Energy 268 (2023) 126671

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

A simple dynamic optimization-based approach for sizing thermal energy storage using process data

Caroline S.M. Nakama [a], Brage R. Knudsen [b], Agnes C. Tysland [a], Johannes Jäschke [a,*]

[a] Department of Chemical Engineering, Norwegian University of Science and Technology, Sem Sælandsvei 4, Trondheim 7491, Norway
[b] SINTEF Energy Research, Kolbjørn Hejes vei 1B, Trondheim 7034, Norway

ARTICLE INFO

Keywords:
Thermal energy storage
Optimal operation
Optimal design
District heating
Energy management

ABSTRACT

Thermal energy storage (TES) can increase waste heat utilization in district heating (DH) by storing excess energy to be used later to compensate for energy deficit. When sizing a TES tank for DH, incorporating operational conditions can prevent suboptimal volumes and improve the utility enabled by the TES. However, the different time scales of the payback period for the tank and DH operation poses a challenge for optimizing the tank volume. We propose a method to optimally design a TES tank considering operational conditions of a DH plant using time varying waste heat. We formulate a multi-objective dynamic optimization model based on heat data for a long period, which is solved with a two-step approach. First, the data is screened by solving the model for short-term periods to detect intervals that allow for peak heating savings. Then, the model is re-solved using all selected intervals to determine an optimal tank volume. We conduct a trade-off analysis of the conflicting objectives, energy-saving and costs. The proposed method is demonstrated on a case study with historical data. Our method can explore the full feasible space of TES tank volumes and efficiently provide a trade-off curve without the need of exhaustive search.

1. Introduction

Current issues regarding environment and climate have turned our attention to the need for developing and using efficient, clean energy sources as a replacement for fossil fuels. Many policy makers and governments agree that the pace of this shift needs to accelerate [1]. Energy is a major contributor of carbon emissions, and many fronts must be investigated and improved to facilitate decarbonization and meet environmental requirements. Heating for residential and commercial buildings is one such front, accounting for ca. 40% of the energy consumption and 36% of the greenhouse gas emissions in Europe [2]. To decarbonize these sectors, district heating (DH) systems, along with several other technologies that have been developed, are expected to play an important role [3]. DH systems that utilize industrial and commercial waste heat as heat supply are of special interest because they use energy that would otherwise be discarded. However, waste heat often comes with high variability and a temporal mismatch with heat demand from the DH system, requiring peak heating sources when the available waste heat is insufficient, i.e., an additional consistent heating source that is more costly. In this scenario, thermal energy storage (TES) may reduce the use of peak heating significantly by enabling excess available waste heat to be stored and used when the demand is higher than the waste-heat supply. Generally, there are three main types of TES, sensible heat storage, latent heat storage and thermal–chemical energy storage, in which sensible heat from reactants and reaction enthalpy of reversible reactions are used. Each type is in a different stage of development, while sensible heat storage has been thoroughly studied and vastly implemented, thermal–chemical energy storage is a more recent technology under research [4].

This paper addresses the design of centralized short-term TES in heating plants utilizing variable waste heat to supply heat to a district heating network (DHN). For that, we state the following problem: given historical (or projected) data for energy supply and demand, we wish to determine the optimal tank volume for the TES. We propose a rigorous optimization approach for optimal sizing of short-term TES based on a systematic analysis of the supply and demand data. Our approach contains three main steps:

1. Setting up a dynamic model of the TES system
2. Optimization-based screening the historical (or projected) data to identify time periods where energy storage is beneficial
3. Formulating an optimization problem that uses these time periods to determine the optimal TES capacity

By automatically selecting time periods in which TES is of advantage, our algorithm discards all data that is not useful for determining the

* Corresponding author.
E-mail address: johannes.jaschke@ntnu.no (J. Jäschke).

https://doi.org/10.1016/j.energy.2023.126671
Received 6 June 2022; Received in revised form 28 November 2022; Accepted 9 January 2023
Available online 11 January 2023

size of the storage tank and reduces the space of solutions, allowing for efficient and fast evaluation. We apply this method to a case study which uses historical operating data for the initial design of a TES tank for the heating plant of the DH system in Mo i Rana, Norway. However, note that this approach could be adapted to design other energy storage systems, e.g., batteries [5].

Although latent heat TES can present large energy storage density and compact sizes, sensible heat TES technology still has lower costs, is easier to control and large-scale plants have been implemented and tested [6]. Therefore, for the application of TES considered in this paper, large, pressurized hot-water tanks are often preferred [7], being a cost-efficient, well-known and robust technology and often enabling a suitable temperature range for conventional high-temperature DH [8]. The foremost challenge for DH operators considering a potential TES investment is determining the optimal capacity of the storage unit, constituting a trade-off in cost, size and utility. Investment cost and payback time are normally the key economic parameters, while for many heating plants, the physical available space for a TES is also a limiting factor for the size of a tank that can be installed. From an operational point of view, large tanks increases the TES charging times, which can negatively impact quick short-term responses [9]. On the other hand, too small volumes result in frequent temperature saturation of the tank, which may increase undesirable heat dumping, and thus the use of expensive peak heating sources. Increasing the TES tank size also increases the surface area and thus heat losses [10]. Besides these fundamental trade-offs in different TES sizes, the final utility of a TES for improving waste heat utilization is greatly affected by the operational conditions and control strategy of both the heating plant and the TES. Accounting for the control and operations of the TES and heating plant during sizing selection can thus reduce the chances of selecting suboptimal sizes of the TES, improving the economic, energetic and environmental benefits of TES.

Methods for sizing TES tanks can generically be categorized as (1) iterative steady-state energy-balance approaches, (2) simulation-based approaches and (3) optimization-based approaches. Methods in approach (1), e.g. [11,12] as well as the novel frequency-domain approach proposed by [13], have the advantage of being fairly simple to apply, but suffer from only considering the heat amount and not the time-varying temperature levels in the input–output streams nor the TES. As a consequence, these methods may overestimate the achievable performance of the TES.

Contrarily, simulation-based approaches (2) enable incorporating high-granularity, dynamic models of the TES, the heating plant and the relevant DH grid connections in the sizing evaluations. These methods typically evaluate a set of TES sizes in a selected, discretized range with repeated simulations to determine a suitable size. This is done by assessing the enabling heat storage and balancing properties of the TES [9], or by using TES-size-evaluation curves, which consider either the estimated investment costs alone [14] or a weighted criteria of costs, heat supply properties of the TES to the DHN, and losses [15,16]. An advantage of simulation-based sizing approaches is that they enable high-fidelity simulation and analysis of a range of operation modes of the TES, including faults [17] and advanced control structures [9]. Yet, no guarantees of system-wide optimality of the identified TES size can be provided.

Optimization-based approaches (3) seek to identify an *optimal* TES size by formulating a design optimization problem, often as a variable in overall design of combined heat and power plants [18] or also including the DHN design aspects [19]. While being able to identify an optimal TES size, these methods often require significant simplifications in the component models and the dynamic interactions within the heating plant, TES, and input and output heat streams. Seeking to capitalize on the advantages of both simulation and optimization based approaches, a popular class of approaches is hybrid, multi-level simulations and optimization schemes. Often, a metaheuristic is used at the design level [20] and a simulation or operational optimization model at the lower level [21]. However, guarantees of optimality are lost when separating design and operations. In addition, operational models at the lower level tend to be significantly simplified to enable the large number of iterations required for design-level evaluations.

Common for most of the optimization-based sizing approaches for TES is that they do not account rigorously for the integrated operational conditions of the TES and the heating plant [22], or do so in a rather ad-hoc fashion. To the best of our knowledge, only a few exemptions exist in the literature; the MPC scheme for hybrid heat-pump and thermal-storage systems with cost-effective sizing evaluations developed by [23], and the approach proposed by [24] for optimizing the capacity of a TES subject to demand uncertainty and incorporation of operational constraints. The latter approach, however, did not account for temperature variations and was based on extrapolation with a representative week to allow evaluation over a 5-year time horizon.

The approach proposed in this work aims to expand available methods for sizing of short-term TES that incorporates the combined operational conditions of the TES and heating-plant. The present paper is outlined as follows. Section 2 describes the methodology proposed for sizing a short-term TES tank for DH systems with varying energy source, explaining how the optimization model can be set up and used in each step of the proposed approach. In Section 3 we present an overview of the industrial plant considered as the case study along with historical data. We also detail the implementation of the proposed method to this process. Section 4 presents and discusses the results, including an analysis of important mathematical properties of the optimization model. Finally, we conclude the paper in Section 5.

2. Methodology

In this section, we present the methodology proposed for calculating the optimal volume of a short-term TES tank for district heating systems with varying energy sources considering operational conditions. This method is illustrated in the flowchart in Fig. 1. It contains the following steps:

- Step 1: Optimization model set-up - the dynamic optimization model for calculating the optimal TES tank volume based on the mathematical model of the system is built. For that, we use a model representing operating conditions that will act as constraints and we define an objective function that accounts for the distinct desirable characteristics of the TES tank: investment and operational costs as small as possible, and robustness to reduce offsets between heat demand and supply.
- Step 2: Interval selection - the optimization model is used to screen the available operational data to determine periods where TES is beneficial. That is done by calculating the optimal volume for short-term intervals and the results are used as basis for the selection of relevant intervals. The screening in this step removes data that is not relevant to computing the tank volume.
- Step 3: Optimal volume calculation - the selected intervals are combined into a single instance of the dynamic optimization problem, which is solved for the concatenation of the selected periods and, in addition, the influence of each term of the objective function is analyzed.

In the following subsections, each step is further described and supporting theory is briefly presented.

2.1. Step 1: Optimization model set-up

The first step is to build an optimization problem for calculating the volume of a short-term TES tank that can offset the mismatch between waste heat supply and heat demand in the DH system taking into account operating conditions. For that, we need a mathematical model describing the process to be used as constraints of the optimization model and an objective function that can numerically express the goal of the TES tank. In this subsection, we describe how the optimization model can be built and solved.

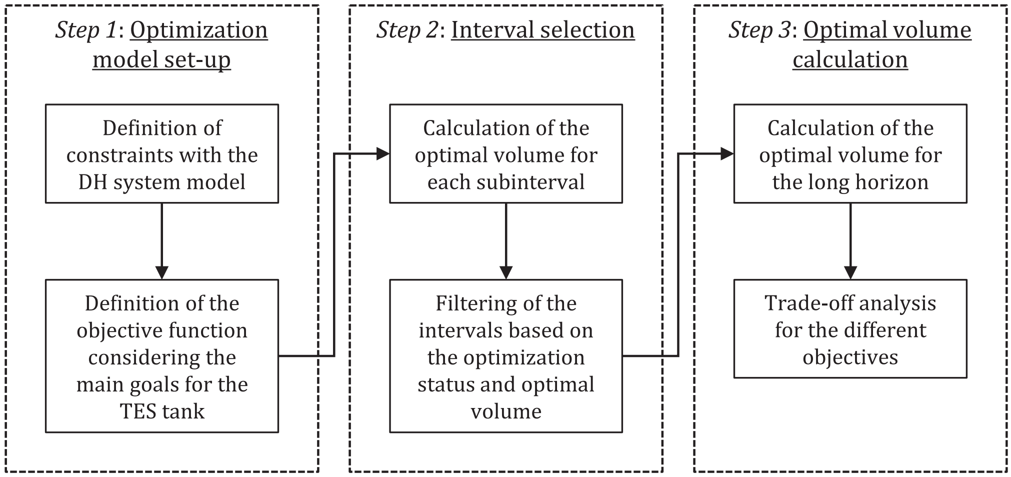


Fig. 1. Flow diagram of the three step method for sizing a TES tank for DH systems with varying heat source.

2.1.1. Model constraints

Mass and energy balances are employed as equality constraints,

$$h(x) = 0,$$

where $h : \mathbb{R}^{n_d} \to \mathbb{R}^{n_e}$ and $x \in \mathbb{R}^{n_d}$ is a vector with all system variables (i.e. temperatures and flows). They ensure that the optimal volume is chosen based on operating conditions by limiting the solution space to containing only points that satisfy the mass and energy balances. In addition, inequalities,

$$g(x) \leq 0,$$

with $g : \mathbb{R}^{n_d} \to \mathbb{R}^{n_i}$, are also considered. They set bounds to the system variable to further restrict the space of possible solutions. Inequalities may represent physical constraints, such as positiveness for temperatures, and for energy and material flows, fixing the direction of the stream. They can also be included to define limits we wish to impose on the problem, for example, upper bounds for flow rates can be set based on the capacity of the pumps in the process.

2.1.2. Objective functions

The optimum TES tank volume for a DH system can be determined by finding a compromise between minimizing (1) initial investment, (2) peak heating usage, and (3) heat dumped. Objective (3) is associated with the ability of the TES tank to efficiently make up and save offsets between heat demand and supply. We assign mathematical expressions to describe each of these objectives and, given their distinct nature, the optimization model can be formulated as a multi-objective optimization problem, i.e., optimization problems in which more than one objective function are present. Generally, the objective function for this type of problems is represented as

$$\min_{x \in \mathbb{R}^{n_d}} \quad \{f_1(x), f_2(x), \dots, f_{n_f}(x)\}$$

where $f_i : \mathbb{R}^{n_d} \to \mathbb{R}$ with $i = 1, \dots, n_f$. When dealing with multi-objective optimization problems, a solution that minimizes all of the objective functions at once is usually not possible. They are likely conflicting, which means that multiple solutions exist. A popular way of handling a multi-objective optimization problem is by aggregation or transformation of the objective functions into a scalar function. The idea is to combine the different objectives into a single expression or to reformulate the problem, for example setting upper bounds to all but one objective, and adding them as inequality constraints [25].

If we analyze the goals we defined for an optimal TES tank, we can see that objective (1) directly conflicts with objective (2); the larger the tank volume, the more heat can be stored and less peak heating is needed, but initial investment increases. Here, we propose to handle the multi-objective problem by combining the different objectives to obtain a scalar expression to be minimized using two different approaches. If we think of the second goal in economical terms, we can formulate a new metric, the payback period. This metric establishes a relationship between the initial investment and financial savings resulting from the use of TES and consequent reduction in the peak heating use. The idea is to obtain one parameter that can economically combine these different objectives and be used in the objective function.

We then propose to combine the payback time with objective (3) to obtain a scalar objective function using the weighted sum method, which simply adds the objective functions and assigns weights to them that add up to 1. These weights represent their relative importance to the user. Here an important aspect to mention is that the objective functions should be in the same order of magnitude, so they need to be scaled if necessary.

2.1.3. Solving the dynamic optimization problem

We can now put together the elements that have been discussed to obtain the optimization model,

$$\min_{x} \quad \alpha \cdot \text{Payback} + (1-\alpha) \cdot \text{Dumped heat} \tag{1a}$$

$$\text{s.t.} \quad h(x) = 0 \tag{1b}$$

$$g(x) \leq 0, \tag{1c}$$

where $0 \leq \alpha \leq 1$ is the weighting parameter for the weighted sum method for multi-objective problems. Given the dynamic nature of the problem posed by this work, $h(x)$ may contain differential equations, characterizing the model representing the process as a system of differential algebraic equations (DAE). Nonlinear programming (NLP) solvers cannot directly handle differential equations as constraints. However, there are strategies we can adopt to solve dynamic optimization problems with this type of solvers, e.g., for large-scale problems, the most used method is the simultaneous approach, in which all time-dependent variables are discretized into $n_t \in \mathbb{N}$ finite elements. Once we have a discretized model, there are two methods we can implement: multiple shooting and orthogonal collocation. The former uses an embedded DAE solver to integrate the system at each finite element, while the latter approximates the integrated intervals to a polynomial of order $n \in \mathbb{N}$, which is the number of collocation points used within the finite element [26].

2.2. Step 2: Optimization-based interval selection

The main idea of this step is to screen the available operation data to identify periods where energy storage has sufficiently large potential

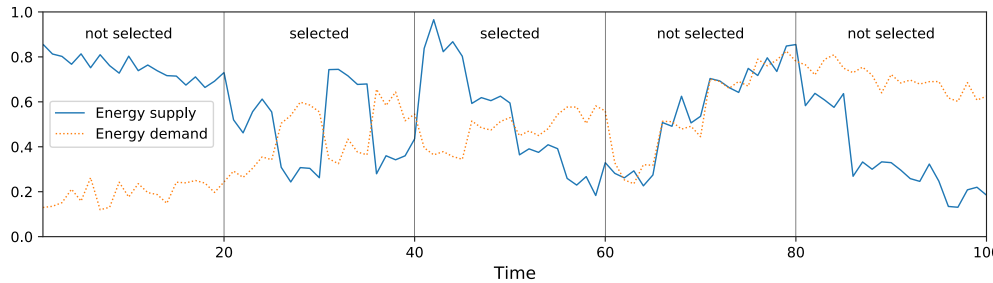


Fig. 2. Example of energy supply and demand data with high variability discretized into 5 intervals. There is little or no savings potential in the intervals not selected.

for affecting the economics of the system (representative intervals). This requires defining the time scale for the energy storage. We use this method to investigate short-term energy storage, which is supposed to offset mismatches between demand and supply for up to a few days.

Ideally, we would like to calculate the volume of the tank with the complete data for the season. However, there are two main issues with that approach: the problem would become too large with too many degrees of freedom, which is challenging to solve, and the operation-related objective function of reducing waste heat dump is associated with the short-term period selected (avoiding waste heat dump based on the whole season would result in an oversized tank for its purpose). Therefore, in this step, we first discretize the season into smaller intervals of length defined to be as long as energy should be stored for.

A simple approach is to define one representative short interval as basis; however, this is not easy due to lack of periodicity in the data. We propose a different approach that selects several representative intervals within the entire long period that have a strong influence on the optimal volume. For that, we set lower and upper bounds to the volume of the tank based on prior knowledge of the process and the available data and solve the NLP problem represented by Eq. (1) for each short interval; the selected ones are those in which a local optimal solution is found and the calculated volume is not at either bound. The reasoning behind this approach is that, if the volume is at the bound, the mismatch between demand and supply is too large and the optimal volume for the TES tank would either be too large or too small, if needed at all. For example, if waste heat supply is greater than heat demand during the entire period, peak heating is not used and excess heat can be used to increase and maintain the TES tank temperature at maximum value. In this case, the volume of the tank is not particularly relevant, since it only influences how much waste heat is dumped once the TES tank reaches its maximum temperature. On the other hand, if waste heat is not enough for the period, the calculated volume can be very large because only the heat already stored in the tank is available to reduce the use of peak heating. Therefore, the intervals of interest should be those in which moments of excess waste heat availability alternates with moments of greater heat demand within approximately the length of the intervals.

Fig. 2 shows an example of energy supply and demand data with high variability and illustrates the discretization into intervals and their selection as discussed. In the first and last intervals, there is no alternating behavior, therefore energy storage is not relevant. In the second and third intervals, there are alternating periods of energy excess and deficit, which makes energy storage beneficial and these intervals can influence the TES optimal capacity. In the fourth interval, supply and demand present similar values, with small excess or deficit; typical TES configuration (size) should make up for these off-sets, therefore this interval is not relevant for sizing energy storage.

2.3. Step 3: Optimal volume calculation

With the representative intervals selected, step 3 consists of calculating the optimal volume for the entire period represented by the data using a single instance of the optimization model defined in step 1. To connect all the selected intervals, we assume that the TES tank is not used during the periods not selected, i.e., the end temperature of the TES tank in an interval is the initial temperature of the next, regardless whether they are consecutive or not. This assumption is reasonable because, for the time scales considered, we can assume that there is negligible heat loss and no energy from the tank is used during the period.

An important factor that influences the optimal volume calculation is how we solve the multi-objective optimization problem since the method used to define the scalar objective function attributes weights to each objective either direct or indirectly. Given that the payback time is an important metric when deciding the volume of a TES tank, we consider the balance between savings and investment cost represented by the payback time to be a suitable cost function candidate. However, in general, the operators of such a plant will also have the desire to save waste heat; therefore, a balance between payback time and how much waste heat will be allowed to be discarded must be found. This trade-off is not straightforward. If we attribute a large weight to dumping excess waste heat, then payback time is not as important and increases, allowing for a greater volume. Analogously, if the dumping heat term has a small weight, decreasing the payback time is prioritized and the optimal tank size becomes smaller. Therefore, a trade-off analysis[1] varying the weights of the summed objective functions is performed to analyze how it influences the optimal volume.

3. Case study

In this section we present a case study that considers the initial process design of a shot-term TES tank for an existing district heating plant using industrial waste heat based on historical data. We show how the proposed method can be used to find an optimal volume and elucidate its relation to the objectives of the TES tank. Below, we describe the process of the heating plant of Mo District Heating system located outside the city of Mo i Rana, Norway and the historical process data used, and detail how the method is applied to this process.

3.1. General process description

The heating plant, located in Mo Industry Park, produces 85–90 GWh per year mainly using waste heat recovered from off-gas from the Elkem Rana ferrosilicon plant. While today about 90% of its annual heat production is recovered waste heat, the asynchronous nature of the availability of waste heat and the heat demand by the city is addressed by peak heating boilers that are used when the waste heat is insufficient to bring the water to the desired supply temperature. These peak heating boilers can operate on CO-gas or electricity, with the decision based on the availability of CO-gas and the electricity price.

[1] Due to the non-convexity of the model and the use of the weighted sum method along with an NLP solver that only finds local solutions, formally, this trade-off analysis should not be called Pareto front.

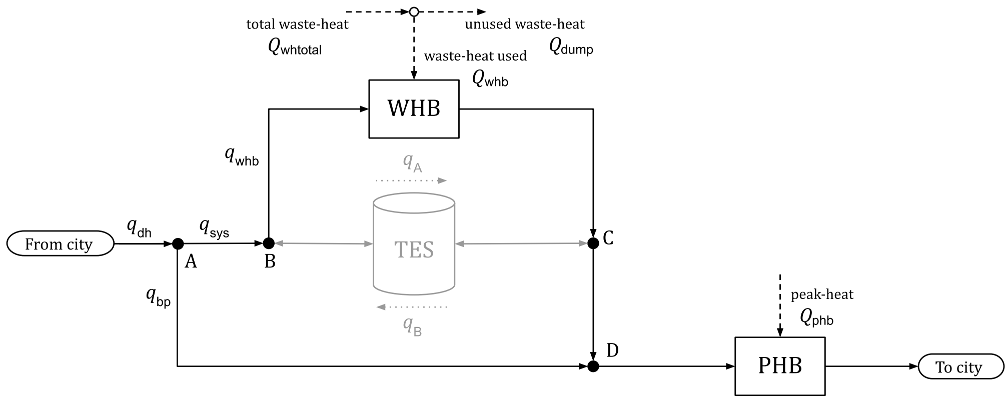


Fig. 3. Simplified representation of the heating plant of Mo District Heating with main flows. Flows from and to the TES tank are bidirectional with q_A and q_B representing the operating direction. Black lines: Existing installation, Gray lines: proposed TES system.

Fig. 3 shows a simplified flow diagram of the described DH plant in black. Essentially, water returns from the city and the waste heat boilers, which have total power peak of 22 MW and maximum outlet temperature of 120 °C, are used to supply heat to the city. If the waste heat is greater than the heat demand, the excess heat is dumped, while insufficient waste heat is compensated by the peak heating boilers, which have a maximum capacity of 21 MW. Also, part of the flow returning from the city can bypass the waste heat boilers to cool the supply water if necessary. These decisions are made at each instant by a controller based on outdoor temperature compensation, i.e., based on the external temperature, the control system determines the outlet temperature of the boilers.

By implementing a TES tank, it is possible to store some of the energy that would otherwise be dumped to be used when peak heating is necessary, reducing its overall energy consumption. The TES tank for the considered DH system is represented in gray in Fig. 3. When integrated in the process, excess heat to be stored can be transferred to the water in the waste heat boilers by directing part of the flow to the tank at node B. Since the volume of the tank is kept constant, the same flow leaves the tank and is merged to the returning water at node A. In contrast, when the available waste heat cannot meet demand, heat from the tank can be discharged to the main flow at node B while part of the returning water is directed to the TES tank at node A.

3.2. Process data

We use historical data from Mo District Heating, supplying heat to the citizens of Mo i Rana, Norway, in the period from November 2018 through April 2019. This data have also been used by other authors [9, 24]. The top plot in Fig. 4 shows the total waste heat available and heat demand from the city for this period for every hour. We consider this period as the period of interest in a year, since we consider only short-term TES and between May and October heat demand is low and peak-heat is generally not required. The bottom plot in Fig. 4 shows the peak heating used during the considered interval. The total waste heat available for the period corresponds to 99.2% of the total heat demand; however, the total peak heating used corresponds to 14.8%. That is, the total available waste heat is almost enough to satisfy demand, but due to a mismatch between heat demand and waste heat availability, peak heating is used today and is responsible for significant costs and emissions. These, however, can be reduced with the implementation of a TES tank.

In addition to heat demand, peak heating and waste heat, measurements for the return and supply temperatures from and to the city, respectively, are available. The total mass flow rate that goes through the process is calculated from heat demand and return and supply temperatures using an energy balance and known properties of water and, therefore, considered known information. The available data have average numerical values for every hour of the considered period.

3.3. Step 1: Optimization model set-up

3.3.1. Mass and energy balances

The mathematical model for the Mo District Heating system is comprised of energy and mass balance equations. For this case study, we adopt some simplifying hypotheses for the model, since we consider the initial design of the tank, and the main focus of this study is to evaluate and demonstrate the method. However, it is important to note that a more detailed model could also be used. For example, we consider a homogeneous TES tank but it could be easily substituted by a more detailed model, such as a stratified TES tank.

We assume heat losses in the system (e.g. natural convection with the environment) are negligible and that the water flow supplied to the city is equal to the returning flow at each instant of time. This implies that the holdup of water in the system remains constant, i.e. no accumulation of mass. The dynamics of the temperature in a large tank are much slower than the dynamics of the flow in the rest of the system; therefore, we only consider dynamics for the energy balance in the TES tank, all other changes in the process are assumed to happen instantaneously. We also assume that the properties of water are constant.

The returning water from the city is split in node A into two streams (Fig. 3), and the corresponding mass balance can be expressed by

$$q_{\text{dh}}(t) - q_{\text{sys}}(t) - q_{\text{bp}}(t) = 0, \tag{2}$$

where $q_{\text{dh}}(t)$ is the water mass flow rate from and to the city, $q_{\text{sys}}(t)$ is the flow rate directed to the waste heat boilers and/or the TES tank, and $q_{\text{bp}}(t)$ is the flow rate that bypasses the waste heat system. Besides the balance in node A, we need an additional balance for node B that specifies when the TES tank is used,

$$q_{\text{sys}}(t) - q_{\text{whb}}(t) - q_A(t) + q_B(t) = 0, \tag{3}$$

where $q_A(t)$ and $q_B(t)$ are the mass flow rates associated with discharging and charging of the TES tank respectively. Here, it is important to note that $q_A(t)$ and $q_B(t)$ are non-negative values that represent a bi-directional flow. Therefore, they cannot assume nonzero values simultaneously, i.e., charging and discharging do not occur at the same time. This logical expression may be represented mathematically as the complementarity

$$0 \le q_A(t) \perp q_B(t) \ge 0. \tag{4}$$

This notation means that q_A and q_B need to be non-negative, and that at least one of them must be zero. Energy balances need to be defined at points where streams of different temperature are split or merged. At node B, the energy balance is given by

$$q_{\text{sys}}(t) C_p T_{\text{dh,ret}}(t) + q_B(t) C_p T_{\text{TES}}(t) - q_{\text{whb}}(t) C_p T_B(t) - q_A(t) C_p T_B(t) = 0, \tag{5}$$

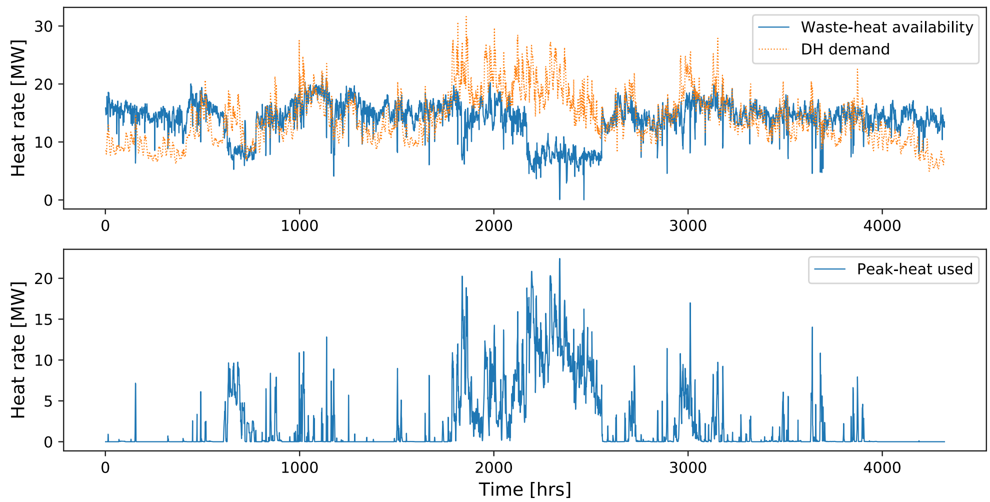


Fig. 4. Heat data from Mo District Heating plant from November 2018 through April 2019.

where C_p^{dh} is the specific heat capacity of water, $T_{\text{dh,ret}}(t)$ is the temperature of the returning water, $T_{\text{TES}}(t)$ is the temperature of the TES tank, and $T_B(t)$ and $T_C(t)$ are the temperatures at nodes B and C respectively, and $q_{\text{whb}}(t)$ is the flow rate directed to the waste heat boilers. Analogously, the energy balance at node C is

$$q_{\text{whb}}(t)C_pT_{\text{whb}}(t) + q_A(t)C_pT_{\text{TES}}(t) - q_{\text{sys}}(t)C_pT_C(t) - q_B(t)C_pT_C(t) = 0, \quad (6)$$

with $T_{\text{whb}}(t)$ as the outlet temperature of the waste heat boilers, while at node D, the energy balance is given by

$$q_{\text{bp}}(t)C_pT_{\text{dh,ret}}(t) + q_{\text{sys}}(t)C_pT_C(t) - q_{\text{dh}}(t)C_pT_D(t) = 0, \quad (7)$$

where $T_D(t)$ is the inlet temperature of the peak heating boilers.

For both waste heat and peak heating boilers, we assume that the heat is uniform and rapidly transferred to the main stream; this way, dynamics are not taken into account. Therefore, the energy balance around the peak heating boilers is given by

$$Q_{\text{phb}}(t) - q_{\text{dh}}(t)C_p(T_{\text{phb}}(t) - T_D(t)) = 0, \quad (8)$$

where $Q_{\text{phb}}(t)$ is the peak heating rate required to bring the water to the demand supply temperature, and $T_{\text{phb}}(t)$ is the outlet temperature of the peak heating boilers. Similarly, the waste heat boilers are described by the following energy balance

$$Q_{\text{whb}}(t) - q_{\text{whb}}(t)C_p(T_{\text{whb}}(t) - T_B(t)) = 0, \quad (9)$$

where $Q_{\text{whb}}(t)$ is the portion of waste heat rate that is transferred to the water. Additionally, an equation comprising the portion that is dumped, $Q_{\text{dump}}(t)$, is necessary, that is

$$Q_{\text{whtotal}}(t) - Q_{\text{whb}}(t) - Q_{\text{dump}}(t) = 0, \quad (10)$$

where $Q_{\text{whtotal}}(t)$ is the total rate of the waste heat available.

Lastly, the energy balance for the TES tank is expressed by

$$\frac{d}{dt}\left(\rho V_{\text{TES}}C_pT_{\text{TES}}(t)\right) = q_A(t)C_p\left(T_{\text{TES}}(t) - T_B(t)\right) - q_B(t)C_p\left(T_{\text{TES}}(t) - T_C(t)\right), \quad (11)$$

where ρ is the water density and V_{TES} is the TES tank volume. Considering that ρ, V_{TES} and C_p are constant, we rearrange this equation and write as the ODE

$$\frac{dT_{\text{TES}}(t)}{dt} = \frac{q_A(t)}{V_{\text{TES}}}\left(T_B(t) - T_{\text{TES}}(t)\right) + \frac{q_B(t)}{V_{\text{TES}}}\left(T_C(t) - T_{\text{TES}}(t)\right). \quad (12)$$

If we take Eqs. (2)–(10) and (12) as constraints, the presence of Eq. (4), which imposes that either q_A or q_B is greater than zero and not both, results in a dynamic optimization problem that can also be classified as a mathematical program with complementarity constraints (MPCC). This type of problem is numerically challenging to solve because the restriction that at least one of the variables in the complementarity must be zero makes the solution space non-smooth. Efficient large-scale NLP solvers require smoothness of the model; therefore, it is common practice to reformulate complementarities so that NLP solvers can be used to solve MPCC problems [27].

Here, however, we can avoid complementarity constraints in the optimization model by using system information known *a priori*. Having both waste heat and heat demand profiles available, we define that the tank is only charged when there is excess heat, and discharged when waste heat surpasses heat demand. This way, the complementarity constraint (4) is replaced with

$$\begin{cases} q_A(t) = 0, & \text{if } Q_{\text{whtotal}}(t) \geq Q_{\text{demand}}(t) \\ q_B(t) = 0, & \text{if } Q_{\text{whtotal}}(t) < Q_{\text{demand}}(t) \end{cases} \quad (13)$$

and the problem becomes a classical dynamic optimization model. Note that the rate at which the tank is charged or discharged is still a free variable, and determined by solving the optimization problem.

3.3.2. Multiple objectives for optimization

We begin setting up the optimization by defining the mathematical model described in the previous subsection as equality constraints. Inequalities corresponding to limitations for the process variables are also added as constraints. Table 1 shows the lower and upper bounds defined for each variable in the optimization problem for limiting their possible value at the solution.

We now need mathematical expressions that can represent the three distinct objectives the short-term TES tank must meet. The first one would be to minimize investment cost, which is a function of the volume of the TES tank. The mathematical expression was obtained from [14], where they used previous implemented projects from [28] to define an equation for investment cost, given by

$$I(V) = 0.0047V_{\text{TES}}^{0.6218}, \quad (14)$$

where $I(V)$ is the initial investment cost in million euros, and V is the tank volume in m^3.

For the second objective we want to reduce the use of peak heating, which economically is equivalent to maximize savings in peak heating cost. This can be described as the difference between the operational cost of peak heating with and without TES, which is expressed by

$$B = C_{\text{peak}}\int_{\text{period}}\left(Q_{\text{phb,noTES}}(t) - Q_{\text{phb}}(t)\right)dt, \quad (15)$$

Table 1
Bounds of the operational variables in the optimization model for sizing a TES tank for DH systems.

Variable	Lower bound	Upper bound	Unit
T_{tes}	40.0	120.0	[°C]
T_B	40.0	120.0	[°C]
T_C	40.0	120.0	[°C]
T_D	40.0	120.0	[°C]
T_{whb}	40.0	120.0	[°C]
Q_{phb}	0.0	∞	[MW]
Q_{whb}	0.0	22	[MW]
Q_{dump}	0.0	Q_{whtotal}	[MW]
q_{whb}	0.0	333.3	$[\frac{\text{kg}}{\text{s}}]$
q_A	0.0	1388.9	$[\frac{\text{kg}}{\text{s}}]$
q_B	0.0	1388.9	$[\frac{\text{kg}}{\text{s}}]$
q_{bp}	0.0	q_{dh}	$[\frac{\text{kg}}{\text{s}}]$
q_{sys}	0.0	q_{dh}	$[\frac{\text{kg}}{\text{s}}]$

where B is the total savings in peak heating, C_{peak} is the price of peak heating per energy unit, and $Q_{\text{phb,noTES}}$ is peak heating consumption without TES.

The third objective is to be able to make up offsets between heat demand and supply, which can be accomplished by storing excess waste heat to be used when demand is greater than waste heat supply. We can express it as minimizing dumped waste heat, $Q_{\text{dump}}(t)$, so that excess energy can be later used in moments of higher demand. Mathematically, this objective can be described as the mean square of waste heat dumped during the considered period,

$$\frac{1}{\Delta_{\text{period}}}\int_{\text{period}} Q_{\text{dump}}(t)^2\,dt, \tag{16}$$

where Δ_{period} is the period length. Raising the waste heat dumped to the power of 2 helps with convergence when solving the optimization problem, which is further discussed in Section 4.1.

As described in Section 2.1.2, the first two objectives are reformulated into a new metric, the payback period, N, given by

$$N = \frac{I(V)}{B}. \tag{17}$$

In addition, to obtain an objective function that results in a scalar, we combine Eqs. (16) and (17) using the weighted sum approach for multi-objective models.

Having the objective function and model constraints, we finally obtain the complete optimization model defined for the problem of sizing a short-term TES tank in this case study, which is mathematically expressed as follows

$$\begin{aligned} \min_{x}\quad & \phi = \alpha N + \beta\frac{1}{\Delta_{\text{period}}}\int_{\text{period}} Q_{\text{dump}}(t)^2\,dt \qquad (18)\\ \text{s.t.}\quad & \text{Eqs. (2), (3), (5)–(13)}\\ & \text{Eqs. (14), (15), (17)}\\ & x_{\text{LB},j} \le x_j \le x_{\text{UB},j} \quad \text{for } j = 1,\dots,n_v, \end{aligned}$$

where β and α are the weighting parameters for the combined objective function, x is a vector containing all variables, x_{LB} and x_{UB} are lower and upper bounds for the variables respectively, and n_v is the total number of variables.

3.3.3. Discretized dynamic optimization problem

To solve the dynamic optimization problems defined for this case study, we use orthogonal collocation of order 1 with Radau collocation points, which is commonly used for dynamic optimization. After the discretization of the resulting dynamic optimization model, we finally obtain a classical NLP problem given by

$$\min_{V_{\text{TES}},q}\quad \phi = \alpha N + \beta\frac{h}{n_t}\|Q_{\text{dump}}\|_2^2 \tag{19a}$$

$$\begin{aligned}
\text{s.t.}\quad & q^i_{\text{dh}} - q^i_{\text{sys}} - q^i_{\text{bp}} = 0 && (19b)\\
& q^i_{\text{sys}} - q^i_{\text{whb}} - q^i_A + q^i_B = 0 && (19c)\\
& q^i_{\text{sys}}C_pT^i_{\text{dh,ret}} + q^i_BC_pT^i_{\text{TES}} - q^i_{\text{whb}}C_pT^i_B - q^i_AC_pT^i_B = 0 && (19d)\\
& q^i_{\text{bp}}C_pT^i_{\text{dh,ret}} + q^i_{\text{sys}}C_pT^i_C - q^i_{\text{dh}}C_pT^i_D = 0 && (19e)\\
& Q^i_{\text{phb}} - q^i_{\text{dh}}C_p(T^i_{\text{phb}} - T^i_D) = 0 && (19f)\\
& Q^i_{\text{whb}} - q^i_{\text{whb}}C_p(T^i_{\text{whb}} - T^i_B) && (19g)\\
& Q^i_{\text{whtotal}} - Q^i_{\text{whb}} - Q^i_{\text{dump}} = 0 && (19h)\\
& T^i_{\text{TES}} = T^{i-1}_{\text{TES}} + h\left(\frac{q^i_A}{V_{\text{TES}}}(T^i_B - T^i_{\text{TES}}) + \frac{q^i_B}{V_{\text{TES}}}(T^i_C - T^i_{\text{TES}})\right) && (19i)\\
& I = 0.0047V_{\text{TES}}^{0.6218} && (19j)\\
& B = C_{\text{peak}}h\sum_{i=1}^{n_t}(Q^i_{\text{phb,noTES}} - Q^i_{\text{phb}}) && (19k)\\
& N\cdot B - I = 0 && (19l)\\
& q^i_A = 0,\quad \text{if } Q^i_{\text{whtotal}} \ge Q^i_{\text{demand}} && (19m)\\
& q^i_B = 0,\quad \text{if } Q^i_{\text{whtotal}} < Q^i_{\text{demand}}, && (19n)\\
& x_{\text{LB},j} \le x^i_j \le x_{\text{UB},j} \quad \text{for } j = 1,\dots,n_v,
\end{aligned}$$

where h is the time step size, $i = 1,\dots,n_t$, and T^0_{TES} is the initial TES tank temperature. This NLP problem is implemented in Julia, using JuMP [29] as mathematical programming language and Ipopt [30] as the NLP solver.

3.4. Step 2: Interval selection

The interval length must be defined for the screening of the data described in Section 2.2. We consider a time scale for energy storage of 3 days, that is, we define the interval length to be 3 days. The idea is that, within 3 days, the TES tank should be able to make up for offsets between heat demand and supply. Bounds for the volume tank are also determined; we consider upper and lower bounds to be 5000 and 100 m^3 respectively. To solve the optimization model in this step, the weighting parameters of the multi-objective function are set to $\alpha = 0.1$ and $\beta = 0.9$, i.e., in this step, the optimization focuses mainly on storing energy to avoid dumping excess heat. In addition, the dynamic variable, T_{TES}, needs an initial value; for the first interval, it is set to 95 °C (which is approximately in the middle between the bounds), and the following ones use the end TES tank temperature of the previous interval. For each three-day period, problem (19) is solved. Any three-day that yields a TES volume between 100 and 5000 m^3 is selected as a heat-storage interval, and is later included in the overall volume calculation in Step 3.

3.5. Step 3: Optimal TES volume calculation

Now the intervals selected in Step 2 are combined into an overall period, which is used for determining an optimal TES volume by solving Eq. (19) one more time. For that, the initial value for T_{TES} is also set to 95 °C. Moreover, to analyze the system thoroughly, we perform a trade-off analysis of the competing objective functions, with β varying from 0.1 to 0.9 and α accordingly.

4. Results and discussion

This section presents numerical results of the case study based on the data from the Mo District Heating system. We start by discussing the optimization model, focusing on an analysis of the degrees of freedom and ill-conditioning handling. Next, results for the interval selection based on 3-day periods are shown, followed by an analysis of the optimal TES tank volume calculated for the complete 6-month period considered for this study.

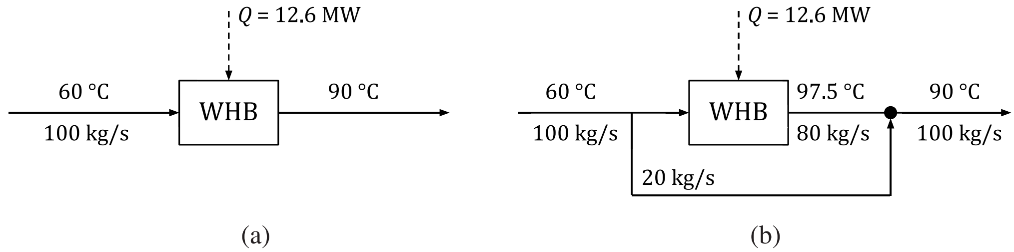


Fig. 5. Example of non-unique solutions.

4.1. Step 1: Optimization model set-up

Before solving an optimization problem, it is important to analyze some aspects of the model to better understand its limitations and interpret the results. A relevant analysis to perform is to inspect the degrees of freedom of the set of equations acting as equality constraints for the problem, as they indicate the flexibility of the model. Here we have 4 free dynamic variables (total of $4 \times n_t$ discretized variables) plus 1 static variable; the latter can be defined to be the volume of the tank and the former, how the water is distributed within the system, i.e., q_{sys}, q_{bp}, q_{whb}, and q_A or q_B, depending on constraints (19m) and (19n).

4.1.1. Handling non-unique solutions

For a design problem, we ideally would like only V_{TES} to be a free variable, since having the flow distribution as free variables translates to non-unique solutions for this case, that is, different configurations can lead to the same optimal value for the objective function. For instance, suppose that 100 kg/s of water returns from the district at 60 °C and that the heat rate at the waste heat boilers is 12.6 MW, as shown in Fig. 5a. If all the water is directed to the waste heat boiler, it reaches 90 °C, but if 20 kg/s of returning water bypasses the system, the remaining stream leaves the waste heat boiler at 97.5 °C, and once they are mixed again (see Fig. 5b), the new temperature stream is 90 °C as well. From an operational point of view, there would be no reason to bypass a fraction of the returning water. However, these two situations are mathematically equivalent with respect to the objective function, no waste heat is dumped and they do not influence the volume of the tank or savings.

Due to the model formulation, there are infinite flow distributions that can result in the same objective function value, which means that the optimization problem is ill-posed. One could implement a complete control model that would determine the exact optimal operation, for example, to tackle this issue. However, it would greatly increase the complexity of the problem. Since this methodology focuses on finding an optimal volume for the TES tank, obtaining the most physically meaningful flow distribution is not a priority; having a mathematical tractable model is more important at this stage. Therefore, to deal with the situations illustrated in the previous paragraph, we add ℓ_2-regularization terms to the objective function to help the solver converge to a local minimum that selects one flow distribution among the possible solutions. The regularized objective function is then given by

$$\phi = \alpha N + \beta \frac{h}{n_t} \|Q_{\mathrm{dump}}\|_2^2 + \kappa_1 \|q_{\mathrm{whb}}\|_2^2 + \kappa_2 \|q_{\mathrm{bp}}\|_2^2, \tag{20}$$

where κ_1 and κ_2 are tuning parameters set to 10^{-10}, which is small enough to help convergence to a unique point and such that its effect on charging and discharging of the TES tank can be neglected.

4.1.2. Quadratic vs. linear penalty terms

To illustrate how the curvature introduced by using quadratic terms in the objective function influences the results, consider a toy example for an 8-hour interval represented in Fig. 6. There is excess waste heat for almost the entire period, except from 3 to 4 h when demand is greater and peak heating is used. In the top plot, we calculated the optimal TES tank volume for this interval with a linear term for waste heat dumped, $\|Q_{\mathrm{dump}}\|_1$, in the objective function, while the bottom top was obtained using the quadratic term, $\|Q_{\mathrm{dump}}\|_2^2$, in Eq. (19a); these results are represented by solid lines (scenario I). We create a second scenario (II) by subtracting 1 MW from waste heat dumped in the first hour and adding it to the second hour, that is, an extra 1 MW of waste heat is used in the first hour and the same amount is discounted in the second hour. The optimization problem is then re-solved. As expected, in both scenarios the formulation with the linear term results in the same objective value of 61.86. However, the formulation with the quadratic term was lower in the first scenario when heat dump is kept approximately steady, resulting in an objective value of 62.65; while for the second scenario this value was 62.92.

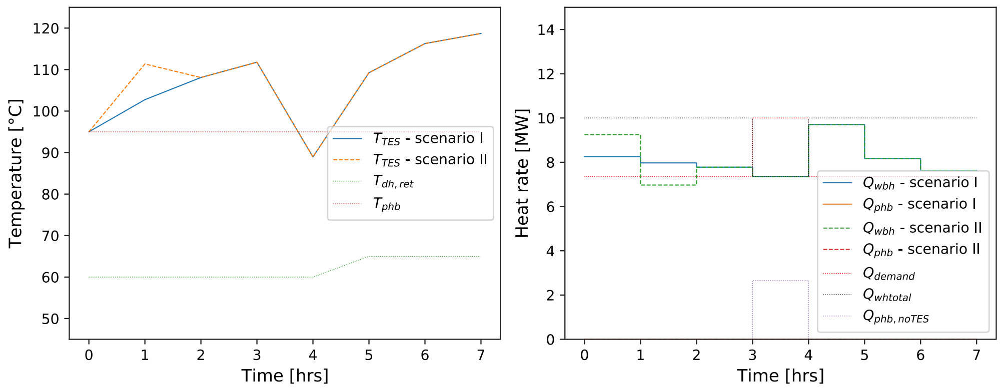
These observations show that the solver might have issues choosing one of these results for the linear term, but the quadratic term is better defined and the solver converges more easily to the first scenario. The overall results, however, are all equivalent when we look at the goals of the TES tank; they all result in the same volume of 100 m^3, peak heating is not used, and the temperature of the tank is the same by the end of the interval, having the same amount of energy stored for future use. Therefore, for this method, we prioritize convergence properties and assume that the local solutions to the optimization problem are mathematically equivalent to the optimal operation conditions, meaning that realistic optimal conditions should result in the same objective value and energy balance.

4.2. Step 2: Interval selection

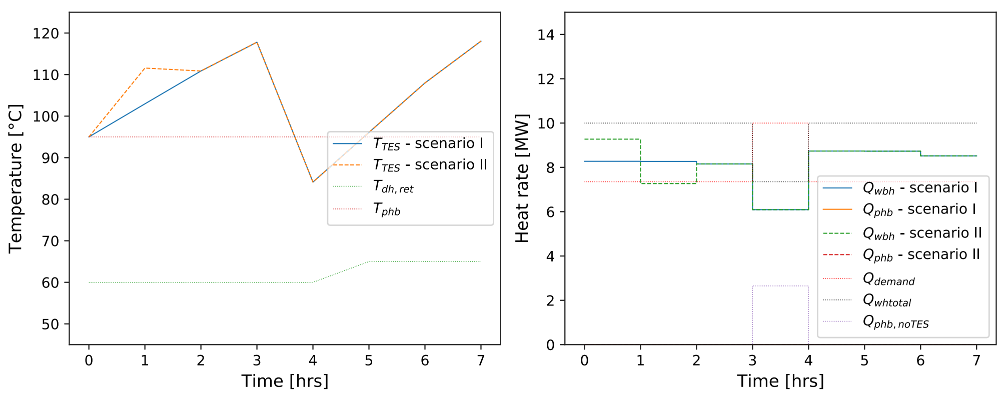
Based on the decision to consider energy storage on a time scale of 3 days, the period from November 2018 to April 2019 was divided into sixty 3-day intervals and the nonlinear optimization problem described by Eq. (19) was solved for each interval. Fig. 7 shows the results for three representative intervals illustrating three possible scenarios. The left plot of each interval presents the TES tank, DH return, and DH supply temperatures, while plots on the right show waste heat supply and heat demand as well as peak heating use with and without a TES tank.

In the first scenario, shown in the top two plots, Fig. 7a, there is mostly excess waste heat with a small use of peak heating at about 15 and 70 h (purple dotted line in left plot), which can be avoided with a small tank volume, so the optimal volume for this interval hits lower bound. Therefore, any volume within the possible range would be suited to eliminate peak heating use for this window, and it is not selected as a relevant interval.

Note that the results shown in Fig. 7a also illustrate the discussion on multiple solutions presented in the previous subsection. For this interval, heat demand (dashed green line in right plot) is only considerably greater than the waste heat available (dashed red line in right plot) at about 14 and 69 h, when peak heating is used. Since the initial temperature of the tank is 95 °C, the tank could be initially charged, then discharged to avoid the use of peak heating, and charged again to store more energy. However, we can see by the temperature variation (solid blue line in the left plot) throughout the interval that the tank



(a) $||Q_{\text{dump}}||_1$



(b) $||Q_{\text{dump}}||_2^2$

Fig. 6. Toy example for comparing the effects of using linear (a) or quadratic (b) terms for waste heat dump in the objective function, both lead to a tank volume of 100 m^3. However, the quadratic formulation gives better convergence properties.

is charging during most of the initial period, discharging at about 10 h for a short period (which decreases its temperature), but ending at a high temperature with stored energy. Even though this operation would not be performed in practice, it represents the flow distribution that minimizes the mean square of waste heat dumped, and the objectives of the TES tank are met with a 100 m^3: peak heating is completely avoided and energy is stored for later use.

For the second period, Fig. 7b, heat demand (dashed green line in right plot) is larger than supply (dashed red line in right plot) during the entire interval, and the TES tank temperature (solid blue line in the left plot) is lower than the return temperature from the district (dashed orange line in the left plot) for some small periods, specifically between 20 and 30 h and about 50 and 65 h. When the return temperature is lower than the TES tank temperature, heat stored in the TES tank can be used, indicated by the decrease in its temperature. In this case, the calculated TES tank volume hits upper bound, since the larger the volume the more heat is available in the tank. However, given the little difference between the TES tank and return temperatures here, potential savings are very small compared to the cost of the tank; hence this interval is also not selected.

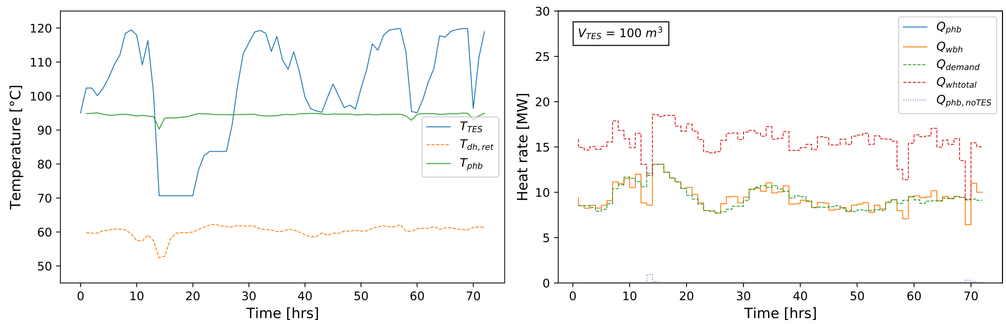
The last 3-day interval, Fig. 7c, has alternating moments of waste heat surplus and shortage. The optimal volume for this interval is within the defined range, and both the TES tank temperature (solid blue line in the left plot) and heat savings (difference between the dotted purple line and the solid blue line in the right plot) show that this interval is relevant for the long-period optimization problem, and, hence, is selected.

Regarding the interval selection for the entire season, 25 out of 60 intervals were selected using the criteria presented in Section 2.2; their optimal TES tank volumes were not at upper or lower bounds. This reduces the size of the final optimization problem for finding the tank size by almost 60%. The distribution of the selected screened optimal tank size values is presented in Fig. 8. We can see that approximately half of the intervals resulted in small tank volumes, i.e., lower than 500 m^3, while the remaining optimal volumes are distributed from 500 to 3500 m^3. Lower optimal volumes can result from intervals in which offsets between heat demand and waste heat supply are not too large. Intervals with several alternating short moments of surplus and shortage of waste heat supply, such as the interval corresponding to the plots in Fig. 7c, also lead to lower optimal volumes. On the other hand, greater volumes are associated with longer periods of waste heat shortage, small waste heat excess compared to heat demand, and/or low initial temperature of the TES tank, since, in these situations, the tank would need to have enough energy stored to be converted into significant savings. Fig. 9 shows the results of an interval that illustrate these situations. Note that heat demand (dashed green line in the right plot) is greater than the waste heat available (dashed red line in the right plot) during most of the interval, except for a period of around 10 h, approximately from 12 to 22 h. The high initial value and decreasing profile of the temperature of the TES tank (solid blue line in the left plot) indicates that, during this interval, energy previously stored in the tank is consumed to reduce peak heating (from the dotted purple line to the solid blue line in the right plot).

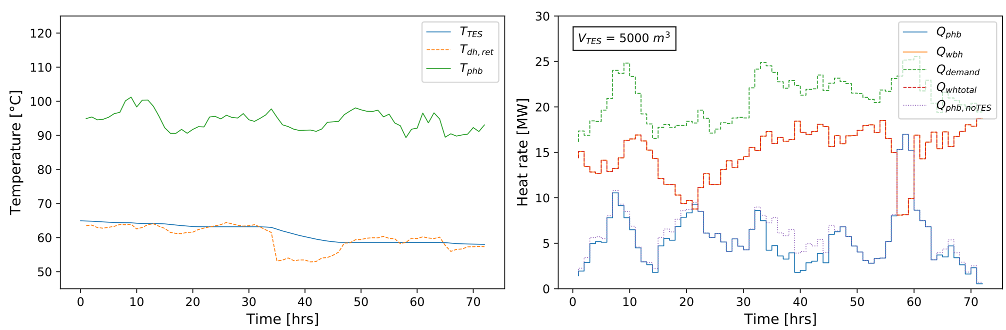
4.3. Step 3: Optimal TES volume calculation

4.3.1. Optimal volume for nominal weights in objective function

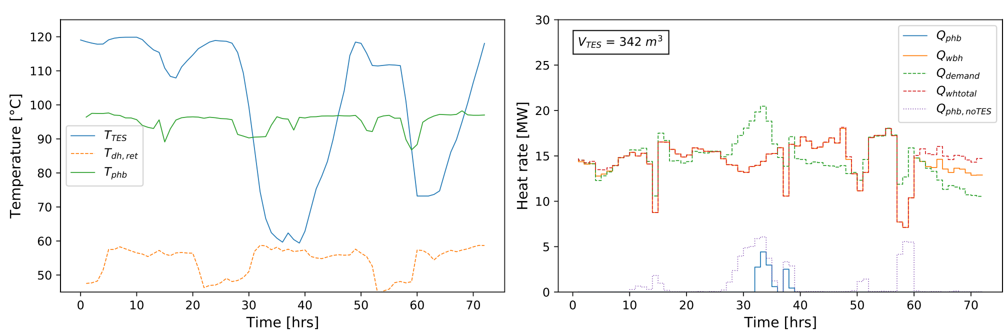
To calculate the optimal volume of the TES tank, data from all the selected intervals was used in the optimization problem (19) to



(a) Too small savings (interval *not* selected for overall sizing problem).



(b) Small savings potential relative to the required size of the tank (interval *not* selected for the overall sizing problem).



(c) Significant savings potential with TES (interval selected for overall sizing problem).

Fig. 7. Temperature and heat profiles for three intervals to illustrate possible scenarios considered for relevance assessment.

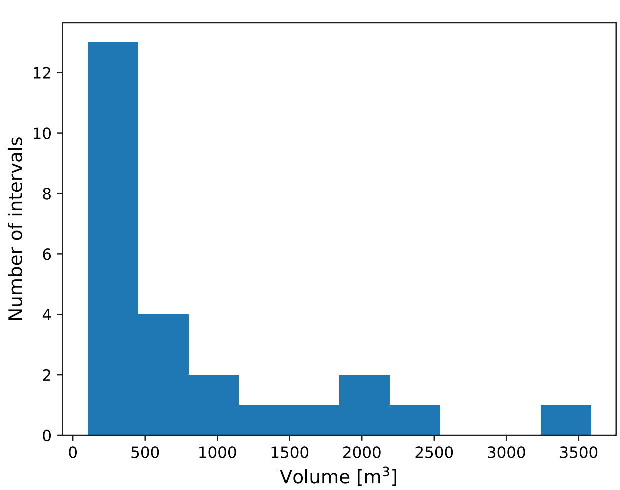


Fig. 8. Histogram with the optimal volumes obtained for the 25 selected intervals.

create a single instance of the optimization model. Using the same weight parameters for the objective function that were employed for the interval selection, i.e. $\alpha = 0.1$ and $\beta = 0.9$, the optimal volume was found to be 4314 m^3. Under the assumption that the selected intervals represent a possible savings of a TES tank in a year, the calculated optimal payback time is 11.66 years and savings are NOK 755,951 per year. Note that, in this case, the weight assigned to dumped waste heat is 9 times greater than the one assigned for the payback time, resulting in large volume and payback time.

4.3.2. *Trade-off analysis*

The results of the trade-off analysis with respect to the weights α and β in the objective function are presented in Fig. 10. The plots were generated by varying α from 0.1 to 0.9, and varying β accordingly such that their sum is 1. The circles describe the relationship between the two contradicting terms in the objective function, total dumped waste heat and the payback time. In addition, the triangles represent how annual savings increase as payback time, and consequently volume, increases. Given that the relationship between the two objectives is

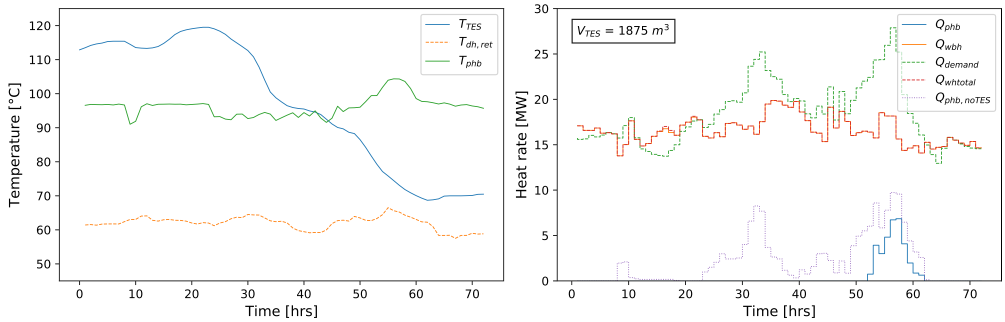


Fig. 9. Temperature and heat profiles for an interval with high heat demand compared to waste heat availability in which energy previously stored is used by the process to reduce peak heating.

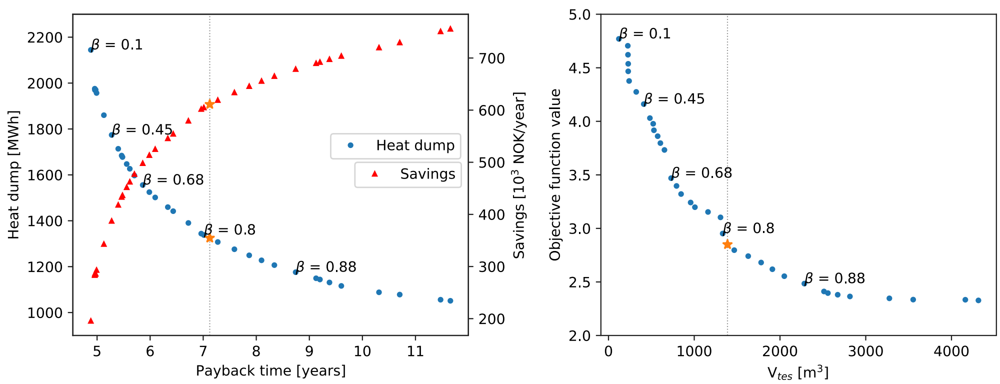


Fig. 10. Trade-off between dumped waste heat and payback time (left) and objective value as a function of volume (right) with varying weight parameters. Values for the weight β are shown for some points. The selected volume (1388 m^3) for the short-term storage tank is marked by the star symbol.

concave, choosing an optimal volume for the TES tank is a trade-off situation, a solution that can minimize both objectives simultaneously is not possible, as expected.

By analyzing Fig. 10, we decide $V = 1388$ m^3, corresponding to a payback time of 7.12 years and savings of NOK 611,159, to be a suitable volume for a short-term TES tank in the Mo District Heating system, which is the highlighted point in the set. Besides being a volume that represents a compromise between both objectives, the payback time seems reasonable [12] and we can see that, starting at this point, the rate of change for the savings presents a more accentuated decline. A 1-year shorter payback time would reduce savings in approximately NOK 86,000 per year. However, increasing the payback time with 1-year, the savings would only increase about NOK 45,000 per year. Moreover, our result is in the same range as found in earlier case studies [9,12] for the heating plant of Mo District Heating. However, differently from these studies, our work uses a rigorous optimizer to determine the optimal volume.

Fig. 11 shows the resulting operating conditions for the entire 6-month period for the selected TES tank volume. The temperature profile for the TES tank is presented in the top plot, original peak heating use is compared against peak heating use with the optimal TES tank in the middle plot, and an analogous comparison is made for waste heat dumping in the bottom plot. The reduction in peak heating use and waste heat dumping are evident, as shown in both middle and bottom plots, specially in periods with alternating waste heat excess and higher demand.

4.4. General discussion

The proposed method has the advantage of being simple to implement using any scientific programming language while being able to consider moderately complex models based on operating conditions of the process. Compared with iterative, steady-state or simulation-based approaches, the suitable TES volume can be identified from a full space of solutions. This avoids exhaustive investigation of discretized TES candidate size, and enables better precision of the sizing decision. The class of dynamic optimization problems considered in this work can be challenging because they are likely to have infinite solutions. Therefore, carefully formulating the problem and understanding its mathematical properties are required. An analysis of the multi-objective optimization model, such as the one presented in Section 4.1, is important to ensure convergence and for the critical evaluation and interpretation of the results.

Another important feature is that this model is general and not limited to the case study presented. Other types of TES for short-term operation, e.g. latent heat storage, can be used as long as a numerical model for operation is available. In this case, the implementation of the steps would remain the same, formulation of the optimization model based on a mathematical representation of the operating conditions of the TES and process, interval screening and solution of the multi-objective model. However, the interval length for discretization can change based on the process and storage necessity.

5. Conclusion

The problem of finding an optimal volume for a short-term TES tank for a DH system using waste heat with high variability based on operating conditions has two main challenges: dealing with the different time-scales for both the payback period and the operation of the TES tank, and finding a trade-off between the conflicting objectives of the tank, namely minimizing investment cost and minimizing waste heat dumping. We have shown that a single multi-objective dynamic optimization model can be systematically used to evaluate decrease of peak heating consumption in short-term periods and select the relevant ones to obtain an optimal volume for a long horizon. The multi-objective formulation can be used to study the trade-off of the different

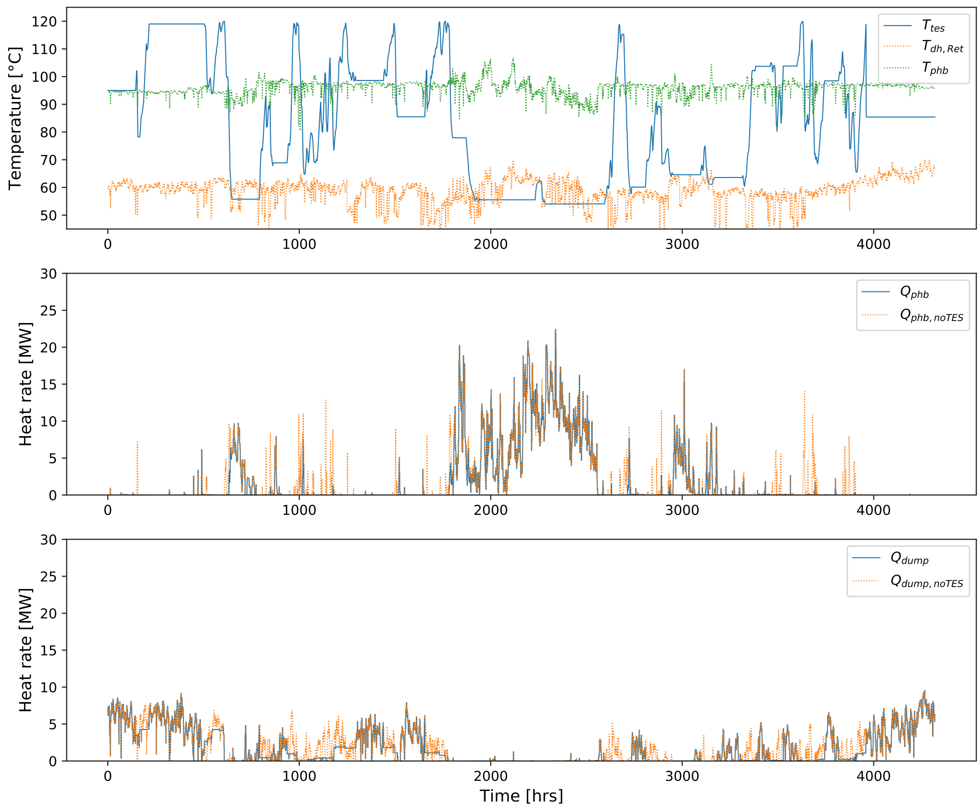


Fig. 11. Optimal operating condition results for optimal TES tank volume of 1388 m^3.

goals set to short-term TES tanks. For the case study considered, by carefully analyzing the results, we selected a volume of 1388 m^3 within a range of 100–5000 m^3 as the optimal volume for the Mo District Heating system.

CRediT authorship contribution statement

Caroline S.M. Nakama: Conceptualization, Methodology, Software, Investigation, Validation, Writing – original draft, Writing – review & editing. **Brage R. Knudsen:** Conceptualization, Validation, Resources, Writing – original draft, Writing – review & editing. **Agnes C. Tysland:** Conceptualization, Software, Writing – review & editing. **Johannes Jäschke:** Conceptualization, Validation, Resources, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

This work was supported by the Research Council of Norway (RCN) through FRIPRO Project SensPATH and HighEFF - Centre for an Energy Efficient and Competitive Industry for the Future under the FME-scheme (Centre for Environment-friendly Energy Research, 257632). The support from the RCN and the user partners of HighEFF is greatly appreciated. The authors thank Jørn Hanssen and Terje Sund-Olsen at Mo Fjernvarme for providing data and information about the case study, and Mandar Thombre for helpful discussions.

References

[1] United Nations Environment Programme. Emissions gap report 2021: The heat is on – a world of climate promises not yet delivered. Technical report, Nairobi; 2021.
[2] In focus: Energy efficiency in buildings. 2020, https://ec.europa.eu/info/news/focus-energy-efficiency-buildings-2020-feb-17_en, Accessed: 2022-02-22.
[3] Connolly D, Lund H, Mathiesen BV, Werner S, Möller B, Persson U, Boermans T, Trier D, Østergaard PA, Nielsen S. Heat roadmap Europe: Combining district heating with heat savings to decarbonise the EU energy system. Energy Policy 2014;65:475–89.
[4] Zhang H, Baeyens J, Caceres G, Degreve J, Lv Y. Thermal energy storage: Recent developments and practical aspects. Prog Energy Combust Sci 2016;53:1–40.
[5] Cao Y, Lee SB, Subramanian VR, Zavala VM. Multiscale model predictive control of battery systems for frequency regulation markets using physics-based models. J Process Control 2020;90:46–55.
[6] Li Z, Lu Y, Huang R, Chang J, Yu X, Jiang R, Yu X, Roskilly AP. Applications and technological challenges for heat recovery, storage and utilisation with latent thermal energy storage. Appl Energy 2021;283:116277.
[7] Olsthoorn D, Haghighat F, Mirzaei PA. Integration of storage and renewable energy into district heating systems: A review of modelling and optimization. Sol Energy 2016;136:49–64.
[8] Guelpa E, Verda V. Thermal energy storage in district heating and cooling systems: A review. Appl Energy 2019;252(March):113474.
[9] Knudsen BR, Rohde D, Kauko H. Thermal energy storage sizing for industrial waste-heat utilization in district heating: A model predictive control approach. Energy 2021;234:121200.
[10] Martínez-Lera S, Ballester J, Martínez-Lera J. Analysis and sizing of thermal energy storage in combined heating, cooling and power plants for buildings. Appl Energy 2013;106:127–42.
[11] Labidi M, Eynard J, Faugeroux O. Optimal design of thermal storage tanks for multi-energy district boilers. In: 4th inverse problems, design and optimization symposium (IPDO-2013). 2013.
[12] Kauko H, Rohde D, Knudsen BR, Sund-Olsen T. Potential of thermal energy storage for a district heating system utilizing industrial waste heat. Energies 2020;13:3923.
[13] Pinnau S, Breitkopf C. Determination of Thermal Energy Storage (TES) characteristics by Fourier analysis of heat load profiles. Energy Convers Manage 2015;101:343–51.
[14] Li H, Hou J, Hong T, Ding Y, Nord N. Energy, economic, and environmental analysis of integration of thermal energy storage into district heating systems using waste heat from data centres. Energy 2021;219:119582.

[15] Hiris DP, Pop OG, Balan MC. Preliminary sizing of solar district heating systems with seasonal water thermal storage. Heliyon 2022;8(2):e08932.
[16] Sartor K, Dewallef P. Integration of heat storage system into district heating networks fed by a biomass CHP plant. J Energy Storage 2018;15:350–8.
[17] Badami M, Fonti A, Carpignano A, Grosso D. Design of district heating networks through an integrated thermo-fluid dynamics and reliability modelling approach. Energy 2018;144:826–38.
[18] Benalcazar P. Optimal sizing of thermal energy storage systems for CHP plants considering specific investment costs: A case study. Energy 2021;234:121323.
[19] Morvaj B, Evins R, Carmeliet J. Optimising urban energy systems: Simultaneous system sizing, operation and district heating network layout. Energy 2016;116:619–36.
[20] Simeoni P, Ciotti G, Cottes M, Meneghetti A. Integrating industrial waste heat recovery into sustainable smart energy systems. Energy 2019;175:941–51.
[21] Urbanucci L, D'Ettorre F, Testi D. A comprehensive methodology for the integrated optimal sizing and operation of cogeneration systems with thermal energy storage. Energies 2019;12(5).
[22] Birk W, Atta KT, Uden F. Improving District Heating System Operation through Control Configuration Selection and Adaptive Control. In: European control conference. 2019, p. 2944–9.
[23] D'Ettorre F, Conti P, Schito E, Testi D. Model predictive control of a hybrid heat pump system and impact of the prediction horizon on cost-saving potential and optimal storage capacity. Appl Therm Eng 2019;148(April 2018):524–35.
[24] Thombre M, Prakash S, Knudsen B, Jäschke J. Optimizing the Capacity of Thermal Energy Storage in Industrial Clusters. In: Computer aided chemical engineering, Vol. 48. 2020, p. 1459–64.
[25] Yang X-S. Chapter 14 - multi-objective optimization. In: Yang X-S, editor. Nature-inspired optimization algorithms. Oxford: Elsevier; 2014, p. 197–211.
[26] Biegler LT. An overview of simultaneous strategies for dynamic optimization. Chem Eng Process: Process Intensif 2007;46(11):1043–53.
[27] Baumrucker B, Renfro JG, Biegler LT. MPEC problem formulations and solution strategies with chemical engineering applications. Comput Chem Eng 2008;32(12):2903–13.
[28] Mangold D, Deschaintre L. Seasonal thermal energy storage: Report on state of the art and necessary further R+D. IEA SHC Task 45, 2015.
[29] Dunning I, Huchette J, Lubin M. JuMP: A modeling language for mathematical optimization. SIAM Rev 2017;59(2):295–320.
[30] Wächter A, Biegler LT. On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. Math Program 2006;106(1):25–57.