District heat network as a short-term energy storage

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Abstract
In this article, we show how a revised district heat network control strategy can be employed to utilize the storage capabilities of the network. An optimization problem is formulated, with minimum operation costs as the objective. By allowing the district heat supply temperature to vary freely within given boundaries, approximately 2% reduction in average heat provision costs were achieved in comparison to reference control scheme in a case study. The benefits of the optimization control scheme are greatest when the district heat generation costs between available heat sources are large. The benefits of energy storage capabilities increase with larger price volatility, if the district heating system includes both combined heat and power generation and heat pumps.

Keywords: district heat, energy storage, optimization, combined heat and power, VRE integration

Nomenclature
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<td>t</td>
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<td>$T_{S,t}'$</td>
<td>DH supply temperature at plants</td>
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1. Introduction

Decarbonizing the energy sector has many difficulties and obstructions, of which variable renewable energy integration is one. Increasing the amount of variable renewable energy in the electricity system is likely to induce larger volatility to the electricity prices, as the matching between input power and consumption becomes more difficult. Short term energy storages have been identified as one solution to balance variability in electricity prices: energy would be stored when the price is low and released at times of higher prices. Electrical energy storage has relatively large investment costs and it has been suggested to be most profitable at very short time span balancing. District heat networks may offer one solution for hour-scale balancing of the electricity network: the water in the distribution network can act as a heat storage, if electricity is used to increase and decrease DH supply temperature momentarily via power-to-heat technologies such as heat pumps and electric boilers. Power-to-heat technologies may be employed at times of low electricity prices, to replace energy input from other heat supply methods. The district heat network (DHN) storage capacity can also be employed in the DH provision without power-to-heat methods, utilizing the flexibility of the network to allow division of the heat load between the heat supply units differently. For example, heat supply from costlier generation units might be reduced, and district heat peak consumption evened out. This way, the storage capability of existing infrastructure can be utilized with no additional investment cost. Altogether, employing the DHN flexibility might reduce district heat costs and benefit electricity network in such occasions when there is excessive amount of power in the grid.

This article presents and evaluates an optimization method for district heat network, where the DH supply temperature is allowed to vary freely within given boundaries, thus utilizing the storage behaviour of the network to best extent. This is compared to current control paradigm, where the supply temperature is mostly determined by the ambient temperature [1, 2]. Modern networks also include more sophisticated control methods, such as feed-forward control with demand and weather prognosis, but to the authors’ knowledge no annual scale evaluation of freely varying DH supply temperature has not been presented. Many DH networks include external heat storage tanks to provide the flexibility, and this control methodology is not contrary to those but supporting the same goal. The focus in this article is to analyse what flexibility can be achieved with the existing grid, and what is the economic benefit of utilizing this flexibility. The scope is in heat generation economics of an existing system — alternative design criteria are considered in e.g. [3].

The effect of heat storages to operation of district heat networks, and the storages’ effect to variable renewable energy generation have been studied on many occasions during the last decade [e.g. 4, 5, 6]. The studies on heat pumps and other power-to-heat technologies as part of a district heat system are also numerous [e.g. 7, 8, 9, 6]. It has been concluded that application of power-to-heat technologies can benefit variable renewable energy integration [10, 11, 12]. Of the studied technologies, heat pumps and thermal storages are distinguished as most favorable options [10, 12]. Heat pumps and thermal storages have also been identified to add flexibility to CHP plant operation, and the related investment to flexibility is often found profitable [13, 6, 4, 14]. The DH system itself, and external factors such as fuel and electricity prices affect the heat pump viability in the system, and hence the optimal sizing of the HP will vary case-by-case [7].

Another branch of study also investigates the DH network operation and variable renewable energy integration via optimization methods, while also considering the DH network topology and allowing the temperature to vary freely [15, 16, 17, 18, 19]. Their optimization models are complex, and they describe the network dynamics in detail. The studies show that the optimized control reduces wind curtailment, operation cost, and energy losses [19]; the utilization of the DH thermal inertia contributes more to optimal operation of CHP, while power-to-heat contributes to reduced wind curtailment [17]. Alas, the

\[ k_X \]  
\[ L_{\text{min,}a} \]  
\[ M \]  
\[ n \]  
\[ P_{\text{max,}a} \]  
\[ Q_{\text{max,}u} \]  
\[ \tau \]  
\[ \Delta T_{\text{max}} \]  
\[ \Delta t \]  
\[ V_{\text{DHN}} \]  
\[ z_{E,a} \]  
\[ \eta_{EL} \]  
\[ \eta_M \]  
\[ \eta_P \]  
\[ \eta_T \]  
\[ \rho \]  
\[ \vartheta \]  

Objective functions

\[ f_{\text{opt}} \]  
\[ f_{\text{ref}} \]  

Abbreviations

CHP  
DH  
DHN  
diff  
EB  
HFO  
HOB  
HP  
NG  
opt  
O&M  
ref  

Other

\[ \vartheta \]  

DH supply temperature curve
models are assessed only with case studies with a short, typically 24-hour time span. These models are well-equipped for dispatch optimization and the daily operation routines. However, a less computation-intensive model will be useful for assessing annual operation under a variety of circumstances.

The novelty of this article is to examine DH network control via optimization in a long term, and to analyze what parameters affect the attainable benefits. The results and the provided calculation model will help DH network operators to determine whether implementation of such control scheme in their systems would be worthwhile.

2. Materials and methods

An optimization program is created to evaluate the feasibility of proposed district heat control scheme. It is available online: [20]. The program is written in Julia language [21] and its JuMP optimization package [22]; CPLEX [23] and Ipopt [24] solvers are used in optimization.

2.1. Model description

In this subsection, we first introduce the optimization problem and then the modelling of the district heat network.

2.1.1. Objective function

In the proposed optimization method, district heat network will be operated based on minimizing total costs C:

$$f_{\text{opt}} = \min C = \min \left( \sum_{t,u} (C_{\text{FU},t,u} + C_{\text{EL},t,u} + C_{\text{SU},t,u} + C_{\text{OM},t,u}) + \sum_{u} (C_{\text{OF},u} + C_{\text{IN},u}) + \sum_{t} C_{\text{PU},t} \right), \quad (1)$$

where abbreviations FU stand for fuel, EL electricity, SU startups, OM variable operation and maintenance, OF fixed operation and maintenance, IN investment, and PU pumping. The cost parameters are determined for the case study in Section 2.2.

In this optimization scheme, the district heat supply temperature at the heat supply units $T_{S,r}^*$ is a free variable, whose value will be provided from optimization results. No other constraints apply to the temperature, apart from minimum and maximum temperatures, and maximum rate of change

$$-\Delta T_{S}^\text{max} \Delta t \leq T_{S,r}^* - T_{S,r-1}^* \leq \Delta T_{S}^\text{max} \Delta t. \quad (2)$$

In the reference method, district heat supply temperature at the plants is set according to a supply curve, depicted in Figure 1. In optimization, the reference control method is formulated as

$$f_{\text{ref}} = \min \left( C + \sum_{t} T_{\text{slack}+1} M \right), \quad (3)$$

where $C$ are the costs from Equation (1), and positive temperature slack variable $T_{\text{slack}+1}$ is the difference between supply temperature $T_{S}^*$ and the deterministic supply temperature $\theta$ from the reference case.

$$T_{\text{slack}+1} \geq T_{\text{slack}}, \quad (4)$$

$$T_{\text{slack}+1} \geq -T_{\text{slack}}, \quad (5)$$

$$T_{\text{slack}} = T_{S}^* - \theta(T_{A,r}) . \quad (6)$$

The addition of a slack variable will guide the optimization to take the supply temperature $T_{S}^*$ to the deterministic value $\theta$. In Equation (3) the slack variable scaling parameter is set to $M = 10^3 \, \text{€/°C}$.

2.1.2. District heat network

A district heat network is modelled at hourly resolution. The supply and return pipelines are reduced to energy buffers, as proposed by Lesko and Bujalski [25]: the average supply temperature in the network $T_{S}$ at time $t$ is calculated from temperature at previous time step, the supply temperature from the heat source $T_{S}^*$, and heat loss to environment at ambient temperature $T_{A,r}$, with linear loss coefficient $k_{X}$; similar conditions apply for average return water temperature $T_{R}$ and temperature of return water at the consumers, $T_{R}^*:

$$T_{S}^* = T_{S}^{t-1} \cdot \frac{m_{\text{DH}S}}{m_{\text{DH}S} + m_{\text{DH}R}} \left( T_{S}^{t} - T_{S}^{t-1} \right) - k_{X}(T_{S}^{t} - T_{A,r}) \Delta t \quad (7)$$

$$T_{R}^* = T_{R}^{t-1} \cdot \frac{m_{\text{DH}R}}{m_{\text{DH}S} + m_{\text{DH}R}} \left( T_{R}^{t} - T_{R}^{t-1} \right) - k_{X}(T_{R}^{t} - T_{A,r}) \Delta t . \quad (8)$$

The total mass of water in the supply or return pipelines is calculated from half of the DH network volume $m_{\text{DH}S} = m_{\text{DH}R} = 0.5 \rho V_{\text{DH}}$. Time resolution $\Delta t$ is one hour and for modelling an initial condition is set for all network temperatures: $T_{r=0} = T_{r=1}$. Another starting condition is set for the supply temperatures: in both control strategies the initial supply temperature is set from the supply curve, Figure 1: $T_{S}^{t=1} = \theta(t_{A,r=1})$.

The simplification allows the network topology to be omitted, which then reduces the computational difficulty and the amount of required initial data significantly. A more detailed network model may be employed in short time scale district heat network optimization, but Equations (7) and (8) should...
provide enough precision to be able to draw conclusions from the heat source point of view [25].

Heat supply $Q_{S,u}$ from unit $u$ and load $Q_L$ are linked to the district heat temperatures and mass flow rate $m$:

$$
\sum_u Q_{S,u} = c_p m (T_{S,u} - T_{R,u})
$$

(9)

$$
Q_L = c_p m (T_{S,u} - T_{R,u})
$$

(10)

Since the mass flow rate of water is a free variable in the model, power demand in pumping must be taken into account. Knowing that the dynamic flow losses $\Delta p$ depend on the mass flow rate, we can calculate the power consumption $P$ from the mass flow rate, given one known operational point ($m_0$, $\Delta p_0$):

$$
P = \frac{\Delta p}{\eta_T} = \frac{m \Delta p}{\rho \eta_p \eta_M} = \frac{m^2 \Delta p_0}{\rho \eta_p \eta_M m_0^3},
$$

(11)

where $\eta_T = \eta_p \eta_M$ is the total efficiency of the pumping system, determined from pump and motor efficiency.

Altogether, Equations (7) to (11) form the nonlinear part of the optimization model, while all remaining equations are linear.

2.2. Case description

A mid-sized district heat network is studied for analyzing the optimization model, with key parameters from Järvenpää–Tuusula region DHN in Southern Finland for year 2017. Those key metrics of the network that are employed in calculations are displayed in Table 1. The heat loss factor $k_X$ in Equations (7) and (8), and the operational point ($m_0$, $\Delta p_0$) are selected so that the annual heat losses and the energy consumption in pumping in the optimized reference case correspond to reported values in Table 1.

In the absence of consumption data, a simulated load demand curve is generated with The Open Energy Modelling Framework [26] demandlib and its standard load profiles [27], matching the reported annual DH consumption. The demand profile is combined from three load profiles in the library: 40% weight on block of flats, 30% detached houses, and 30% business/commerce/services total load profile. The load demand curve is displayed in Figure 2, with historical temperature and electricity price data.

For the reference control method, supply temperature curve in Figure 1 is employed. In the optimization method, supply temperature at plants is limited to the same minimum and maximum temperatures as in the reference case; minimum average temperature of supply water $T_{S_{\text{min}}}$ is set to 65°C, corresponding to lowest temperatures that are recorded in the reference case. Return temperature from consumers depends on their equipment, and it is typically not controlled by the DH company. Thus, return temperature is set at a fixed value throughout the year. The maximum temperature gradient $\Delta T'_{S_{\text{max}}}$ is set to 7°C/hour: in normal operation the supply temperature change rate should be 1°C...2°C/6 minutes [1, sec. 7.1.2], and this

Table 1: Key metrics of studied district heat network, and other modelling parameters.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
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<tbody>
<tr>
<td>DH generation [28]</td>
<td>378.4 GWh</td>
</tr>
<tr>
<td>DH network losses [28]</td>
<td>45.5 GWh</td>
</tr>
<tr>
<td>Pumping energy / DH generation a</td>
<td>0.5 %</td>
</tr>
<tr>
<td>DH network volume $V_{\text{DHN}}$ b</td>
<td>5437 m³</td>
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<tr>
<td>Mass flow $m_0$</td>
<td>500 kg/s</td>
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<tr>
<td>Pressure loss $\Delta p_0$</td>
<td>938.5 kPa</td>
</tr>
<tr>
<td>Heat loss factor $k_X$</td>
<td>1.515 · 10⁻²</td>
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<tr>
<td>Pump efficiency $\eta_p$</td>
<td>0.7</td>
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<tr>
<td>Motor efficiency $\eta_M$</td>
<td>0.9</td>
</tr>
<tr>
<td>Max. temperature rate $\Delta T'<em>{S</em>{\text{max}}}$</td>
<td>7°C</td>
</tr>
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<td>Min. average supply temperature $T_{S_{\text{min}}}$</td>
<td>65°C</td>
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<td>Min. supply temperature at plants $T_{S_{\text{min}}}$</td>
<td>75°C</td>
</tr>
<tr>
<td>Max. supply temperature at plants $T_{S_{\text{max}}}$</td>
<td>115°C</td>
</tr>
<tr>
<td>Return temperature $T_R$</td>
<td>45°C</td>
</tr>
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</table>

a Average for networks where pumping is reported [28].

b Applying similar length-to-volume ratio from Helsinki DHN [28], volume from [6].

Figure 2: Load profile and load duration curve, ambient temperature, and electricity price for the analyzed case.
value is selected to be safely below that. Sensitivity to this, and other main operational parameters, is evaluated in Section 3.3.

In the case study, a biomass combined heat and power (CHP) plant, and biomass, natural gas (NG) and heavy fuel oil (HFO) heat-only boilers (HOBs) are already available, and a heat pump (HP) and an electric boiler (EB) are investigated as investment options. The input parameters are specified in Table 2.

The annual district heat production costs in Equations (1) and (3) are distributed in following parts:

\[ C_{FU,t} = \phi_{FU}(c_{FU} + c_{FT})\Delta t \]  
\[ C_{EL,t} = P_{EL}(c_{EL} + c_{ED} + c_{ET})\Delta t - P_{O,t} c_{EL} \Delta t \]  
\[ C_{SU,t} = c_{SU} z_{t} \Delta t \]  
\[ C_{OM,t} = Q_{S,t} c_{OM,t} \Delta t \]  
\[ C_{OF,t} = Q_{S,max} c_{OF} k_p : u \in \{ HP, EB \} \]  
\[ C_{PF,t} = (Q_{S,max} c_{OF} + P_{max} c_{EC} + c_{ECB} z_{E,t}) k_p : u \in \{ HP, EB \} \]  
\[ C_{IN,t} = c_{IN} Q_{S,max} k_A k_p z_{E,t} \]  
\[ C_{P,t} = P_{P}(c_{EL} + c_{ED} + c_{ET})\Delta t \]  

The cost parameters for the case study are introduced in Table 2, and in addition electricity-related costs in Table 3 are employed.

For each plant, an energy balance is set:

\[ \phi_{fu} O_{fu} = Q_{S,t} + P_{O,t} + Q_{R,t} : u \in \{ CHP, HOBs \} \]  
\[ P_{t} C OP = Q_{S,t} : u = HP \]  
\[ P_{t} C PF = Q_{S,t} : u = EB \]  

Here the positive variables are: \( \phi \) fuel input, \( Q_S \) heat supply, \( P_O \) electricity output and \( P_I \) electricity input, \( Q_R \) rejected heat in CHP condensing mode, \( \eta_T \) total efficiency and COP the coefficient of performance.

Heat rejection, or condensing mode, is only permitted for CHP plant:

\[ Q_{R,t} \geq 0 : u = CHP \]  
\[ Q_{R,t} = 0 : u \neq CHP \]  

A binary variable \( z \) denotes unit commitment: when the unit is on or off. It is employed to formulate the implementation of start-up costs and unit minimum load. Equation (25) sets the maximum heat output of the unit to either 0 or its maximum output, depending on \( z \):

\[ Q_{S,t} + Q_{R,t} \leq Q_{S,max} z_{t} \]  

Unit existence \( z_{E,t} \in \{ 0, 1 \} \) is set as condition for simulation, and also limits the unit commitment

\[ z_{E,t} \leq z_{t} \]  

CHP power output is restricted by maximum electric efficiency \( \eta_{EL,max} \)

\[ \eta_{EL,max} = \frac{P_{max}}{(Q_{S,max} + P_{max})/\eta_T} \]  
\[ P_{O,t} \leq \phi_{fu} \eta_{EL,max} : u = CHP \]  
\[ P_{O,t} = 0 : u \neq CHP \]  

Also, a minimum boiler load is set for the CHP plant,

\[ Q_{S,t} + P_{O,t} + Q_{R,t} \geq L_{min} (Q_{S,max} + P_{max}) z_{t} : u = CHP, z_{E,t} \in \{ 0, 1 \} \]  

where \( z \) is unit commitment binary variable. Unit start-ups and shut-downs are determined by constraint

\[ z_{t} \leq Q_{S,t} + Q_{R,t} \]  

Maximum size \( Q_{S,\max} \) for the heat pump and electric boiler is given to optimization as a parameter, whose effect is studied in Section 3.2. The investment cost of those plants is divided into annual payments with annuity factor

\[ k_n = \frac{r(1 + r)^n}{(1 + r)^n - 1} \]  

where \( r \) is the annual interest rate and \( n \) investment horizon in years. In this article, 8% and 20 years are employed. Parameter \( k_p \) adjusts the model when optimization length is less than a year:

\[ k_p = \frac{\sum \Delta t}{8760} \]  

2.3. Sliding time window method

The described optimization model is both nonlinear and includes integer variables, in order to include relevant characteristics of the DH network operation. Solving a mixed-integer nonlinear problem (MINLP) at hourly resolution for the whole year would require large computational resources, and from an operational point-of-view, it is not relevant to compute DH temperatures one year ahead. In order to reduce problem size, and to provide a model that would be usable for network operators, a sliding time window method is employed, extending the method by Fang and Lahdelma [31]. Figure 3 depicts the algorithm:

1. Beginning from time \( t = 1 \) predictions are formed for DH demand \( Q_{O,t} \), ambient temperature \( T_{A,t} \) and electricity price \( c_{el,t} \). In this article, historical data from 2017 are employed.
2. A mixed integer linear problem (MILP) is formed for the first 10 days, \( t \in T_{MILP} \). Nonlinear conditions in Equations (7) to (11) are substituted with a linear district heat model (see Equation (35)). This model is solved, and unit commitment variables \( z_{E,t}, z_{p,t} \) are obtained.
3. A nonlinear problem (NLP) is formed for the first 48 hours, \( t \in T_{NLP} \). Binary variables \( z_{E,t}, z_{p,t} \) and \( z_{t} \) are removed: For those units \( u \) that have a specified minimum load or start-up costs, commitment variables \( z_{t} \) are replaced from the MILP model solution, and \( z_{t} \) are calculated from \( z \). Initial values for \( T_{S,t=0} \), \( T_{E,t=0} \) and \( z_{t=0} \) are fixed from previous 24 hour solution.
The time horizons of the MILP and NLP parts are selected based on modelling solutions and weather forecasts: a 48-hour forecast can be considered accurate enough for production planning. In addition, optimization results on deterministic input data converge with increasing NLP time horizon, and a longer horizon length than 48 days does not affect the optimization outcome. MILP time horizon of ten days is a balance between long enough a horizon to accommodate longer term decisions, such as start-ups and shut-downs of the CHP plant, and a length of time where weather forecasts can still be considered credible.

To obtain the MILP model, the nonlinearity in the original MINLP problem is removed: the district heat model described in Section 2.1.2 is replaced with a simpler one, where heat balance

$$\sum_u Q_{S,U,t}=Q_{L,T}+Q_{X,t}$$

(35)

describes the operation of the units. Here, heat demand $Q_{L,T}$ at time $t$ is fulfilled by heat supply $Q_{S,U,t}$ from units $u$, taking into account heat losses $Q_{X,t}$. Heat losses $Q_{X,t}$ are calculated in accordance to the original DH network model in Equations (7) and (8):

$$Q_{X,t} \Delta t = c_p m_{DHN} k_T (T_{S,t} + T_R - 2T_{A,t}) .$$

(36)

In Equation (36), average supply and return temperatures $T_{S,t}$ and $T_R$ are approximated as the mean value from previous 24 hours in the NLP solution.

3. Case results

3.1. Comparison without additional investments

District heat generation profiles for the two control methods are displayed as load duration curves in Figure 4. Changing the DH temperature control strategy does not affect the overall merit order, but some general changes arise: with the proposed optimization strategy, part-load operation of the CHP plant is reduced. The CHP plant is operated at full load or near full load for increased amount of hours. Also, CHP operation is increased at such operating point where the CHP boiler is run at minimum load, but no heat rejection via auxiliary condenser is

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### Table 2: Plant modelling data for case study. CHP and HOBs are existing plants, HP and EB are investment options. Total efficiency $\eta_T$ is based on fuel lower heating value, and thus it can be that if $\eta_T > 1$ when water in the flue gas is condensed, as in the CHP plant.

<table>
<thead>
<tr>
<th>Plant</th>
<th>$Q_{S,\text{max}}$</th>
<th>$P_{\text{max}}$</th>
<th>$L_{\text{min}}$</th>
<th>$\eta_T$</th>
<th>COP</th>
<th>$c_{\text{SU}}$</th>
<th>$c_{\text{IN}}$</th>
<th>$c_{\text{OM}}$</th>
<th>$c_{\text{OF}}$</th>
<th>$c_{\text{FU}}$</th>
<th>$c_{\text{FT}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bio-CHP</td>
<td>63</td>
<td>22</td>
<td>0.4</td>
<td>1.10</td>
<td>-</td>
<td>2500</td>
<td>0</td>
<td>3.9</td>
<td>29</td>
<td>21.5</td>
<td>0</td>
</tr>
<tr>
<td>HFO-HOB</td>
<td>24</td>
<td>-</td>
<td>-</td>
<td>0.85</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0</td>
<td>3.7</td>
<td>35</td>
<td>22</td>
</tr>
<tr>
<td>NG-HOBs</td>
<td>126</td>
<td>-</td>
<td>-</td>
<td>0.85</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0</td>
<td>3.7</td>
<td>27.5</td>
<td>17.4</td>
</tr>
<tr>
<td>Bio-HOB</td>
<td>18</td>
<td>-</td>
<td>0.85</td>
<td>0</td>
<td>0</td>
<td>5.4</td>
<td>0</td>
<td>35</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HP</td>
<td>b</td>
<td>b</td>
<td>-</td>
<td>3.0</td>
<td>0</td>
<td>680</td>
<td>0</td>
<td>5.5</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>EB</td>
<td>b</td>
<td>b</td>
<td>-</td>
<td>1.00</td>
<td>0</td>
<td>145</td>
<td>0.5</td>
<td>1.1</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

* Assumed same as for NG-HOBs.

* Effect of installation size is studied. In the first case, no investment is made and $Q_{S,\text{max}} = 0$.

### Table 3: Electricity costs [30].

<table>
<thead>
<tr>
<th>Distribution cost $c_{\text{CED}}$</th>
<th>Tax $c_{\text{ET}}$</th>
<th>Connection base cost $c_{\text{CECB}}$</th>
<th>Connection power cost $c_{\text{CECP}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.8/17.5€/MW</td>
<td>27.9372€/MWh</td>
<td>2604€/a</td>
<td>54720€/MWh/a</td>
</tr>
</tbody>
</table>

* Higher distribution cost on winter days: December to February, Monday to Friday at 7-21.

---

Figure 3: Sliding time window method.

4. First 24 hours of the NLP model are stored as a partial solution, and time horizons are shifted 24 hours forward.

This sliding time window algorithm allows to separate the large problem into smaller subproblems, which can be solved more easily. It also provides the possibility to use the optimization algorithm in production planning, if actual forecasts are included. The MILP part addresses longer-term decisions, such as CHP plant shutdowns and start-ups, while the NLP part concentrates on generation and storage optimization.
Heat generation per unit

<table>
<thead>
<tr>
<th></th>
<th>Opt</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>BioCHP</td>
<td>367.3</td>
<td>358.4</td>
</tr>
<tr>
<td>Bio-HOB</td>
<td>13.2</td>
<td>17.8</td>
</tr>
<tr>
<td>NG-HOBs</td>
<td>1.6</td>
<td>1.8</td>
</tr>
<tr>
<td>HFO-HOB</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Figure 4: Load duration curves for the case study plants.

Figure 6: DH supply temperature as ambient temperature function

Table 4: Main optimization outcomes. Opt stands for optimization control method, ref for reference control method.

<table>
<thead>
<tr>
<th></th>
<th>Opt</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average heat production cost</td>
<td>23.93</td>
<td>24.37</td>
</tr>
<tr>
<td>Heat losses, of input heat</td>
<td>12.89</td>
<td>11.94</td>
</tr>
<tr>
<td>Heat rejection, of input heat</td>
<td>6.19</td>
<td>6.79</td>
</tr>
<tr>
<td>Pumping energy, of input heat</td>
<td>0.31</td>
<td>0.50</td>
</tr>
</tbody>
</table>

required. The optimization control method reduces the amount of heat that is produced with heat-only boilers.

Table 4 displays the main optimization outcomes. The results show that in the studied system, 1.8% reduction in average heat production cost can be achieved, with no investment and by only changing the control scheme. Heat losses are higher for the optimization control method than in the reference method, but heat rejection from CHP plant and the energy consumption in pumping are lower in the optimization method. Figure 5 displays the source of cost savings: on average, greatest benefit from the optimization control method results from greater CHP electricity sale income and lower pumping costs.

District heat supply temperature distribution is displayed in Figure 6 against ambient temperature. In the optimization control method, supply temperatures stay below 100°C when ambient temperatures are less than −15°C. This results from the relationship between energy consumption in pumping and heat losses to the environment: if the transfer capacity of the DH distribution pipelines allow, it is cost-effective to reduce the DH supply temperature during the coldest hours. The lowest supply temperatures in the winter occur only a few hours at a time, typically during the night.

The behaviour of the district heat supply under the optimization control strategy is displayed for selected periods in Figures 7, 8 and 9. In Figure 7, the CHP plant is operated near full load and the flexibility provided by the DH grid is often employed in charging the network during night, when heat load is otherwise small. This accumulated heat is mostly consumed during morning consumption peak, to minimize the usage of heat only boilers. However, when electricity price during the night is low and the consumption in the following morning can be met with CHP only, the DH temperature may be allowed to sink during the night. The DH supply temperature is usually higher than the reference method control curve temperature θ, to allow for flexibility actions.

Figure 8 shows the operation under low load in the summer. The CHP plant operates at partial mode, and in condensing mode during the nights, but still it is not shut down due to its start-up costs, efficiency and low fuel price. Therefore, district heat generation cost is higher nightly. DH supply temperature rises occasionally above minimum supply temperature, when the CHP boiler can be operated with no heat rejection.

Operation during cold period under high load is examined in Figure 9. The flexibility in supply temperature is usually employed to allow the CHP to run near full load during the night. When the ambient temperature is very low, the supply temperature may be reduced during the night, to be increased again in the morning consumption peak.

3.2 Investment options

Investment to a heat pump is profitable in the case study, as displayed in Figure 10 — the average DH generation costs are reduced for both control schemes when an investment to a heat pump is made. The marginal benefit of heat pump size increase is reduced after approximately 20 MW installed size. The savings from the optimization control scheme are highest with no
Figure 7: Operation near CHP full load with optimization control strategy.

Figure 8: Operation under low load with optimization control strategy.

Figure 9: Operation in cold period under high load with optimization control strategy.

Figure 10: Effect of heat pump investment. Opt refers to optimization control scheme, ref to reference control scheme and diff to difference in annual DH generation costs between the schemes, show on the right axis.

heat pump installation, decreasing to 1.3% level at 30 MW installed HP size.

Figure 11 displays the effect of heat pump installation to the runtime of other plants. CHP operation hours are reduced with the HP addition, most significantly from minimum load operation. The heat pump, occasionally boosted by heat-only boilers, provides the district heat during the lowest load in summer and the CHP plant can be shut down. The heat pump is also often employed during the nights and daily consumption peaks, depending on the electricity price. The CHP plant is mostly operated at base load and the heat pump replaces more costly bio-HOB generation.

Investment to an electric boiler is not a feasible option in the analysed case study. The economic operation of a large-
scale EB would be limited only to a few hours in the examined year, and thus the investment with these parameters would not be viable.

3.3. Sensitivity analysis

In this section, the key parameters that affect case study results are addressed.

Benefits of the studied control scheme are increasing with larger allowed temperature gradient $\Delta T_{S_{\max}}$, as shown in Figure 12. Larger maximum temperature gradient allows the DH network storage level to be controlled more rapidly, and thus responding better to variable operating conditions. Maximum annual benefit of the optimization control scheme is 2.0% reduction in DH generation costs, or 0.5 €/MWh. The benefit in comparison to the reference method evens out after 10°C/hour change rate, corresponding to the maximum temperature gradient allowed by the network pipelines [1].

Figure 13 displays the result dependence on various CHP parameters. The CHP plant in the case study has a flue gas condenser, and thus it is very effective in comparison to the HOBs in the study. As the CHP efficiency is lowered in Figure 13a towards the same value as the HOBs have, the annual benefit of the optimization control scheme is reduced. Figure 13b indicates that the CHP plant in the case study is well dimensioned: if the plant were smaller or larger, annual generation costs would increase. The optimization control scheme displays greatest benefit at the optimal CHP plant size. These two sensitivity curves suggest that the optimization control scheme is of greatest use when there is a large difference in the DH generation costs between plants. In this case study, the CHP has the lowest marginal generation costs under most circumstances and thus the added flexibility is employed in favour of the CHP plant.

In the case study, both control schemes have the CHP running even during times of low consumption due to the high start-up costs. Figure 13c displays the outcome if the start-up costs were lowered. Below 1000 € start-up cost, alternative generation is less costly than running the CHP plant in condensing mode, and then average generation costs start to decrease. At the same point, benefits of the optimization control scheme start to increase. The model may leave some benefits unrevealed, because the sliding time window method in Section 2.3 solves the unit commitment variables $z$ before considering any storage capabilities. It is to be expected that a heat storage might enable more favourable CHP start-up and shut-down timing near the...
4. Discussion

The optimization control method yields lower district heat generation costs than the reference control method under all examined circumstances. The annual benefits in the case study are around 2% of the annual district heat generation costs, and are mostly affected by the generation cost differences between available heat sources. As the optimization algorithm strives to minimize DH generation costs, runtime of those plants is increased, whose variable costs are the lowest. This results in a reduction of CHP condensing mode operation, and reduction of part load operation and increase in full load operation of plants first in the merit order.

Implementing the optimization control method and an investment to a heat pump drive the system towards similar results: they both reduce heat provision from heat-only boilers and alter CHP part-load operation. However, these two actions are not competing but complementary to each other. The optimization control method has a positive effect on the heat pump included system, and the method increases the full load operation of both CHP and HP in comparison to the reference control method. The heat pump benefits from low electricity prices, and therefore it can for example absorb variable renewable energy production peaks into the district heating network. The implementation of the optimization control scheme further allows the storage capability of the network to be utilized, and for example the DH supply temperature increased above reference supply temperature curve at times of such VRE absorbing actions. The results indicate that in systems with both CHP and HP, the optimization control method is especially useful when electricity price volatility increases.

The exact optimization outcome and the monetary benefits of the control scheme implementation are specific to each district heat system, but we suggest that the general results are transferable to all district heat systems — especially to those with combined heat and power generation. Even without differences in the heat generation costs, the proposed method will be able to determine the most suitable supply temperature according to predictions on ambient temperature, electricity price and heat demand.

Due to the simplification of the district heat network to two energy buffers, the provided calculation model [20] can be employed with little input data, to explore networks’ flexibility options and the approximate annual savings that could be achievable. Only information on the heat load, generation units and their operation parameters, as well as key metrics of the DHN are required. However, exact implications on particular networks, such as supply temperature at customers and temperature gradients at network nodes, cannot be accessed with this model. To include those elements, a full flow model of the DHN is required. Therefore we recommend that if this program is to be employed in plant control or dispatch optimization, it is either extended to include the network flow model, or that this program is included as an input signal to existing control systems.

The sliding time window method outlined in Section 2.3 serves well to reduce computational effort and include the pos-

![Figure 14: Sensitivity to electricity price scenarios. Solid lines display the effect of electricity price scaling with Eq. (37), dashed lines the effect of change in electricity price volatility with Eq (38).](image-url)

(a) No investment option.

(b) 15 MW heat pump installed.
sibility to employ the model in short-term control. However, this method cannot ensure that the results are the global optimum. Especially, the possibilities of the optimization control scheme extending CHP plant runtime at minimum load cannot be examined: the unit commitment variable $z$ is fixed in the MILP part without knowledge on the network storage capability. If the model is to be employed in production planning, a more rigorous method of solving a short-term MINLP model is to be recommended.

The results of this study are somewhat in alignment with similar analyses. Huang et al. [17] concluded that when optimizing for minimum coal consumption, utilization of the DHN heat capacity reduces coal-fired CHP fuel consumption, whereas electric boilers contribute to reduced wind power curtailment. While our optimization aimed at lowest annual costs, we similarly find that the optimization control scheme benefits units with lowest heat provision costs, and that power-to-heat technologies can help absorb variable renewable energy in the DH network.

Other studies with variable DH temperature are scarce, and especially those that report cost savings. Of those 24 hour models that mentioned costs, Gu et al. [16] calculated 7 % savings in a system with gas turbines, gas HOBs and wind turbines; costs reported by Li et al. [18] correspond to 13.5 % savings in a small case and 0.8 % savings in a larger actual power system, with coal CHP and wind power generation. Above mentioned studies include a large amount of wind power, which is considered of no cost and also an electricity demand that must be met. These differences cause the results not to be directly comparable. On basis of this research, cost savings in the order of 10 % seem very large, and not achievable in a district heat system with electricity bought at market price. In their analysis of the same DH network, Hast et al. [4] found the most economical size of a prospective heat pump to be 20 MW to 25 MW. This is similar to what is concluded in this article.

5. Conclusions

Actively utilizing the district heating storage capability results in price reduction over the traditional district heat temperature control paradigm, under all examined circumstances. The optimization control method increases operational hours of those plants, whose variable costs are the lowest. The benefits of the control scheme are greatest when there is a large difference between DH generation costs from the available heat sources. In the presented case study, the switch of control method resulted in more full or near full load operation for the CHP plant, reduced CHP condensing mode operation and reduced heat-only boiler utilization. Approximately 2 % reduction in average heat provision costs were calculated. A system with a heat pump also benefits from the added flexibility of the optimization control scheme, especially when the electricity price volatility increases. We suggest that the switch in control method would benefit all district heating networks, but additional analysis and expand of the calculation method are required before implementation.

References


