Optimal design and operation for heat prosumer-based district heating systems

Haoran Li [a], *Juan* Hou [a], *Natasa* Nord [a]

[a] Department of Energy and Process Technology, Norwegian University of Science and Technology, Kolbjørn Hejes vei 1 B, Trondheim 7491, Norway.

Abstract. Heat prosumers will become important participants for future district heating (DH) systems. However, the current unidirectional heating price models reduce interest in prosumers and hinder the promotion of prosumers in DH systems, because the prosumers gain no economic benefit from supplying heat to the central DH system. This study aimed to break this economic barrier by introducing water tank thermal energy storage (WTTES) and optimizing the operation of heat prosumers with WTTESs, considering the widely used heating price models in Norway. Firstly, a generalized heating price model was introduced, which could represent the current widely used heating price models in Norway. Secondly, the WTTES was integrated into the heat prosumer to improve the self-utilization rate of the prosumer's heat supply from its distributed heat sources, meanwhile, shave the prosumer's peak load. Afterwards, an optimization framework was formulated to optimize the operation of the prosumer with the WTTES under the generalized heating price model. Finally, a numerical method for solving the proposed nonlinear optimization problem was given. A case study showed that the proposed method could cut the prosumer's annual heating cost by 7%, and the investment of WTTES could be recovered in four years.

Keywords. nonlinear optimization, thermal energy storage, heating price, distributed heat sources.
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1. Introduction

The widely used heating price models in Norway charge a heat prosumer's heating bill mainly based on heat prosumer's heat use and peak load [1]. Accordingly, two potential ways to minimize a heat prosumer' heating cost in a district heating (DH) system are: 1) decreasing the heat supply from the central DH system by increasing the heat supply from prosumer's distributed heat sources (DHSs), which are free and may come from renewables and waste heat, and 2) shaving the peak load by shifting the heat supply from peak hours to non-peak hours.

Thermal energy storages (TESs) may be used to achieve the above two goals. Firstly, TESs can increase the self-utilization rate of the heat supply from DHSs, because for the periods when the heat supply from the DHSs is higher than the demand of the prosumer, the surplus heat can be stored into the TESs and used for later heat supply instead of being fed into the central DH system [2, 3]. Secondly, TESs can shave the prosumer's peak load, because the peak demand can be satisfied by the stored heat from the non-peak hours [4, 5]. However, TESs are investment intensive. The high investment costs and the long payback periods are hindering the implementation of TESs in DH systems.

This study proposed a comprehensive method for optimal design and operation of prosumer-based DH systems with short-term TESs. The method was based on the heating price models in Norway but can also give references for DH systems outside Norway.

2. Method

This section explains the proposed method. Firstly, a generalized heating price model is introduced, which may represent the current widely used heating price models in Norway. Secondly, WTTES is integrated into the heat prosumer-based DH system to improve the self-utilization of the heat supply from the DHSs and shave the peak load. Afterwards, an optimization framework is formulated to optimize the operation of the proposed DH system under the generalized heating price model. Finally, a numerical method for solving the proposed nonlinear optimization problem is given.

2.1 The method to obtain a generalized heating price model

Although heating price models may vary in Norway, this study introduced a generalized heating price model, which could approximate and generalize the widely used heating price models. According to the review article [1], a heating price model may include four components: energy demand component (EDC), load demand component (LDC), fixed component (FXC), and flow demand component (FDC). The EDC is charged based on the heat use, and it is used to cover the fuel cost. The LDC is charged according to the peak load, and it aims to maintain a certain capacity of heat production. The FXC is the fee for connecting to the central heating grid. The FDC motivates the low return temperature, and it is charged based on the volume of the circulating water.

Fig. 1 gives the existence and the average share of each component for investigated heating price models in Sweden. Firstly, it can be found from Fig. 1 that, the LDC and the EDC are the most important components, which together share 96% of the total heating cost. Moreover, 87% of the investigated heating price models have the LDC and all the heating price models have the EDC. In contrast, the FXC and FDC play limited roles in the investigated heating price models, which only share less than 2% of the total heating cost. Furthermore, only about half of the investigated heating price models have the FXC and FDC.

Based on the above situations, a generalized heating price model used to approximate a prosumer's heating cost was introduced as Equation (1), in which the total heating cost includes the LDC and the EDC.

$$C_{tot} = C_{ldc} + C_{edc} \tag{1}$$

where C_{tot} refers to the total heating cost, C_{ldc} and C_{edc} are the LDC and the EDC, respectively, which can be obtained by Equation (3) and Equation (4).

$$C_{ldc} = LP \cdot \dot{Q}_{pea} \tag{2}$$

$$C_{edc} = \int_{t_0}^{t_f} EP(t) \cdot \dot{Q}(t) dt \tag{3}$$

where LP and $EP(t)$ are the LDC heating price and EDC heating price, respectively. $\dot{Q}_{pea}$ refers to the yearly peak load [6, 7] and $\dot{Q}(t)$ is the heat supply flow rate.

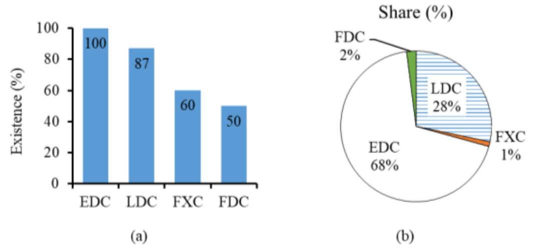

Fig. 1. The existence (a) and average share (b) of each component in investigated heating price models [1]

2.2 System design for heat prosumer-based DH system with TES

As introduced in Section 2.1, to minimize the heating cost of a heat user, it is required to decrease the LDC and the EDC heating cost, which are related to the peak load and the heat use, respectively. Moreover, as explained in Section 1, TESs may be used to achieve the above goals. Fig. 2 illustrates the proposed system for a heat prosumer-based DH system, which integrates a TES. In Fig. 2, DHS was a low-temperature heat source utilizing free heat from renewables or waste heat. DHS was integrated into the prosumer's local DH system using the R2R mode, in which DHS extracted water flow from the return line and fed it back into the return line after the heating process. The R2R mode was used because it is preferable for a low-temperature heat source [8].

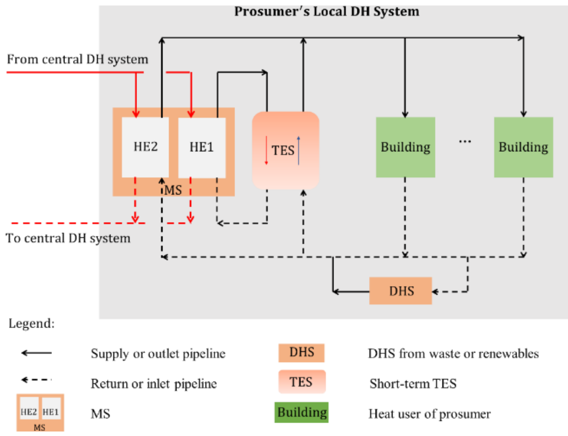

Fig. 2. System design for a heat prosumer's local DH system with TES

Moreover, MS in Fig. 2 referred to the main substation, which connected the central DH system with the prosumer's local DH system. Two types of heat exchanger (HE) were installed in the MS. HE1 was used for charging the TES. For the period with low heat demand, HE1 supplied heat to the local DH system through TES when the heat supply from the DHS was not enough. For the period with high heat demand, HE1 was used for peak load shaving by charging heat at non-peak hours. HE2 in the MS functioned as a high-temperature heat source, it boosted the supply temperature of the local DH system to the required level when the water temperature after the DHS was not high enough.

In addition, the TES was a short-term TES. As introduced in Section 1, the TES functioned in two ways to minimize the prosumer's heating cost. Firstly, it improved the self-utilization rate of heat supply from the DHS. For the period with low heat demand, the DHS from renewables and waste heat may have a higher heat supply than the demand, and the surplus heat supply would be stored in the TES and for later use instead of being supplied to the central DH system. Secondly, the TES may shave the prosumer's peak supply from the central DH system. For the periods around the peak periods, the central DH system may charge the TES at non-peak hours and the stored heat may shave the heat supply at the peak hours.

Fig. 2 gives an example of a community heat prosumer, which has a cluster of buildings as the heat users. However, for the cases of individual heat prosumers, the heat user is a single building.

2.3 Optimization framework for the operation of heat prosumer-based DH system

An optimization framework for the operation of a heat prosumer-based DH system is proposed in this section. The framework was based on the system design presented in Section 2.2, considering the generalized heating price model introduced in Section 2.1. The mathematical formulation of this framework is presented in Equations (4), (5), (6), (7), and (8). Equation (4) is the objective function, in which the first part is the EDC heating cost, and the second part is the LDC heating cost. Equation (5) represents the effort to shave the peak load, Equation (6) describes the system dynamics and Equation (7) defines the initial states of the system. Equation (8) is the system constants.

Minimize:

$$\int_{t_0}^{t_f} EP(t) \cdot \dot{Q}(t)dt + LP \cdot \dot{Q}_{pea} \tag{4}$$

subject to:

$$\dot{Q}(t) \leq \dot{Q}_{pea} \tag{5}$$

$$F(t, \boldsymbol{z}(t)) = 0 \tag{6}$$

$$F_0(t_0, \boldsymbol{z}(t_0)) = 0 \tag{7}$$

$$z_L \leq \boldsymbol{z}(t) \leq z_U \tag{8}$$

where $\dot{Q}(t)$ is heat supply flow rate from the central DH system. $\dot{Q}_{pea}$ is the peak load, which is a parameter to be minimized. LP and $EP(t)$ are the heating price for the LDC and the EDC, respectively. $\boldsymbol{z} \in \mathbb{R}^{n_z}$ are the time-dependent variables, including the manipulated variable $\boldsymbol{u} \in \mathbb{R}^{\mathrm{n_u}}$, the differential variable $\boldsymbol{x} \in \mathbb{R}^{\mathrm{n_x}}$, and the algebraic variable $\boldsymbol{y} \in \mathbb{R}^{\mathrm{n_y}}$. $z_L \in [-\infty, \infty]^{\mathrm{n_z}}$ and $z_U \in [-\infty, \infty]^{\mathrm{n_z}}$ are the lower bounds and upper bounds, respectively. The system dynamics described in Equation (6) contained the dynamics of the MS, DHS, TES, distribution network, and buildings. The interactions between these subsystems were defined in Equations (9), (10), (11), (12), and (13).

$$\dot{Q}(t) = \dot{Q}_{HE1} + \dot{Q}_{HE2} \tag{9}$$

$$\dot{Q}_{HE1} + \dot{Q}_{HE2} + \dot{Q}_{DHS} = \dot{Q}_{Bui} + \dot{Q}_{TES} + \dot{Q}_{loss,TES} + \dot{Q}_{loss,pip} \tag{10}$$

$$\dot{Q}_{HE1} = c \cdot \dot{m}_{HE1} \cdot (T_{HE1,sup} - T_{HE1,ret}) \tag{11}$$

$$\dot{Q}_{HE2} = c \cdot \dot{m}_{HE2} \cdot (T_{HE2,sup} - T_{HE2,ret}) \tag{12}$$

$$\dot{Q}_{DHS} = c \cdot \dot{m}_{DHS} \cdot (T_{DHS,sup} - T_{DHS,ret}) \tag{13}$$

where $\dot{m}_{DHS}$, $\dot{m}_{HE1}$, and $\dot{m}_{HE2}$ refer to the water mass flow rate of DHS, HE1, and HE2, respectively. $\dot{Q}_{DHS}$, $\dot{Q}_{HE1}$, and $\dot{Q}_{HE2}$ represent the heat supply flow rate of the DHS, HE1, and HE2, respectively. $\dot{Q}_{TES}$ is the heat flow rate of the TES for discharging (negative values) and charging (positive values). $\dot{Q}_{Bui}$ represents the building heat demand. $\dot{Q}_{loss,pip}$ and $\dot{Q}_{loss,TES}$ refer to the heat loss flow rate from the pipeline and the TES, respectively. $T_{DHS,sup}$, $T_{HE1,sup}$, and $T_{HE2,sup}$ represent the supply temperature of DHS, HE1, and HE2, respectively. $T_{DHS,ret}$, $T_{HE1,ret}$, and $T_{HE2,ret}$ refer to the return temperature of DHS, HE1, and HE2, respectively. c is the specific heat capacity of water.

The manipulated variables $\boldsymbol{u}$ in this study were $T_{HE1,sup}$, $T_{HE2,sup}$, $\dot{m}_{HE1}$, $\dot{m}_{HE2}$, and $\dot{m}_{Bui}$.

This article focuses on the introduction of the optimization framework, the detailed information on the sub-system models is given in the journal articles [9] and [10].

2.4 Algorithm to solve the optimization problem

Section 2.3 defines a dynamic optimization problem, which is challenging to solve because of the nonlinearity of the dynamic model. This study used the direct collocation method [11] to transform the original infinite-dimensional nonlinear programming (NLP) problem into a finite-dimensional NLP, which could be solved by NLP solvers.

Fig. 3 illustrates the direct collocation method. A time grid from t_0 to t_N was created over the optimization horizon by dividing the horizon into N internals with a constant interval. Afterwards, the state variables $x(t)$ were discretized on each time grid, and thus the state points from s_0 to s_N were obtained. The manipulated variables $u(t)$ were parameterized at each time grid, and thus on each interval $[t_k, t_{k+1}]$, a constant control signal q_k was yielded. Moreover, for each collocation interval $[t_k, t_{k+1}]$, a set of collocation points were generated from $t_{k,1}$ to $t_{k,d}$, and then a polynomial $p_k(t,\ v_k)$ was used to approximate the trajectory of the state within the interval. Therefore, Equation (6) was discretized into Equation (14) in the time interval $[t_k, t_{k+1}]$.

$$c_k(v_k, s_k, q_k) = \begin{bmatrix} v_{k,0} - s_k \\ F\left(\dot{p}_k\left(t_{k,1}, v_k\right), v_{k,1}, t_{k,1}, q_k\right) \\ \vdots \\ F\left(\dot{p}_k\left(t_{k,i}, v_k\right), v_{k,i}, t_{k,i}, q_k\right) \\ \vdots \\ F\left(\dot{p}_k\left(t_{k,d}, v_k\right), v_{k,d}, t_{k,d}, q_k\right) \end{bmatrix} = 0 \tag{14}$$

Besides, continuity conditions should be satisfied at the time grid points $k = 0,1,\cdots N-1$, i.e., the lengths of the red lines in Fig. 3 should be zero. Therefore, Equation (15) was added for these points.

$$p_k(t_{k+1}, v_k) - s_{k+1} = 0 \tag{15}$$

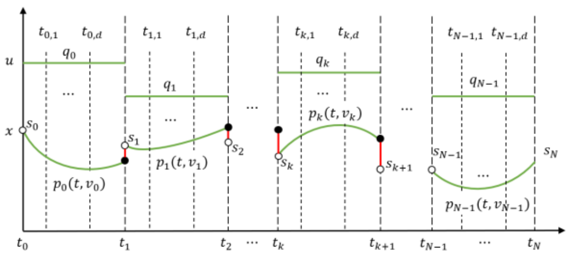

Fig. 3. Illustration of the direct collocation method

Finally, an NLP was yielded and it can be described in the following general form as Equations (16), (17), (18), (19), and (20).

Minimize:

$$\sum_{k=0}^{N-1} L_k(v_k, s_k, q_k) \cdot (t_{k+1} - t_k) + P \tag{16}$$

subject to:

$$x(0) = s_0 \tag{17}$$

$$c_k(v_k, s_k, q_k) = 0 \tag{18}$$

$$p_k(t_{k+1}, v_k) - s_{k+1} = 0 \tag{19}$$

$$h(s_k, v_k) \leq 0 \tag{20}$$

where $k = 0,1,\cdots N-1$. Equation (16) is the discretized form of Equation (4). In Equation (16), the first term approximates the integration term of Equation (4), and the second term represents the parameter to be minimized in Equation (4). Equation (17) represents the initial conditions described in Equation (6), Equations (18) and (19) discretize the system dynamics in Equation (6), and Equation (20) is the discretized constraints in Equation (8).

The NLP was solved by NLP solvers. Firstly, the inequality constraints were got rid of using the interior-point method, and then a local optimum was obtained via solving the first order Karush-Kuhn-Tucker condition using iterative techniques based on Newton's method. The optimization process was conducted using the open-source platform JModelica.org [12].

3. Case study

A DH system at a university campus in Norway was used as the case study, as presented in Fig. 4. The studied DH system was a prosumer, which got heat supply from the central DH system via the MS, meanwhile, recovered the waste heat from the university DC [2, 3].

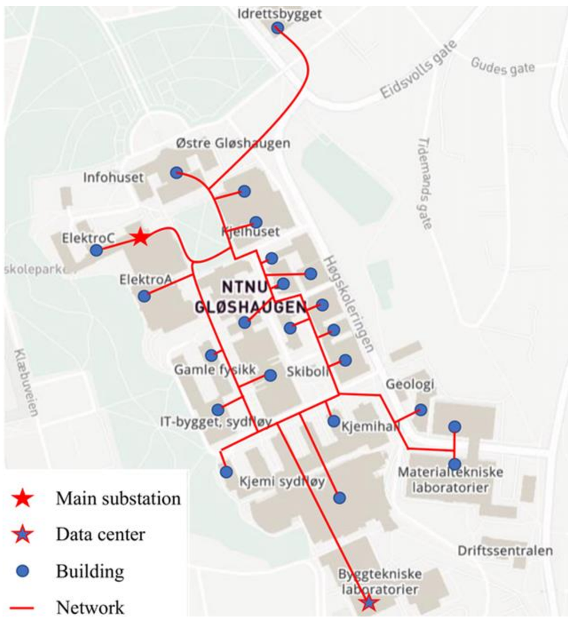

Fig. 4. DH system at the university campus [2, 3]

Fig. 5 presents the measured building heat demand and waste heat supply. The following problems can be observed 1) the mismatch between the waste heat supply from the DC and the building heat demand, which led to the surplus waste heat supply as shown with the red line in Fig. 5 and reduced the self-utilization rate of the heat supply from DHSs. 2) the high peak load during the wintertime as shown with the yellow line in Fig. 5.

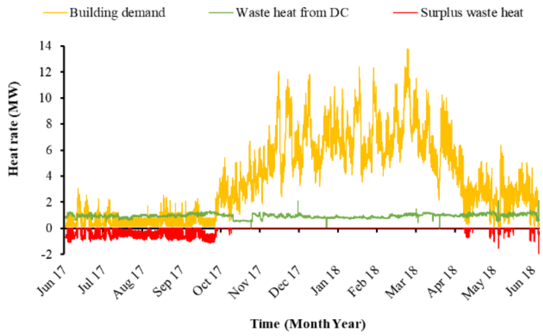

Fig. 5. Measured building heat demand, waste heat supply from the DC, and surplus waste heat

This study introduced a WTTES into the university DH system as proposed in the system design in Section 2.2 and used the optimal operation strategy proposed in Section 2.3 to optimize the economic performance of the studied DH system. The size of the WTTES was 1,700 m^3 and the heating price was obtained from the website of the local DH company [13].

4. Results

This section presents the simulation results, which demonstrate the improved economic performances of the heat prosumer by applying the proposed method. The scenario Ref and WTTES refer to the situation before and after introducing WTTES, respectively.

Fig. 6 and Fig. 7 present the annual heat use and the yearly peak load for the scenario before and after introducing WTTES, respectively. These two indicators quantified the heat supply from the central DH system to the heat prosumer through the MS. It can be observed from Fig. 6 that introducing WTTES reduced the annual heat use from 26.2 GWh to 25.9 GWh, meaning a heat use saving of 1%. Compared to this less significant heat use saving, a more obvious peak load shaving was obtained as shown in Fig. 7, the yearly peak load was shaved from 12.4 MW to 9.5 MW, a shaving of 24%.

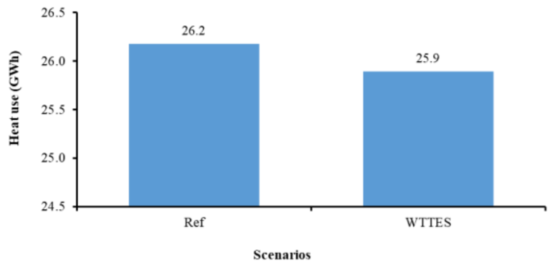

Fig. 6. Annual heat use for the scenario before and after introducing WTTES

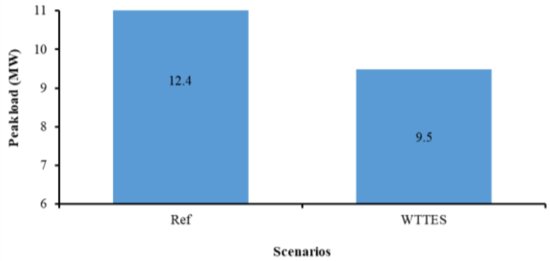

Fig. 7. Yearly peak load for the scenario before and after introducing WTTES

The resulting annual heating cost for the scenario before and after introducing WTTES is presented in Fig. 8. The proposed method cut the annual heating cost from 20.7 million NOK to 19.3 million NOK, which meant a cost saving of 7% was achieved. Moreover, this cost-saving could recover the investment of the WTTES in four years. These economic performances proved that the proposed system design and the operation strategy were economically feasible.

Fig. 8. Annual heating cost for the scenario before and after introducing WTTES

5. Conclusions

This study proposed a method to improve the economic performance of heat prosumers under the heating price models in Norway. The method included a type of system design, which integrated a WTTES into the heat prosumer-based DH system, and an operational strategy to minimize the heating cost considering the widely used heating price models in Norway. A case study showed that the proposed method was economically feasible. The method could cut the prosumer's annual heating cost by 7% and recover the investment of WTTES in four years.

6. References

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