH network usually includes hundreds of edges and vertices, thus the calculation of steady state hydraulic conditions still involves a substantial computational effort. Moreover, the computed pressures appear as *undesired* by-products since these are usually not required for DH network optimization purposes, as pressure control can be taken care of by pump control, only. The flow rates are needed only to obtain the proper delays in the pipeline network. With simpler networks (*e. g.* tree topology), a significant computational benefit can be obtained by omitting the solving of the pressure-flow equations and accumulating the flows directly based on consumption data. Assuming a simple network geometry, or additional knowledge on the relative flow in distribution pipes, the flow in the network can be calculated based on individual user consumption data.

Transient thermal model

The primary interest in modeling DH networks is to simulate the evolution of energy transport through the system. Similarly to the hydraulic model, the energy transport equation is solved utilizing spatial discretization, that is, temperatures are computed only at vertex locations while the temperature profile along the edge is out of interest.

Using eq. (3), the transport equation for the e^{th} edge representing a single pipe is formulated:

$$\frac{\partial T_\mathrm{e}(x,t)}{\partial t} + \frac{4\dot{m}_\mathrm{e}(t)}{\pi\rho D_\mathrm{e}^2}\frac{\partial T_\mathrm{e}(x,t)}{\partial x} + \frac{\mu_\mathrm{e}}{c_v\rho D_\mathrm{e}}[T_\mathrm{e}(x,t) - T_\mathrm{w,e}] = 0 \tag{7}$$

By applying spatial discretization, the vertex temperatures are [16]:

$$T_i(t) = T_\mathrm{w,e} + [T_j(t-\tau_\mathrm{e}) - T_\mathrm{w,e}]\exp\left(\frac{\mu_\mathrm{e}\tau_\mathrm{e}}{c_v\rho D_\mathrm{e}}\right) \tag{8}$$

where $i \neq j \in \{1,\dots, N\}$, are two distinct vertices connected by edge e and $\tau_\mathrm{e} = \tau_\mathrm{e}(t)$ is the transport delay, *i. e.*, the time required by the flow to travel along the edge form one vertex to another. The transport delay is obtained by solving:

$$\int_{t-\tau_\mathrm{e}}^{t} \frac{4\dot{m}_\mathrm{e}(\tau)}{\pi\rho D_\mathrm{e}^2}\mathrm{d}\tau = L_\mathrm{e} \tag{9}$$

where L_e, [m] denotes the physical length of the corresponding edge. For simulation purposes (8) can be further approximated, see [17].

By using the decoupled pseudo-steady-state modeling framework the following conclusions can be drawn for a DH system: (a) the heat pulse from the boiler is distributed to the users according to the flow dynamics of the of the work fluid of the network. Hence, delays depend on the (time-varying) flow rates, as well as the distances between the boiler and the user, (b) heat losses depend on the temperature gradient between the supply water and its surroundings, and the flow rates: the larger the gradient or the slower the flow, the larger the losses to the surrounding environment.

Several commercial software are available for modeling and simulation of DH networks (*e. g.* Grades Heating, Apros, Termis, Bentley sisHYD, *etc.*). These may, or may not, be used for testing and development of control strategies, depending on the availability of application programming interface (API). While the use of commercial software is practical in many ways, the development with API also involves several drawbacks: concerns in computational efficiency, and regulations and restrictions by the external service and API support, among others. Therefore, the models and solvers used in this work were implemented in Matlab, simulations were conducted using a standard office PC.

Operational optimization of DH systems

The aim of DH system operational optimization is to satisfy the industrial and residential heat demand while minimizing the operational costs under various constraints. This requires an (optimal) control strategy (or policy) implemented as operational rules for the DH system, under which efficient (or cost optimal) operation can be achieved. In the following section a mathematical formulation of the outlined problem is introduced.

Problem statement

In the authors' previous paper [18] an optimal control approach was proposed for mass (water) distribution systems which provides the control decisions by utilizing permutational symmetries of the dynamics of the underlying system. In [19] the generalization of the proposed method for mass/energy distribution systems was hinted.

Let the dynamics of the system of interest be described by a non-linear discrete time state-space model of the form:

$$\vec{x}(k+1) = \vec{f}[\vec{x}(k), \vec{u}(k), \vec{w}(k), k], \quad k = 0, \ldots, K-1 \tag{10}$$

where $\vec{x}(k) = [x_1(k), ..., x_n(k)]^T \in X$ is the state vector. The control vector $\vec{u}(k) = [u_1(k), ..., u_m(k)]^T \in U$ denotes the manipulated inputs of the system, and $\vec{w}(k) = [w_1(k), ..., w_z(k)]^T \in Z$ represents uncertainty (disturbance or noise). The available information on uncertain variable $\vec{w}(k)$ is characterized by the uncertainty set $W(k)$.

The state vector $\vec{x}(k)$ represents all meaningful past and present information available at time k which can be used with advantage in selecting the appropriate control $\vec{u}(k)$. Assume that the state $\vec{x}(k)$ of the physical system (10) can be decoupled:

$$\hat{x}(k+1) = \hat{x}(k) + \Delta t B\vec{\phi}(k) + D\vec{f}_d[\check{x}(k), \vec{w}(k), k] \tag{11}$$

$$\check{x}(k+1) = \vec{f}_d[\check{x}(k), \vec{w}(k), k] \tag{12}$$

$$\tilde{x}(k+1) = \vec{f}_a\{\tilde{x}(k), \hat{x}(k), \vec{u}(k), \vec{f}_d[\check{x}(k), \vec{w}(k), k]\} \tag{13}$$

subject to:

$$\vec{\phi}(k) = \vec{f}_q\{\hat{x}(k), \vec{u}(k), \vec{f}_d[\check{x}(k), \vec{w}(k), k]\} \tag{14}$$

The controlled state domain $\hat{x}(k) \in \hat{X}$ represents the laws of conservation, quantifying the change in the amount of stored mass/impulse/energy in control volumes. Here, $\vec{\phi}(k)$ denotes the vector of mass/impulse/energy flow in or out of the volume (*e. g.* due to matter flowing in or out of a tank, the effect of external heat, friction, work done by the system, *etc.*) and Δt is the sampling time. The third term in the right hand side of eq. (11) represents the mass/impulse/energy loss or gain which is solely caused by disturbance and is independent of the state and control variables.

The uncontrolled component $\check{x}(k) \in \check{X}$ includes a non-linear disturbance model. The auxiliary state component $\tilde{x}(k) \in \tilde{X}$ is required for the calculation of the step cost

$c[\vec{x}(k), \vec{u}(k), \vec{w}(k), k]$, and has no effect on the system dynamics. Finally, eq. (14) is the thermo-hydrodynamic model of the system, which describes the dependence of mass/impulse/energy flows on controllable and uncontrollable state components, control variables and disturbances.

The aim is to find an optimal control law (policy), π^*, providing the control decision(s) based on the system's state. This policy consists of a sequence of functions $\vec{\pi}_k : X \to U$, $\pi^* = \{\vec{\pi}_0, ...\vec{\pi}_{k-1}\}$, which map the states into feasible controls $\vec{u}(k) = \vec{\pi}_k[\vec{x}(k)]$ for all $\vec{x}(k) \in X$ and minimizes the associated cost:

$$\lim_{K\to\infty} \frac{1}{K}\left(E\left\{ \sum_{k=0}^{K-1} c[\vec{x}(k), \vec{u}(k), \vec{w}(k), k] \right\} \right) \tag{15}$$

The expectation is computed with respect to the joint distribution of the random variables $\vec{w}(k)$. The cost function is defined over an infinite horizon requiring the minimization of the average expected cost per stage, where $c[\vec{x}(k), \vec{u}(k), \vec{w}(k), k]$ is the state transition cost which accumulates over time. Equations (10)-(15) define an infinite horizon non-stationary stochastic optimal control problem.

One of the main properties of the DH systems is that, the uncertainty is subject to periodic events such as weather conditions, consumer behavior, *etc.* The analysis of the corresponding data reveals repeating patterns on many different timescales. The dominating frequencies in data spectrum point to the fact that uncertain events exhibit periodicity on daily, weekly, seasonal, and yearly basis (at least). Consequently, the disturbance pattern can be modeled as periodic. Likewise, the state transition function $\vec{f}(..., k)$ and the step cost can be considered as periodic. Taking into account the periodicity of the system, the optimal policy can be considered as a periodic sequence of control laws $\vec{\pi}_k = \vec{\pi}_{k+lT_p}$, $l \in \{0, 1, ...\}$ and $T_p \in \{T_p^{\text{day}}, T_p^{\text{week}}, ...\}$. Assuming that the expected step cost is bounded the average step cost becomes well defined over an infinite number of stages, and it can be meaningfully minimized.

Optimization method

In general, the DH network model will be non-linear, high dimensional and stochastic, and the optimization problem will have non-quadratic constrained components. Due to the unit commitment problem involved with startups/shutdowns, the problem is of mixed integer programming nature. The determination of the optimal control policy for the outlined problem is a very challenging task. In fact, with the methods and computing power available today, such policy cannot be obtained under reasonable time, *i. e.*, the problem of interest is (computationally) intractable. In what follows, an approximate solution is considered.

An optimization technique based on dynamic programming under permutational invariance has been successfully used in optimization of pump scheduling in a water distribution network [18]. This was the optimization method adopted for this work. The method is applicable to systems in the form (10)-(15). While the permutational invariance is not strictly true for the DH system (due to heat losses in the pipeline), it is a reasonable approximation, however. Ensuring the applicability of the method for DH network optimization problems was one of the motivations for the preliminary study. The approach approximates the value of the optimal policy at a given state assuming perfect state information, that is, the exact value of the state $\vec{x}(k)$ is available at each time instant, *k*. Thus:

$$\vec{\pi}_k[\vec{x}(k)] = \arg\min_{\vec{u}(k)} E_{\vec{w}(k)}\{ c[\vec{x}(k), \vec{u}(k), \vec{w}(k), k] + \tilde{V}[\vec{x}(k+1), k+1]\} \tag{16}$$

where $\tilde{V}$ is an approximate cost-to-go function, calculated on-line. The further details are omitted here, please see [18] and references therein.

Costs and constraints

The main operational cost of DH networks is due to the fuel prices. Typically, the main load power plant is efficient at full load and uses a less expensive fuel (wood, peat, coal, *etc.*). The peak load plants are more flexible in load and start/shutdown but use a more expensive fuel (gas, oil, *etc.*). In co-generation plants, the price of the electricity at the spot-market may be of primary significance. In a more extensive setting the pumping costs can be taken into account. In a longer perspective, a boiler may have the possibility to use (mixtures of) different fuels or operate at various load levels, which will have effects not only on fuel costs but also on emission levels, usage of fuel sources, corrosion, running times and required permissions, co-generation capabilities, possibilities for frequency control, *etc.*

The purpose of the DH system is to provide the heat required by the consumers, under all circumstances. It is common that DH provides the only heat source for room temperature and hot service water in commercial or residential buildings, or that redundant sources are expensive and laborious to startup. Therefore, reliable operation of the DH network is a major constraint for the operational optimization. This requires that both the pressure and the supply temperature at the user are sufficiently high, but not excessive. In the operational optimization framework, the pressure control can be handled at a lower level.

Typical additional constraints are due to safety, maintenance and material restrictions. They can be taken into account, *e. g.* via penalization of power increments, or by constraining the rates of temperature changes in the DH network. There are upper and lower limits on supply and return temperatures at the boiler, as well as temperatures at the consumer. Some of these may be considered as soft constraints, while others are strictly determined by the contracts. Clearly, the maximum flow rate is restricted by the physical network and/or pumping. The frequency of shutdowns and startups of peak boilers is constrained; once a peak boiler is started it should not be shut down immediately and vice versa. A sample cost function might consist of fuel costs c_{fuel} and constraints on supply and return temperatures at the primary network: $c_{\mathrm{fuel,\ total}} = \Sigma_{\mathrm{plant}}\, c_{\mathrm{fuel,\ plant}}$ subject to $T_{\min} \leq T \leq T_{\max}$; $\Delta T_{\min} \leq \Delta T \leq \Delta T_{\max}$ where the temperatures are selected from a sufficient number of representative points.

Feasibility study at Kemi DH network

In this section, a feasibility study of the optimization approach at Kemi DH network is presented. Kemi is a small town (with a population of 22,000) located in Northern Finland. The Kemi DH system is characterized by 434 individual consumers, 165 GWh yearly heat consumption, and a total heat production capacity of 140 MW in six production sites. The network consists of 1615 branches with a total length of 95 km.

Important supplementary goals were to examine the feasibility of the formulation of the optimization problem, to familiarize with the associated modeling efforts, and to learn about the efficiency of the selected optimization method for this particular problem.

To achieve these, a deterministic model for DH network dynamic simulation was used. In particular, perfect foreknowledge of the future heat consumption was assumed by using an anticipated scenario. However, the main features of the dynamic optimization problem were still maintained in the formulation:

– time-varying network flows and delays determined by an hourly-based heat consumption scenario,

– base load and peak load boilers with different fuel costs,
– heat losses in the pipelines, and
– optimization of network loading, *i. e.*, predictive control of the supply temperature (temperature at boiler output).

The geometry of the DH network was adopted from a part of the real Kemi network, following the true geometric data (pipe lengths and diameters) and an aggregated network structure. This resulted in a loop with three tree branches and two boilers. Figure 1(a) shows the structure of the full Kemi network, out of which the model structure highlighted by black contour was extracted. A schematic drawing is shown in fig. 1(b). Some major simplifications were made: (a) A fixed temperature drop across each consumer was used to determine the mass-flow through the consumer from supply to return pipeline in the primary network. Here, the following formula was used:

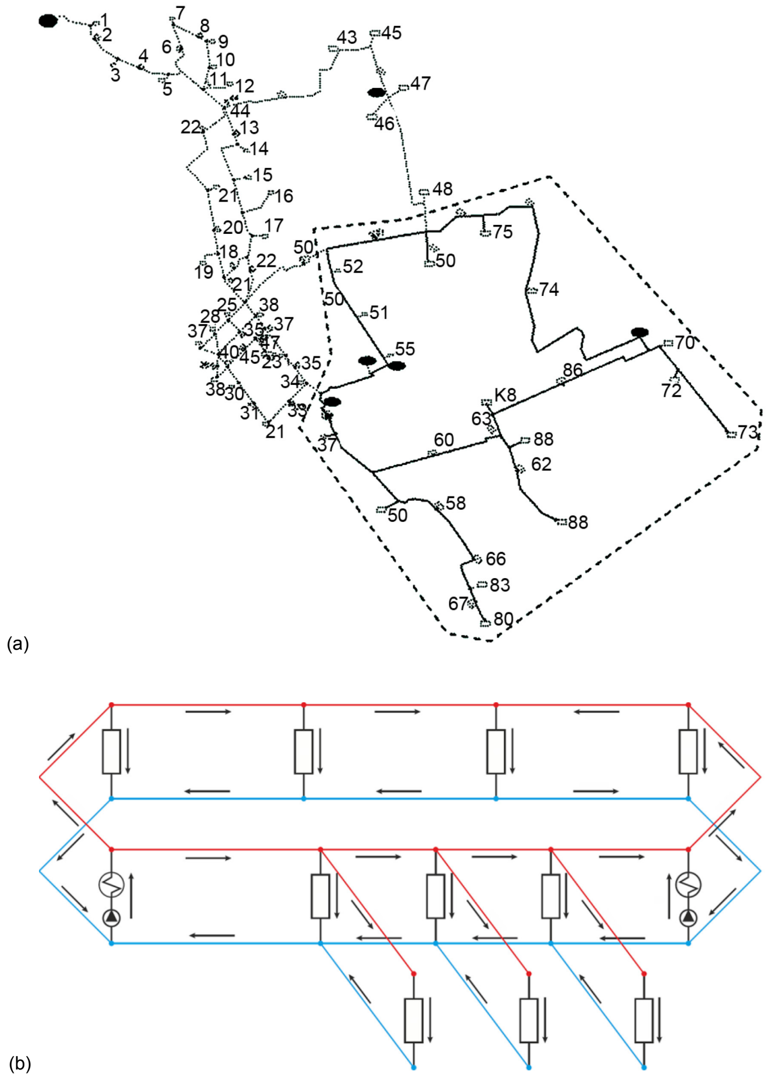

Figure 1
(a) model of the DH network of Kemi, Finland. Heat production sites are indicated by black markers, (b) graph representation of the Kemi sub-model

$$\dot{m}(t) = \frac{Q_{\text{cons}}(t)}{c_v \Delta T} \tag{17}$$

where $Q_{\text{cons}}(t)$, [W] is the heat required by the consumer at time, t and ΔT, [K] denote the temperature difference between primary supply and return temperatures. (b) The network flows were obtained directly from consumption profiles, assuming a fixed flow distribution (thereby omitting the need for iterative hydrodynamic calculations). (c) The heat losses were assumed independent of the temperature difference between DH water and the ground.

These simplifications are to be replaced by more proper expressions in further model developments. The simulation procedure consists of the following steps to be performed at each sampling instant: (1) By using (17), mass flows through each consumer in the DH network are calculated. (2) Mass flows in the DH network branches are calculated. (3) Time delays between nodes in the DH network are calculated. (4) Heat losses in the DH network branches are evaluated. (5) Supply and return temperatures at each vertex in the DH network are calculated.

The user scenario for simulations was selected such that the peak consumption equals the production capacity of the base boiler. Taking into account that there are losses in the pipeline, the consumption cannot be satisfied without starting up the peak boiler, unless network loading is used. Figure 2 shows a 24 hours' simulation of the boiler power outputs (in percentages of full production of the main power plant), and the total accumulated consumption in the network. In the zero case (115 ºC supply temperature), the main production site is not able to provide the required heat during the high load periods, and peak production site participates to the production between 6-10 hours and 16-20 hours.

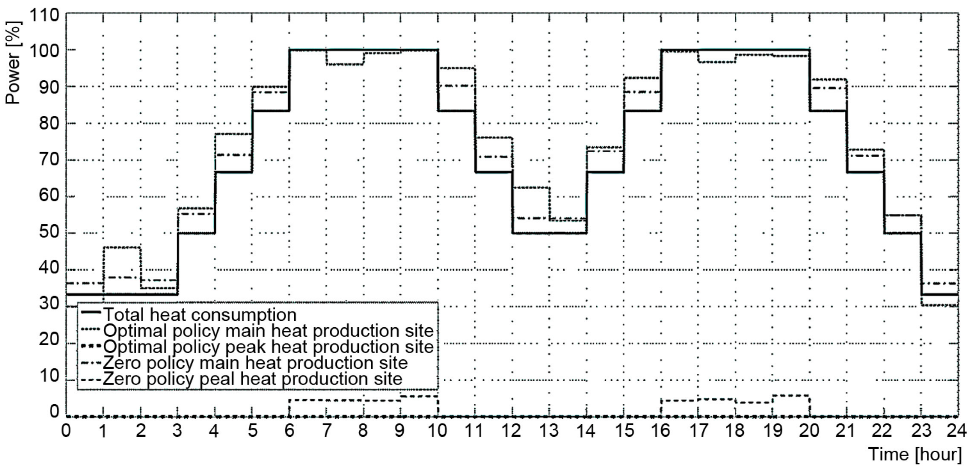

Figure 2. Heat production with fixed and optimized supply temperatures

The capacity of loading was then examined using different ranges for the network minimum and maximum supply temperatures. The dashed lines indicate the optimal policy with constraints 80-130 ºC. The start-up of the peak boiler can be omitted completely.

Concluding discussion

A feasibility study of a stochastic optimization approach was evaluated for DH operational optimization problems under certainty equivalence. The optimization method based on dynamic programming with permutational invariance was found to be feasible and efficient for solving the supply temperature problem of a DH network. The results encourage continuing further with more detailed studies including heat consumption uncertainty, and the authors are currently working towards building a more detailed, comprehensive and realistic model of the Kemi DH network.

Given a sufficiently detailed model, the optimization approach can be used for solving a real life full scale optimal control problem. The direct outcome of the optimization will provide the optimal policy (a sequence of supply temperatures) for a given consumer scenario. These results can be used in the analysis and evaluation of the optimized performance against the current practices, and to devise better process control, via implementation of a full MPC or by extraction of relevant signals for design of improved feedback. They can also be further applied to perform what-if type of analysis, *e. g.* on potential additional components (such as storages or new heat sources), modified user policies (*e. g.* contracts on user flexibility), or robustness against extreme meteorological conditions.

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