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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 operating costs as the objective. Allowing the district heat supply temperature to vary freely within given boundaries results in approximately 2 % reduction in annual heat provision costs, in comparison to a reference control scheme in a case study. The benefits of added heat storage functionality in the network are greatest when there is a large difference between district heat generation costs from the available heat sources. In general, supply temperature optimization results in increased operational hours of those plants, whose variable costs are the lowest.

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

Nomenclature

Indices

t	time
u	unit

Variables

C	total cost	€
$C_{EL,t,u}$	electricity cost	€
$C_{FU,t,u}$	fuel cost	€
$C_{IN,u}$	investment cost	€
$C_{OF,u}$	fixed O&M cost	€
$C_{OM,t,u}$	variable O&M cost	€
$C_{PU,t}$	pumping cost	€
$C_{SU,t,u}$	start-up cost	€
$\dot{m}_t$	mass flow rate of DH water	kg/s
Δp	dynamic flow losses	Pa
$P_{I,t,u}$	electricity input	MW
$P_{O,t,u}$	electricity output	MW
$P_{P,t}$	electricity to pumping	MW
$Q_{L,t}$	heat load	MW
$Q_{R,t,u}$	heat rejection	MW
$Q_{S,t,u}$	heat supply	MW
$Q_{X,t}$	heat losses	MW
S_t	network accumulation	MWh
$T_{A,t}$	ambient temperature	°C
$T_{S,t}$	DH average supply temperature	°C
$T'_{S,t}$	DH supply temperature at plants	°C

$T_{R,t}$	DH average return temperature	°C
$T'_{R,t}$	DH return temperature at consumers	°C
$T_{slack+,t}$	positive temperature slack variable	°C
$T_{slack,t}$	temperature slack variable	°C
$\phi_{t,u}$	fuel input	MW

Binary variables

$z_{t,u}$	unit commitment
$z_{+,t,u}$	start-ups
$z_{-,t,u}$	shut-downs

Parameters

c_p	specific heat capacity of water	kJ/kg/°C
c_{ECB}	electricity connection base cost	€/a
c_{ECP}	electricity connection power cost	€/MW/a
$c_{ED,t}$	electricity distribution cost	€/MWh
$c_{EL,t}$	electricity cost	€/MWh
$c_{ET,u}$	electricity tax	€/MWh
$c_{FT,u}$	fuel tax	€/MWh
$c_{FU,u}$	fuel cost	€/MWh
$c_{IN,u}$	investment cost	€
$c_{OF,u}$	fixed O&M cost	€/MW/a
$c_{OM,t,u}$	variable O&M cost	€/MWh
$c_{SU,u}$	start-up cost	€
COP	coefficient of performance	
k	scaling factor	
k_A	annuity factor	
k_P	period conversion factor	

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k_X	temperature loss coefficient	
$L_{\min,u}$	minimum load	
M	slack variable scaler	€/ °C
m_{DHN}	total mass of water in DHN	kg
n	investment horizon	years
$P_{\max,u}$	maximum electric power	MW
$Q_{S\max,u}$	maximum DH supply from unit	MW
r	interest rate	
$\Delta T'_{S\max}$	maximum supply temperature rate	°C/h
Δt	length of time step	h
V_{DHN}	total volume of water in DHN	m ³
$z_{E,u}$	unit existence	
η_{EL}	electric efficiency	
η_M	motor efficiency	
η_P	pump efficiency	
η_T	total efficiency	
ρ	density of water	kg/m ³

Objective functions

f_{opt}	optimization control scheme	€
f_{ref}	reference control scheme	€

Abbreviations

CHP	combined heat and power
DH	district heat
DHN	district heat network
diff	difference
EB	electric boiler
HFO	heavy fuel oil
HOB	heat-only boiler
HP	heat pump
NG	natural gas
opt	optimization
O&M	operation & maintenance
ref	reference

Other

θ	DH supply temperature curve
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compressed air energy storage and flywheel energy storage; chemical storage methods employ some platform chemical as storage, e.g. hydrogen or biofuels; and thermal storage methods employ heat capacity or phase change in e.g. steam accumulators, phase change materials and water tanks. A thorough analysis of the technologies and their applications in the energy transition context can be found for example in a publication by Gallo et al. [2].

District heat (DH) networks may offer one solution for hour-scale balancing of the electricity network: the water in the distribution network can act as 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 the existing infrastructure can be utilized with no additional investment cost. The active regulation of supply temperature should not cause problems to customers as long as the minimum temperature is guaranteed, or to the network if the maximum temperature change rate is not exceeded. Altogether, employing the DHN flexibility might reduce district heat costs and benefit electricity network on such occasions when there is an 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 the best extent. This is compared to current control paradigm, where the supply temperature is mostly determined by the ambient temperature [3, 4]. 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 flexibility, and this control methodology is not contrary to those but supporting the same goal. The focus of 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. [5].

The effect of heat storages to the 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. 6, 7, 8]. The studies on heat pumps and other power-to-heat technologies as part of a district heat system are also numerous [e.g. 9, 10, 11, 8]. It has been concluded that application of power-to-heat technologies can benefit variable renewable energy integration [12, 13, 14]. Of the studied technologies, heat pumps and thermal storages are distinguished as

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.

Currently available energy storage methods can be grouped into electrical, mechanical, chemical and thermal systems [1]. The electrical storage methods include technologies such as supercapacitors and different battery energy storage systems; mechanical storage includes e.g. pumped hydroelectric storage,

most favourable options [12, 14]. 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 [15, 8, 6, 16]. 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 [9].

Another branch of research 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 [17, 18, 19, 20, 21]. 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 [21]; the utilization of the DH thermal inertia contributes more to optimal operation of CHP, while power-to-heat contributes to reduced wind curtailment [19]. Alas, the 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 display outcomes of district heat network supply temperature optimization on an annual scale. We analyze what is the attainable economic benefit over conventional operation, and provide a sensitivity analysis and a qualitative assessment on which parameters affect the extent of benefits from the added flexibility. An open-source calculation model is provided, which can be adapted by DH network operators with a small effort to determine the general effects and possible monetary benefits of supply temperature optimization in their systems. The article also contributes to the understanding of district heat networks' operational dynamics.

2. Materials and methods

An optimization program is created to evaluate the feasibility of proposed district heat control scheme. The source code of the program is freely available online for review and utilization: [22]. The program is written in Julia language [23] and its JuMP optimization package [24]; CPLEX [25] and Ipopt [26] 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 :

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

Figure 1: Supply temperature curve in the reference case, modified from Koskelainen et al. [3, sec. 7.1.2]. District heat supply temperature T'_S is set based on the ambient temperature T_A : $T'_S = \theta(T_A)$.

where abbreviations FU stand for fuel, EL electricity, SU start-ups, 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 is a free variable, whose value will be provided from optimization results. No other constraints apply to the temperature, apart from the minimum and maximum temperatures, and the maximum rate of change

$$-\Delta T'_{S \max} \Delta t \leq T'_{S,t} - T'_{S,t-\Delta t} \leq \Delta T'_{S \max} \Delta t. \quad (2)$$

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

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

where C are the costs from Equation (1), and positive temperature slack variable $T_{\text{slack},t}$ is the difference between supply temperature T'_S and the deterministic supply temperature θ from Figure 1:

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

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

$$T_{\text{slack},t} = T'_{S,t} - \theta(T_{A,t}). \quad (6)$$

The addition of a slack variable will guide the optimization to take the supply temperature T'_S to the deterministic value θ . In Equation (3) the slack variable scaling parameter is set to $M = 10^3 \text{ €/}^\circ\text{C}$.

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 [27]: the average supply temperature in the network T_S at time t is calculated from the temperature during a previous time step, the supply temperature from the heat source T'_S , and heat loss to the environment at ambient temperature T_A , 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 :

$$T_{S,t} = T_{S,t-\Delta t} + \frac{\dot{m}_t \Delta t}{m_{\text{DHN},S}} (T'_{S,t} - T_{S,t-\Delta t}) - k_X (T_{S,t} - T_{A,t}) \Delta t \quad (7)$$

$$T_{R,t} = T_{R,t-\Delta t} + \frac{\dot{m}_t \Delta t}{m_{\text{DHN},R}} (T'_{R,t} - T_{R,t-\Delta t}) - k_X (T_{R,t} - T_{A,t}) \Delta t \quad (8)$$

The total mass of water in the supply or return pipelines is calculated from half of the DH network volume $m_{\text{DHN},S} = m_{\text{DHN},R} = 0.5 \rho V_{\text{DHN}}$. Time resolution Δt is one hour and for modelling an initial condition is set for all network temperatures: $T_{t=0} = T_{t=1}$. 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: $T'_{S,t=1} = \theta(t_{A,t=1})$.

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 [27].

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

$$\sum_u Q_{S,t,u} = c_p \dot{m}_t (T'_{S,t} - T_{R,t}) \quad (9)$$

$$Q_{L,t} = c_p \dot{m}_t (T_{S,t} - T'_{R,t}) \quad (10)$$

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 Δp depend on the mass flow rate, we can calculate the power consumption P from the mass flow rate, given one known operational point $(\dot{m}_0, \Delta p_0)$:

$$\frac{\Delta p}{\Delta p_0} = \left(\frac{\dot{m}}{\dot{m}_0} \right)^2$$

$$P = \frac{\dot{V} \Delta p}{\eta_T} = \frac{\dot{m} \Delta p}{\rho \eta_P \eta_M} = \frac{\dot{m}^3}{\rho \eta_P \eta_M} \frac{\Delta p_0}{\dot{m}_0^2}, \quad (11)$$

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 the 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 $(\dot{m}_0, \Delta p_0)$ 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.

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

DH generation [30]	378.4	GWh
DH network losses [30]	45.5	GWh
Pumping energy / DH generation ^a	0.5	%
DH network volume V_{DHN} ^b	5437	m ³
Mass flow $\dot{m}_0$	500	kg/s
Pressure loss Δp_0	938.5	kPa
Heat loss factor k_X	$1.515 \cdot 10^{-2}$	
Pump efficiency η_P	0.7	
Motor efficiency η_M	0.9	
Max. temperature rate $\Delta T'_{S \max}$	7	°C
Min. average supply temperature $T_{S \min}$	65	°C
Min. supply temperature at plants $T'_{S \min}$	75	°C
Max. supply temperature at plants $T'_{S \max}$	115	°C
Return temperature T'_R	45	°C

^a Average for networks where pumping is reported [30].

^b Applying similar length-to-volume ratio from Helsinki DHN [30], volume from [8].

In the absence of consumption data, a simulated load demand curve is generated with The Open Energy Modelling Framework [28] demandlib and its standard load profiles [29], matching the reported annual DH consumption. The demand profile is combined from three load profiles in the library: 40 % weight on blocks 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, the 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; the minimum average temperature of supply water $T_{S \min}$ 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 $\Delta T'_{S \max}$ is set to 7 °C/hour: in normal operation the supply temperature change rate should be 1 °C...2 °C/6 minutes [3, sec. 7.1.2], and this 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)

Table 2: Plant modelling data for the case study. CHP and HOBs are existing plants, HP and EB are investment options. Total efficiency η_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.

Plant	$Q_{S,max}$ MW	P_{max} MW	L_{min}	η_T	COP	c_{SU} €	c_{IN} 10^3 €/MW	c_{OM} €/MWh	c_{OF} 10^3 €/MW/a	c_{FU} €/MWh	c_{FT} €/MWh
Bio-CHP	63	22	0.4	1.10	-	2500	0	3.9	29	21.5	0
HFO-HOB	24	-	-	0.85	-	0	0	0	3.7 ^a	35	22
NG-HOBs	126	-	-	0.85	-	0	0	0	3.7	27.5	17.4
Bio-HOB	18	-	-	0.85	-	0	0	5.4	0	35	0
HP	b	b	-	-	3.0	0	680	0	5.5	-	-
EB	b	b	-	1.00	-	0	145	0.5	1.1	-	-
Reference	[6]			[31]		[6]	[31]			[6]	

^a Assumed same as for NG-HOBs.

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

Figure 2: Load profile and load duration curve, ambient temperature, and electricity price for the analyzed case.

Table 3: Electricity costs [32].

Distribution cost c_{ED}	7.8/17.5 ^a	€/MWh
Tax c_{ET}	27.9372	€/MWh
Connection base cost c_{ECB}	2604	€/a
Connection power cost c_{ECP}	54720	€/MW/a

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

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:

$$\phi_{t,u}\eta_{T,u} = Q_{S,t,u} + P_{O,t,u} + Q_{R,t,u} : u \in \{\text{CHP, HOBs}\} \quad (20)$$

$$P_{I,t,u}COP = Q_{S,t,u} : u = \text{HP} \quad (21)$$

$$P_{I,t,u}\eta_{T,u} = Q_{S,t,u} : u = \text{EB} . \quad (22)$$

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

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

$$Q_{R,t,u} \geq 0 : u = \text{CHP} \quad (23)$$

$$Q_{R,t,u} = 0 : u \neq \text{CHP} . \quad (24)$$

and (3) are distributed in following parts:

$$C_{FU,t,u} = \phi_{t,u}(c_{FU,u} + c_{FT,u})\Delta t \quad (12)$$

$$C_{EL,t,u} = P_{I,t,u}(c_{EL,t} + c_{ED,t} + c_{ET})\Delta t - P_{O,t,u}c_{EL,t}\Delta t \quad (13)$$

$$C_{SU,t,u} = c_{SU,u}z_{+,t,u} \quad (14)$$

$$C_{OM,t,u} = Q_{S,t,u}c_{OM,t,u}\Delta t \quad (15)$$

$$C_{OF,u} = Q_{S,max,u}c_{OF,u}k_P : u \notin \{\text{HP, EB}\} \quad (16)$$

$$C_{OF,u} = (Q_{S,max,u}c_{OF,u} + P_{max,u}c_{ECP} + c_{ECB}z_{E,u})k_P : u \in \{\text{HP, EB}\} \quad (17)$$

$$C_{IN,u} = c_{IN,u}Q_{S,max,u}k_Ak_Pz_{E,u} \quad (18)$$

$$C_{PU,t} = P_{P,t}(c_{EL,t} + c_{ED,t} + c_{ET})\Delta t . \quad (19)$$

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 :

$$Q_{S,t,u} + Q_{R,t,u} \leq Q_{S,max,u}z_{t,u} . \quad (25)$$

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

$$z_{t,u} \leq z_{E,u} . \quad (26)$$

CHP power output is restricted by maximum electric efficiency $\eta_{EL \max}$

$$\eta_{EL \max, u} = \frac{P_{\max, u}}{(Q_{S \max, u} + P_{\max, u}) / \eta_{T, u}} \quad (27)$$

$$P_{O, t, u} \leq \phi_{t, u} \eta_{EL \max, u} : u = \text{CHP} \quad (28)$$

$$P_{O, t, u} = 0 : u \neq \text{CHP} . \quad (29)$$

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

$$Q_{S, t, u} + P_{O, t, u} + Q_{R, t, u} \geq L_{\min, u} (Q_{S \max, u} + P_{\max, u}) z_{t, u} : \\ u = \text{CHP}, z_{t, u} \in \{0, 1\} , \quad (30)$$

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

$$z_{+, t, u} - z_{-, t, u} = z_{t, u} - z_{t-\Delta t, u} : z_{+, t, u}, z_{-, t, u} \in \{0, 1\} , \quad (31)$$

from which the start-up costs in Equation (14) can be calculated. To enable proper identification of start-ups, a constraint is also added to guide variable z to 0 for those hours that do not have any heat output:

$$z_{t, u} \leq Q_{S, t, u} + Q_{R, t, u} . \quad (32)$$

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

$$k_A = \frac{r(1+r)^n}{(1+r)^n - 1} , \quad (33)$$

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:

$$k_P = \frac{\sum_t \Delta t}{8760} . \quad (34)$$

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 an 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 [33]. Figure 3 depicts the algorithm:

1. Beginning from time $t = 1$ predictions are formed for DH demand $Q_{L, t}$, ambient temperature $T_{A, t}$ and electricity price $c_{el, t}$. In this article, historical data from 2017 are employed.

Figure 3: Sliding time window method.

2. A mixed integer linear problem (MILP) is formed for the first 10 days, $t \in t_{\text{MILP}}$. 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 $z_{t \in t_{\text{MILP}}, u}$ are obtained.
3. A nonlinear problem (NLP) is formed for the first 48 hours, $t \in t_{\text{NLP}}$. Binary variables $z_{t, u}$, $z_{+, t, u}$ and $z_{-, t, u}$ are removed: For those units u that have a specified minimum load or start-up costs, commitment variables $z_{t, u}$ are replaced from the MILP model solution, and z_{+} and z_{-} are calculated from z . Initial values for $T_{S, t=0}$, $T'_{S, t=0}$, $T_{R, t=0}$ and $z_{t=0, u}$ are fixed from previous 24 hour solution.
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 separating the large problem into smaller subproblems, which can be solved more easily. It also provides the possibility to use the optimization method 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.

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 than 48 hours does not affect the optimization outcome. MILP time horizon of ten days is a balance between long

Figure 4: Load duration curves for the case study plants. *Opt* refers to results from supply temperature optimization method, *ref* to reference method.

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

$$\sum_u Q_{S,t,u} = Q_{L,t} + Q_{X,t} \quad (35)$$

describes the operation of the units. Here, heat demand $Q_{L,t}$ at time t is fulfilled by heat supply $Q_{S,t,u}$ 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):

$$Q_{X,t} \Delta t = c_p m_{\text{DHN}} k_X (T_{S,t} + T_R - 2T_{A,t}) . \quad (36)$$

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, the part-load operation of the CHP plant is reduced. The CHP plant is operated at full load or near full load for an 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 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 the CHP plant and the energy consumption in pumping are lower in the optimization method. Figure 5

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

	Opt	Ref	
Average heat production cost	23.93	24.37	€/MWh
Heat losses, of input heat	12.89	11.94	%
Heat rejection, of input heat	6.19	6.79	%
Pumping energy, of input heat	0.31	0.50	%
Heat generation per unit			
BioCHP	367.3	358.4	GWh/a
Bio-HOB	13.2	17.8	GWh/a
NG-HOBs	1.6	1.8	GWh/a
HFO-HOB	0.0	0.0	GWh/a

Figure 5: The cost difference between optimization and reference control schemes. Abbreviations refer to cost components in Equation (1); positive bars indicate benefit to optimization method over reference method.

displays the source of cost savings: on an annual average, the 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 temperature T'_s varies largely between the minimum and maximum temperatures, and it is not much affected by the ambient temperature. Contrary to the reference 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 allows, 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.

Figure 6: DH supply temperature as ambient temperature function

Figure 7: Operation near CHP full load with the optimization control strategy. The temperature curve θ displays the reference temperature, indicating supply temperature T_s' with the reference control method.

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

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. The flexibility provided by the DH grid is often employed in charging the network during the night when the 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 the 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.

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.

Figure 11: Load duration curves with varying installed heat pump capacities, optimization control scheme.

3.2. Investment options

Investment into 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 into 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 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 into 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.

Figure 12: Sensitivity to maximum allowed DH supply temperature gradient $\Delta T'_{S_{max}}$.

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 [3].

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 the 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, the 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 heat storage might enable more favourable CHP start-up and shut-down timing near the minimum load.

(a) Net LHV efficiency η_T .

(b) Installed maximum heat load $Q_{S \max}$.

(c) Start-up cost c_{SU} .

Figure 13: Sensitivity to CHP plant parameters.

When a CHP plant is a part of the DH supply portfolio, electricity prices have a large effect on the economic outcome. Figure 14 shows the results under different price scenarios: here, electricity price is either scaled linearly with parameter k

$$c_{EL,t, \text{scale}} = k c_{EL,t}, \quad (37)$$

or alternatively the price volatility is increased around the annual mean price $\bar{c}_{EL}$:

$$c_{EL,t, \text{var}} = k (c_{EL,t} - \bar{c}_{EL}) + \bar{c}_{EL}. \quad (38)$$

Due to CHP electricity generation, increase in electricity prices reduces the average DH generation costs in Figure 14a and increases the benefit of the optimization control scheme. However, when only the electricity price volatility is increased but the mean electricity cost does not change, no significant difference arises.

(a) No investment option.

(b) 15 MW heat pump installed.

Figure 14: Sensitivity to electricity price scenarios. Solid lines (*scale*) display the effect of electricity price scaling with Eq. (37), dashed lines (*var*) the effect of change in electricity price volatility with Eq (38).

The investment into a 15 MW heat pump changes the situation slightly in Figure 14b: the benefit of the optimization control method is somewhat constant over electricity price scaling between $\pm 20\%$. This is because CHP generation benefits from the electricity price increase and HP generation is harmed by the price increase. When heat pumps are part of the generation profile, benefits of the optimization control scheme will increase with increasing price volatility, suggesting that HPs and employing DHN flexibility support each other.

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. This is mostly influenced by the generation cost differences between available heat sources. As the optimization method strives to minimize DH generation costs, the runtime of those plants is increased, whose variable costs are the lowest. This results in a reduction of CHP condensing mode operation, and a reduction of part load operation and an 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 if the electricity prices are decreased by variable renewable energy production peaks, the heat pump can help absorb the peaks into the district heat network. The implementation of the optimization control scheme allows further utilization of the storage capability of the network; for example the DH supply temperature increases above reference supply temperature 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. This active utilization of the network heat storage capability therefore benefits the district heat system and aids in cost reduction.

In comparison to other energy storage technologies, the global effects of the control method change are small. Implementing heat storage tanks in the district heat networks allows for greater flexibility: Hast et al. [6] determined that the cost-optimal heat storage size for the analyzed network would be in the order of 100 000 m³, approximately 20 times larger than the network volume. The district heat networks' applicability to grid electricity storage via power-to-heat methodologies is also restricted by the network and customer load: it offers flexibility to the electric grid as the DH load allows, and therefore may not be available to VRE absorbing actions at all times.

Due to the simplification of the district heat network to two energy buffers, the provided calculation model [22] can be employed with little input data, to explore the network 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 possibility to employ the model in short-term control. The solution time for both reference and optimization control methods with the sliding window algorithm is approximately 20 minutes

for the annual solution, or 4 seconds for each 24-hour period — on a regular laptop computer. Most of the time is spent on solving the NLP problem. We consider the calculation method efficient and reliable for the given use case: exploring the possibilities of district heat temperature optimization and producing sensitivities on an annual scale. The method also reflects on how dispatch optimization is made: it always takes into account the current situation and the insights to affecting factors in the near future and strives to produce the most cost-optimal outcome. The sliding window implementation may however lead to only locally optimal solutions due to the separation of MILP plant dispatch calculation and NLP production optimization. Because the unit commitment z is fixed in the MILP part, the method cannot reveal possibilities of extending CHP plant runtime at minimum load. 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. [19] 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. [18] calculated 7 % savings in a system with gas turbines, gas HOBs and wind turbines; costs reported by Li et al. [20] 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. Aforementioned 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 the 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.

Actual operation data is not accessible for result verification, and published statistics do not reveal the individual plant outputs [30]. However, the resulting district heat generation prices reflect well on the fuel prices, and the plant dispatch order follows the lowest marginal cost. These factors suggest that the reference scenario outcome aligns with reality. In their analysis of the same DH network, Hast et al. [6] found the most economical size of a prospective heat pump to be 20 MW to 25 MW, which is similar to what is concluded in this article. Hast et al. [6] calculated lower district heat generation prices, which most likely results from higher electricity prices and thus higher CHP electricity sales income in their model.

Supply temperature optimization may be included in current district heating networks by adjusting the control system logic. One practical option is to perform optimization separately from the control system, and include the calculated optimal supply temperature as an input signal to the existing control logic —

thus replacing the supply temperature curve. The other option is to extend existing dispatch optimization routines to include the supply temperatures. When implemented into an actual system, the optimization model must include the network topology, or other measures must be taken to ensure minimum supply temperatures and appropriate flows in all parts of the network. A sliding window method, where the optimization considers future events but redoes optimization continuously when the actual running period proceeds, seems very reasoned for such control actions. In an actual control system, running the optimization every 24 hours may be too long a period, and the time resolution of one hour may also be set finer.

5. Conclusions

This article presents new information on the annual effects of district heat supply temperature optimization. We present novel results on the attainable benefit over conventional operation, and discuss the factors that affect the usefulness of employing the district heat network storage functionality.

In the presented case study, active utilization of the district heat network storage capability results in district heat generation price reduction over the traditional district heat temperature control paradigm, under all examined circumstances. The switch of control method results 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 for the case study. A system with both combined heat and power generation and a heat pump also benefits from the added flexibility of the optimization control scheme, especially when the electricity price volatility increases.

In general, supply temperature optimization results in increased operational hours of those plants, whose variable costs are the lowest. The added flexibility in most district heat networks would thus reduce generation from peak supply units in favour of base load units. The benefits of added heat storage functionality in the network are greatest when there is a large difference between district heat generation costs from the available heat sources.

The amount of benefits from employing district heating networks in variable renewable electricity balancing on an electricity grid level is yet to be quantified. This study suggests that the district heat supply temperature can respond rapidly to electricity price signals, and power-to-heat technologies in the network benefit from supply temperature optimization. We suggest that supply temperature optimization would benefit all district heat networks. The implementation still requires expansion of the presented calculation method.

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