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Data-based modeling for optimizing the operation of seasonal underground storages

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Abstract

Underground thermal energy storages (UTES) are essential for decarbonizing the existing heating networks. To accurately simulate the storage and the connected heat supply system, typically detailed numerical models of the UTES and the heat supply system are required. In a co-simulation these models must be coupled, which is often time-consuming and has therefore not been used to operate systems in real-time. In this contribution, we present a method that leads to a data-based surrogate model of low complexity, which can then be directly integrated in the operational optimization. To illustrate the method, we derive a surrogate model from a Feflow model of a borehole thermal energy storage (BTES) as a particular type of UTES and integrate the surrogate model into a supply system that is optimized for electrical energy consumption using the Python toolbox Pyomo.

1. Introduction

Seasonal thermal energy storages (STES) are a central component for implementing the transformation to renewable heat generation by counteracting the mismatch between renewable energy potentials and heat demand. A particular class of STES of increasing popularity are underground thermal energy storages (UTES), since they show a high scalability, low investment costs and, since the heat is stored underground, they require relatively low surface area, which makes them a favorable storage option in densely populated areas with space limitations in particular for larger heat supply systems such as district heating networks. However, the large-scale roll out of UTES is still hindered due to the fact that the selection of a suitable UTES technology strongly depends on site specific geological conditions, diverse regulatory framework conditions on national level and unused optimization potential within the system integration. (Fleuchaus 2020; Yang et al. 2021; Lyden et al. 2022)

Furthermore, the structure and complexity of heat supply systems where the UTES is integrated changes due to the ongoing transformation of the heat supply system, as well. Future heat supply systems contain besides STESs, multiple heat sources such as waste heat, renewable heat, or power-to-heat devices and short-term thermal storages.

To ensure high performance and operation efficiency on the condition of a robust system operation, these heat supply systems require advanced control and operation strategies. To achieve this, an important and already successfully implemented control strategy at several demosites, is the management of the heat demand using the thermal storage potentials of buildings allowing for lowering the heat supply temperatures and shaving of peaks in the heat demand (VITO NV 2023).

To further improve the operation performance of future district heating networks this demand-side management must be combined with a supply-side management of multiple heat sources including the UTESs.

In this note, we focus on the thermal management of several heating sources on the supply side, such as waste and solar thermal heat in combination with UTES. The goal of the control strategy is to optimize the operational costs. Here we consider a heat pump and an electric heater whose electricity costs are minimized, leading to the minimization of the deployment of rare and expensive peak load energy.

To allow for optimal operation of the system, we require control-oriented models of the subcomponents of the system, such as the power-to-heat units, the heat sources, and the heat storages. Here we consider rather simple models for these components. In fact, the heat flow produced by the heat sources is given and can be determined from data of the demosite. During operation, only the electrical power of the Power-to-Heat components and the mass-flows can be controlled to optimally charge and discharge the heat storages.

The most challenging part is to accurately model the UTES. In the context of simulations, the use of finite-element models (FEMs) is quite popular and simulation software packages such as Feflow provide accurate models. Such software packages are generally limited to the simulation of the system behavior under known inputs and can only be used to a very limited extent for operational optimization, especially when the required simulation time is large (Gosavi 2015). Therefore, we use a different approach by constructing reduced order black box models that still capture the dynamics of the UTES. These models are constructed using a standard method from system identification called the Kalman-Ho algorithm, see e.g. (De Schutter 2000). The dynamical black-box models can be used as constraints in an optimization problem, which describes e.g. the minimization of operational costs. The construction of dynamic black-box models and reduced order models for UTES is not new. For borehole thermal energy storages (BTES), a similar approach was used in (Fiorentini et al. 2023) for design optimization of a BTES within a heating network. Other approaches to include simplified models of UTES in the context of optimizing the system operation have been used in Saloux and Candanedo, where an RC-type model was developed, and in Gabrielli et al.(2018), where the g-function was utilized. The drawback of these models is that it is not clear whether they capture the important dynamical features of the storage dynamics which is required for accurate prediction of the system behavior. Also, the interaction of the storage with the ambient ground and air involves several parameters accounting for the site-specific geological conditions and might also involve restrictive assumptions on the geometry of the UTES. In our approach, we directly use the simulation data that can be obtained from various simulation tools, with the ultimate aim that our method can later be applied to the data from a suitable real-world measurement campaign. We pursue the objective to provide a control focused integrated UTES model with sufficient accuracy for operation optimization purposes, to replace time-consuming co-simulation and provide a software independent approach with high transferability.

2. Modeling of heat supply system with multiple sources

The overall heat supply system is depicted in Fig. 1. It can be viewed as a graph whose edges model the transmission pipes or heat sources allowing for heat exchange and whose vertices represent either pipe junctions or heat storages. The heat exchange is established via the edges, where each edge has a mass flow $\dot{m} \geq 0$, ingoing and outgoing temperatures T_{in} and T_{out}, respectively. Hence, the heat flow $\dot{Q}$ that is exchanged via the considered edge is given by

$$\dot{Q} = c_p \cdot \dot{m} \cdot \Delta T, \qquad \Delta T = T_{out} - T_{in}, \tag{1}$$

where c_p is the specific heat of water. To allow for optimal operation and control of the thermal system, we consider dynamic models for the change of temperature in each of the multiple heat sources.

The system operation on the supply side can be described as follows: The water stored in the UTES at temperature T_{utes} is pumped via mass flows $\dot{m}_{sol}$ and $\dot{m}_{wst}$ towards the solar thermal and the waste

heat source, respectively. The heated water then enters the buffer storage (TES). The mass flow exiting the buffer storage is then split up into $\dot{m}_{tes\to utes}$ and $\dot{m}_{tes\to hp}$ where $\dot{m}_{tes\to utes}$ is directly pumped into the UTES and $\dot{m}_{tes\to hp}$ is used as a heating source for the heat pump. An additional feed $\dot{m}_{utes\to tes}$ enables mass flows from the UTES to the buffer storage.
We assume that the heat sources have an internal controller that regulates the output temperature in such a way that a certain constant temperature increase ΔT is achieved. Therefore, at any time instance $k \geq 0$, the mass flows $\dot{m}_{sol}(k)$ and $\dot{m}_{wst}(k)$ can be determined from known heat powers by

$$\dot{Q}_{sol}(k) = c_p \cdot \dot{m}_{sol}(k) \cdot \Delta T_{sol}, \qquad \text{and} \qquad \dot{Q}_{wst}(k) = c_p \cdot \dot{m}_{wst}(k) \cdot \Delta T_{wst}. \tag{2}$$

Furthermore, the system contains a heat pump between the supply side and the demand side, which could represent a district heating network.

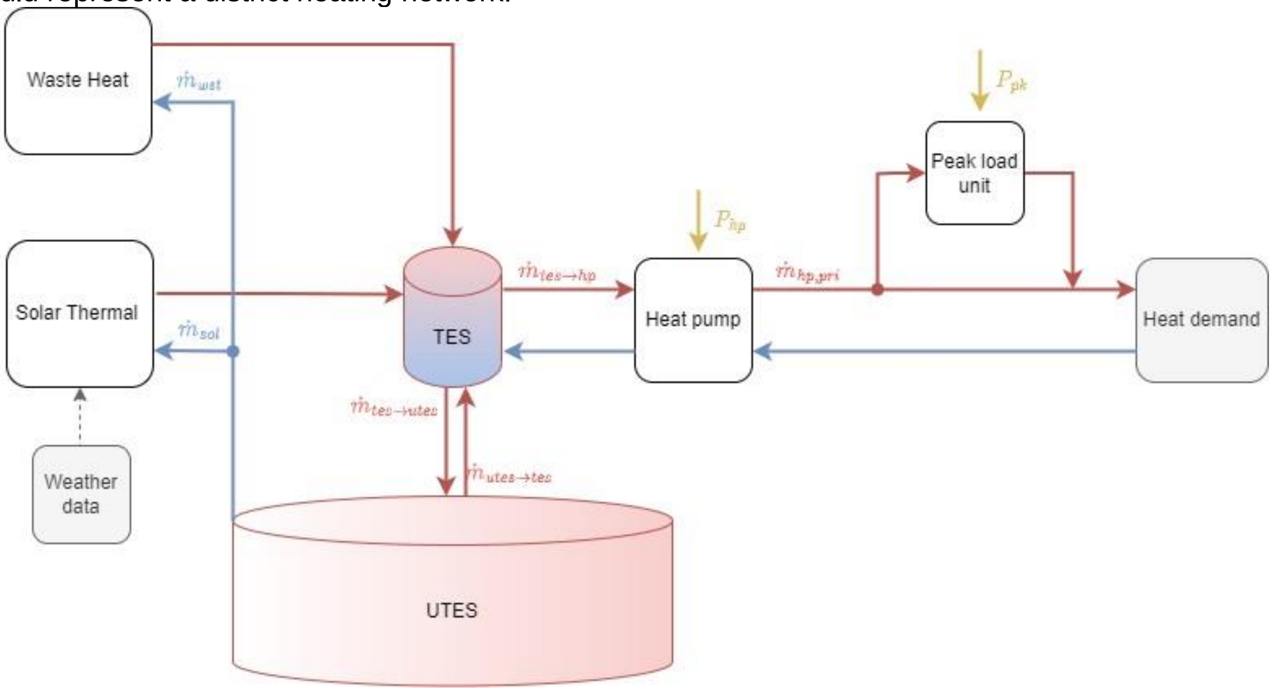

Fig. 1: Sketch of the heat supply system including the mass flows $\dot{m}$ between the units.

The heat pump is described by the following set of equations

$$\dot{Q}_{hp,pri}(k) = COP(k) \cdot P_{hp}(k) = \eta \cdot \frac{T_{hp,pri}(k)}{T_{hp,pri}(k) - T_{hp,sec}(k)} P_{hp}(k), \tag{3}$$

where COP is the coefficient of performance, η is the Carnot efficiency, P_{hp} is the electric power consumed by the heat pump, $T_{hp,sec}$ is the fluid temperature on the secondary side of the heat pump, and $T_{hp,pri}$ is the temperature on the primary side, which is typically fixed by the heat supplier. Besides the heat pump, there is an electric heater on the demand side to cover potential peak demands with an efficiency of η_{pk}. The heat flow on the secondary side of the heat pump $\dot{Q}_{hp,sec}(k)$ is described by (1) with a constant $\Delta T_{hp,\,sec}$. On the primary side, we assume a given heat demand $\dot{Q}_{\mathrm{dem}}$, which must be met by the heat generated by the peak load unit and the heat pump

$$\dot{Q}_{dem}(k) = \eta_{pk} P_{pk}(k) + COP(k) P_{hp}(k),\ k \geq 0. \tag{4}$$

Furthermore, the considered heat supply system has two storage units: an underground thermal energy storage (UTES) as well as a buffer storage (TES) between the multiple heat sources and the secondary side of the heat pump. The time evolution of the water temperature T_{tes} in the buffer storage is described by

$$c_p \rho_w V_{tes} T_{tes}(k+1) = c_p \rho_w V_{tes} T_{tes}(k) + \Delta t \cdot \left(\dot{Q}_{in}(k) - \dot{Q}_{out}(k)\right), \qquad k \geq 0, \tag{5}$$

where ρ_w is the density of water, V_{tes} is the storage volume, Δt is the discretization step size, $\dot{Q}_{in}$ and $\dot{Q}_{out}$ are the thermal input and output powers, respectively. In (5) it is assumed that there are no storage losses. For the UTES a linear-time invariant (LTI) black box model is used that is identified from data as described in the following section.

3. Control-oriented black box models and optimization

In this section, we describe a general approach to obtain control-oriented black box models based on simulation data. By a control-oriented model, we mean a linear time-invariant system with matrix coefficients (A, B, C, D) of the following form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k),\ k \geq 0, \qquad x(0) = x_0, \\ y(k) &= Cx(k) + Du(k), \end{aligned} \tag{6}$$

where $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$, $C \in \mathbb{R}^{l\times n}$, and $D \in \mathbb{R}^{l\times m}$ are unknown system matrices, $x(k) \in \mathbb{R}^n$ is an unknown system state, $y(k) \in \mathbb{R}^l$ is the output and $u(k) \in \mathbb{R}^m$ is the control input.

We describe a method for obtaining the unknown matrices (A, B, C, D) that fit to the simulated system input-output data $\{(u(k), y(k))\}_{k\geq 0}$. For simplicity we assume there that the system is given by (6) with initial value $x(0) = 0$, and the input sequence $u(0) = 1,\ u(k) = 0,\ k \geq 1$. The resulting output values can be used to form the Hankel matrix and the shifted Hankel matrix

$$H_{r,r'} = \begin{pmatrix} y(1) & y(2) & \dots & y(r') \\ y(2) & y(3) & \dots & y(r'+1) \\ \vdots & \vdots & & \vdots \\ y(r) & y(r+1) & \dots & y(r'+r-1) \end{pmatrix}, \quad \overline{H}_{r,r'} \begin{pmatrix} y(2) & y(3) & \dots & y(r'+1) \\ y(3) & y(4) & \dots & y(r'+2) \\ \vdots & \vdots & & \vdots \\ y(r+1) & y(r+2) & \dots & y(r'+r) \end{pmatrix}.$$

In the following we state the Kalman-Ho algorithm, see e.g. Section 3.3 in De Schutter (2000) that allows us to recover the matrices (A, B, C, D) by essentially using the singular value decomposition of the Hankel matrix. Here one computes non-singular $U, V \in \mathbb{R}^{n\times n}$ satisfying $UH_{r,r}V = \begin{pmatrix} I_\rho & 0 \\ 0 & 0 \end{pmatrix}$, where $I_\rho \in \mathbb{R}^{\rho\times\rho}$ is the identity. Then using $E_{p,q} = (I_p \quad 0_{p,q-p})$ the system matrices are given by

$$A = E_{\rho,r} P \overline{H}_{r,r} Q E_{\rho,r}^\top, \quad B = E_{\rho,r} P H_{r,r} E_{1,r}^\top, \quad C = E_{1,r} H_{r,r} Q E_{\rho,r}^\top, \quad D = y(0). \tag{7}$$

In the case study, we consider the system setup as shown in Fig. 1, where the UTES is a particular BTES for which the stimulation response data have been obtained from a FEM simulation model. In a preparatory step, the Feflow simulation data $\{(u(k), y(k))\}_{k\geq 0}$ of the input heat flow u and the output heat flow y is generated. Then, (7) is applied to obtain a dynamic black box model (A, B, C, D) for a borehole thermal energy storage (BTES). The aim is to minimize the annual operational costs

of the system
$f(P_{hp}, P_{pk}) = \sum_{i=1}^{N} \nu_{pk}(i) P_{pk}(i) + \nu_{hp}(i) P_{hp}(i)$,
where ν_{pk} and ν_{hp} are the electricity costs to run the electric heater and the heat pump, respectively, and $N = 8760$, which means that we consider time-steps of one hour starting on the first day in January and assuming a perfect forecast of weather and heat demand data. The constraints of the optimization problem consist of the BTES dynamics (6) together with the equations (2) - (5) which are non-linear and non-convex. So far, these constraints are directly passed to optimization problem. For the optimization, we used the Python optimization toolbox Pyomo, see (Bynum et al. 2021), with the solver library IPOPT.

5. Conclusion and discussion

In this contribution, we presented a dynamic model for a heat supply system, which incorporates the mass flows and temperatures. We proposed a method to obtain a control-oriented black box model from FEM simulation data of UTESs that can be incorporated easily within a dynamic optimization model aimed at minimizing the operating costs of a heat supply system by adjusting the electrical power used. Regarding the particular PUSH-IT demosite in Bochum, we plan to create digital FEM models of the Mine storage (MTES) using the Spring software system. Once the model is ready, the methodology presented here can be applied easily to generate the control-oriented black box models for the optimization. Based on the optimization, we will identify scenarios that are economically attractive for UTESs. Due to the rather fast computation of the optimal solution, we anticipate it to be possible to include an outer loop for design and sizing optimization of the heat supply system.

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