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Optimizing the Capacity of Thermal Energy Storage in Industrial Clusters

Mandar Thombre^a, Sandeep Prakash^a and Johannes Jäschke^{a,*}

^aNorwegian University of Science and Technology, Trondheim 7491, Norway johannes.jaschke@ntnu.no

Abstract

A key factor for energy-efficient industrial clusters is the recovery of waste heat. To this end, thermal energy storage (TES) is an appealing technology that facilitates dynamic heat integration between supplier and consumer plants. A long-term strategy for energy savings must involve adequate consideration for the optimal design of the TES. From an industrial perspective, finding the capacity of the TES unit is often based on heuristic rules which may lead to suboptimal design. This approach does not account for the short-term variability in operation of the TES system. Scenario-based stochastic programming approaches, where the operational uncertainty is described in form of discrete scenarios, can be used to find the best design for the TES system. We present two problem formulations for finding the optimal capacity of the TES unit. The first is a single-level formulation where the design and operating constraints are combined for all scenarios, with the objective of minimizing the combined cost of design and operation. The second is a bilevel formulation where the design decisions are taken on the upper level to minimize overall system cost, whereas the lower level problems (one per scenario) represent the optimal operation for the chosen design variables, each minimizing the operating cost for their respective scenarios. We compare the results of the two approaches with an illustrative case study of an industrial cluster with one supplier plant and one consumer plant exchanging heat via a TES unit.

Keywords: thermal energy storage, bilevel programming, industrial cluster

1. Introduction

The storage and reuse of industrial waste heat is vital for improving the energy efficiency of many energy-intensive processes. When multiple industrial plants operate in close proximity of each other, waste heat can be recovered from one plant and supplied to another plant in need of it. Thermal energy storage (TES) can mitigate the issue of asynchronous heat supply and demand by storing energy during off-peak periods and discharging it during peak demands, leading to savings in operating costs. The capital investment costs for installing a TES system are proportional to the capacity of the TES, and may become significantly high. In order to find a trade-off between high capital costs (large capacity) and high operating costs (small capacity), it is worth investigating methods for optimally sizing the TES. A well designed TES system still has to contend with operational uncertainty, for example the daily/weekly fluctuations in heat supply and demand. By incorporating this uncertainty information in the design phase itself, it is possible to size a TES system that is robust against this uncertainty. Solving a single deterministic optimization problem that spans across the entire operation horizon of the TES (typically

multiple years), and accounts for all the heat profile fluctuations therein, is computationally intractable. To overcome this, stochastic programming approaches can be used to optimize the design decisions over a set of representative scenarios of operation.

Our aim is to find a measure for the optimal sizing of the TES equipment - the volume of a TES unit and the areas of the heat exchangers delivering/extracting heat from the TES unit - by rigorously accounting for the uncertain heat supply and demand in operation phase. For the TES system, the decisions can be divided into two stages - design and operation. In the extensive form of stochastic programming (Birge and Louveaux, 2011), the design variables are "here-and-now", whereas the "wait-and-see" operation variables are assigned to each scenario. This results in a single-level optimization problem, where the objective function represents the overall system cost. The design constraints and the operating constraints for each scenario are all imposed together in this formulation.

Another stochastic approach is the bilevel formulation, based on a Stackelberg leaderfollower hypothesis. The upper level problem (leader) identifies the optimal design decisions that minimize the overall cost over a set of scenarios. On the other hand, the lower level problems (followers), representing different scenarios, aim to minimize their corresponding operating cost (see Xu et al. (2017), for example). Bilevel problems are typically nonconvex and NP-hard. However, for cases where the lower level problems can be replaced with their Karush-Kuhn-Tucker (KKT) optimality conditions Dempe and Franke (2019). The KKT reformulation turns the bilevel problem into a single-level mathematical program with complementarity constraints (MPEC). The complementarity constraints can be further linearized using disjunctive programming (Fortuny-Amat and McCarl, 1981), rendering the problem a mixed-integer program.

In this paper, we develop a linear model for the TES system and present the two formulations for optimizing the TES design. The results are compared with the help of a case study that is motivated from an industrial district heating network in northern Norway. We compare the results of the two approaches in terms of design parameters for the TES - its volume and the heat exchanger area.

2. Methodology

The topology of a TES system with one supplier and one consumer is shown in Figure 1. We employ a simplified linear model in terms of heat duties (MW) to represent the TES system. The heat supplier needs to reject $Q_{supply}(t)$ amount of duty, whereas the consumer has a heat demand $Q_{demand}(t)$ to be met. If the TES cannot meet the total demand of the consumer, the excess energy $Q_{peak}(t)$ is imported from an external peak heating source. Similarly, if all of supplied heat cannot be extracted from the supplier, the excess energy $Q_{dump}(t)$ is rejected into a cooling water system. The resulting heat flows into and out of the tank are denoted by $Q_{tes}^{in}(t)$ and $Q_{tes}^{out}(t)$. The energy in the TES unit is denoted by $E_{tes}(t)$ (MWh). Heat losses from the TES unit to the surroundings are denoted by $Q_{loss}(t)$, which proportional to its energy content. The peak heating and heat dumping duties, along with the energy in the TES unit represent the operating variables in the system. $x_{opr} := \{Q_{peak}(t), Q_{dump}(t), E_{tes}(t)\}$ The associated costs (kr/MWh) of importing and dumping heat are $C_{peak}(t)$ and $C_{dump}(t)$ respectively. Considering an operating period from t_0 to t_f , the total operating cost is: $C_{opr} := \int_{t_0}^{t_f} \left(C_{peak}(t) Q_{peak}(t) + C_{dump}(t) Q_{dump}(t) \right) dt$.



Figure 1: An industrial cluster with one supplier and one consumer exchanging heat through a TES unit.

In context of the system design, the required total energy capacity of the TES unit (MWh) is denoted by CAP_{tes} , whereas the required maximum power rating for heat exchange with the TES unit (MW) is POW_{tes} . For taking design decisions, the former gives the basis for choosing the total volume of the tank. Similarly, the power rating is related to the area of the heat exchangers needed to deliver the heat to the TES unit. Thus, CAP_{tes} and POW_{tes} represent the design variables in the system. $x_{des} := \{CAP_{tes}, POW_{tes}\}$ The prices associated with these variables are $C_{cap}(kr/MWh)$ and $C_{pow}(kr/MW)$ respectively. The total design cost is: $C_{des} := C_{cap}CAP_{tes} + C_{pow}POW_{tes}$.

Our aim is to identify the optimal design parameters for TES system under some information about the operational uncertainty. This uncertainty is modeled in terms of Nscenarios, each scenario representing a discrete combination of the heat supply and demand profiles, $Q_{supply}(t)$ and $Q_{demand}(t)$, across the operating period. We consider two different formulations of the design optimization problem, a single-level formulation and a bilevel formulation.

2.1. Single-level formulation

N7

 $CAP_{tes} \ge 0$

Considering N scenarios of operation, the single-level problem is formulated as (1).

$$\min_{x_{opr}, x_{des}} \qquad C_{des} + \sum_{n=1}^{N} \omega_n C_{opr,n}$$
(1a)

s.t.

$$POW_{tes} \ge 0 \tag{1c}$$

$$\dot{E}_{tes,n}(t) = Q_{tes,n}^{in}(t) - Q_{tes,n}^{out}(t) - Q_{loss,n}(t)$$
 $n = 1, ..., N$ (1d)

$$0 \le Q_{peak,n}(t) \le Q_{peak,max} \qquad n = 1, \dots, N \qquad (1e)$$

$$0 \le Q_{dump,n}(t) \le Q_{dump,max} \qquad n = 1, \dots, N \qquad (1f)$$

$$0 \le Q_{tes,n}^m(t) \le POW_{tes} \qquad n = 1, \dots, N \qquad (1g)$$

$$0 \le Q_{tes,n}^{out}(t) \le POW_{tes} \qquad n = 1, \dots, N \qquad (1h)$$

$$0 \le E_{tes,n}(t) \le CAP_{tes} \qquad n = 1, \dots, N \qquad (1i)$$

Here, the subscript *n* represents the *n*th scenario of operation. In the objective (1a), ω_n is the probability associated with the *n*th scenario. Equation (1d) is the energy balance equation for the TES unit, where is the $\dot{E}_{tes,n}(t)$ is the derivative of the energy in the TES

(1b)

unit. The heat flows in and out of the TES unit are upper bounded by the POW_{tes} , and the energy in the TES unit is upper bounded by its capacity CAP_{tes} . For implementation, we discretize all the continuous variables in (1) using constant time steps. The integral in the objective (1a) is thus replaced by the summation over all the discretized time steps. Moreover, we employ a forward Euler scheme to discretize the energy balance equation (1d). This transforms (1) into an LP, solvable by solvers like Gurobi.

2.2. Bilevel formulation

s.t.

In the bilevel formulation (2), the lower level operating variables are constrained to be the optimal solutions of the lower level problems (2d), corresponding to their respective scenarios of operation. The upper level objective function is the overall cost (same as (1)), whereas the objective function of each lower level problem is the operating cost for the corresponding scenario.

$$\min_{x_{des}, x_{opr}} \qquad C_{des} + \sum_{n=1}^{N} \omega_n C_{opr,n}$$
(2a)

$$CAP_{tes} \ge 0$$
 (2b)

$$POW_{tes} \ge 0$$
 (2c)

$$x_{opr,n} \in \underset{x_{opr,n}}{\operatorname{arg\,min}} \quad C_{opr,n} \tag{2d}$$

s.t.

$$\begin{aligned}
\dot{E}_{tes,n}(t) &= Q_{tes,n}^{in}(t) - Q_{tes,n}^{out}(t) - Q_{loss,n}(t) \\
0 &\leq Q_{peak,n}(t) \leq Q_{peak,max} \\
0 &\leq Q_{dump,n}(t) \leq Q_{dump,max} \\
0 &\leq Q_{tes,n}^{in}(t) \leq POW_{tes} \\
0 &\leq Q_{tes,n}^{out}(t) \leq POW_{tes} \\
0 &\leq E_{tes,n}(t) \leq CAP_{tes}
\end{aligned}$$

The notation used for various variables is the same as in (1). Note that the lower level constraints involve the upper level variables. We also use the same discretization scheme as (1) to convert (2) into a linear bilevel program. This linear bilevel program is still non-convex is nature owing to the constraints (2d). However, since the lower level problems (2d) are LPs after discretization, the bilevel problem (2) can be reformulated as an MILP as explained in Section 1, and can thus be solved by solvers like Gurobi.

The formulation (2) has a more restrictive feasible set than (1). The bilevel formulation is thus expected to result in more conservative solutions of the scenario-based stochastic problem, compared to the corresponding single-level formulation.

3. Case study - design basis

An industrial TES system with one supplier and one consumer of heat is studied. To formulate the design problem, 5 years of operation is assumed for the TES unit. The overall objective function (Equations (1a) and (2a)) in the formulation then consists the design cost and the operating cost for 5 years of operation. On the operation level, we consider only hourly variation in the heat duties and, to maintain computational tractability, an operating horizon of one week (168 hours). On the design level, we approximate the total 5-year operating cost by extrapolating the weekly operating cost from the operation level over 5 years of operation. The scenarios for weekly operation are taken from the 2017 winter data for heat supply/demand provided by Mo Fjernvarme, a district heating company in northern Norway. Further, all scenarios are considered equally likely in the formulations (1) and (2). The prices for peak heating, C_{peak} are taken to be the corresponding hourly 2017 electricity prices in northern Norway. The prices for heat dumping, C_{dump} , are assumed to be 1/10th of the peak heating prices. The maximum peak heating and heat dumping rates $Q_{peak,max}$ and $Q_{dump,max}$ are set to be 1 GW each. The design basis for calculating the TES volume and heat exchanger area is as follows. The maximum energy storage capacity CAP_{tes} is related to the TES volume and depends on the total enthalpy change of the TES fluid in the tank between the fully charged and fully discharged state, $CAP_{tes} = \rho C_p V_{tes} \Delta T$. Assuming water as the storage medium and an operating window of 20°C for the storage tank, the following relation is obtained.

$$\mathcal{W}_{tes}\left(\mathrm{m}^{3}\right) = 43.06 * CAP_{tes}\left(\mathrm{MWh}\right) \tag{3}$$

The maximum power rating POW_{tes} corresponds to the maximum duty transferred across the heat exchangers to and from the TES unit, given by $Q = UA(\Delta T)_{LMTD} = mC_p\Delta T$. The ability of the heat exchanger to transfer heat depends on the temperature of the TES unit. Charging to a nearly fully charged TES or discharging from a nearly discharged TES unit would give the maximum area requirement of the heat exchangers. We assume that the TES unit is large enough to have a nearly flat profile across the heat exchanger and use a 10°C approach temperature in the heat exchangers. Using the fluid properties of water, we estimate the lowest $(\Delta T)_{LMTD}$ to be 19.5°C, and get the relation between POW_{tes} and an upper bound for the area required for the heat exchanger as:

$$A_{hex} \left(\mathbf{m}^2 \right) = 60.24 * POW_{tes} \left(\mathbf{MW} \right) \tag{4}$$

Finally, we use a linearized approximation of the total purchased equipment cost as provided by Sinnott and Towler (2009), to estimate our design costs C_{cap} and C_{pow} . Following the factorial method to convert the purchase costs to total design costs, we get the following approximate relations:

$$C_{cap}(\text{mil. NOK } 2017) = 0.7 + 0.11 * CAP_{tes} (MWh)$$
 (5)

$$C_{pow}(\text{mil. NOK } 2017) = 0.095 + 0.3 * POW_{tes}(\text{MW})$$
 (6)

4. Results and discussion

We compare the results between the two formulations while considering 5, 10 and 20 weekly scenarios, chosen from the 2017 winter data. Also, when considering real data, care has to be taken to avoid any outliers that may skew the results of the design optimization. Figure 2 shows that the single-level formulation results in higher TES capacities, whereas the bilevel formulation emphasizes higher HEX areas for efficient heat transfer. This implies that, at higher TES capacities, optimal lower level solutions result in a higher design cost for the bilevel formulation. The bilevel formulation prioritizes minimizing the design objective at the expense of operation objective. Although this results in a higher operation cost for the bilevel formulation (Figure 3), it ensures that the chosen design parameters lead to optimal operation on the lower level. Also interesting to note is that the design costs from the bilevel formulation remain unchanged when scenarios are increased from 10 to 20. The single-level formulation leads to lower overall costs, but



Figure 2: TES volume and HEX area for the two formulations



Figure 3: Design and operating costs for the two formulations

optimal operation is not guaranteed explicitly for any of the chosen scenarios. Including more scenarios seems to reduce the design cost in single-level formulation. Availability of more data would allow us to check if this cost converges to a particular value.

5. Conclusion

In this paper, we compared two stochastic formulations for design optimization of TES systems. The results show that the bilevel formulation prioritizes minimizing the design cost, leading to higher operating costs. On the other hand, the single-level formulation minimizes the overall cost, but does not explicitly account for optimal operation.

References

- J. R. Birge, F. Louveaux, 2011. Introduction to Stochastic Programming, 2nd Edition. Springer Publishing Company, Incorporated.
- S. Dempe, S. Franke, 2019. Solution of bilevel optimization problems using the kkt approach. Optimization 68 (8), 1471–1489.
- J. Fortuny-Amat, B. McCarl, 1981. A representation and economic interpretation of a two-level programming problem. Journal of the Operational Research Society 32 (9), 783–792.
- R. Sinnott, G. Towler, 2009. Chemical Engineering Design. Butterworth-Heinemann/IChemE series. Butterworth-Heinemann.

URL https://books.google.com/books?id=ISQ91AEACAAJ

B. Xu, Y. Wang, Y. Dvorkin, R. Fernández-Blanco, C. A. Silva-Monroy, J. Watson, D. S. Kirschen, 2017. Scalable planning for energy storage in energy and reserve markets. IEEE Transactions on Power Systems 32 (6), 4515–4527.

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