Modeling thermal energy storage – the effect of self-discharge rates on dispatch

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***Abstract*—This paper investigates the impact of different self-discharge rates on the dispatch of pit thermal energy storage (PTES) within the sector-coupled energy system model *Enertile*. We analyze how varying self-discharge rates of PTES influence district heating (DH) generation across different *DH type networks* with distinct renewable heat potentials. Our findings indicate that lower self-discharge rates facilitate increased integration of heat pumps, particularly in DH networks with high shares of these technologies. Additionally, low self-discharge rates lead to a more long-term pattern in storage dispatch. This relationship between self-discharge rates and dispatch behavior significantly affects the overall efficiency and operational strategy of PTES in DH systems. The results underscore the need to account for self-discharge dynamics in energy system modeling, as traditional efficiency metrics may not adequately represent real-world performance without context on dispatch conditions.**

***Index Terms*—Energy system modelling, district heating, thermal energy storage**

I. Introduction

To achieve climate neutrality, all sectors need to be decarbonized. This includes the district heating (DH) sector, which so far relies mainly on fossil fuels [1]. DH is an important option in the decarbonization of the buildings sector, especially in densely populated areas. The future DH generation mix will be heterogenous, and based on many different heat sources, such as electricity, ambient heat, geothermal energy, solar thermal energy, excess heat, e.g. from industrial process, biomass and waste as well as hydrogen [2]. The overall mix will depend on the availability of renewable heat sources and energy carrier prices. Large-scale heat pumps will likely play a major role in the DH generation mix in the EU [3]. This coupling of the electricity and the heating and cooling (H&C) sector is generally referred to as Power-to-heat (P2H). P2H has been shown to have significant potential to provide flexibility to the overall energy system [4] and the electricity sector [5] . To fully leverage the flexibility that DH can provide, thermal energy storages (TES) are needed, as they allow the shifting of DH generation, e.g. from heat pumps to times of low electricity prices, thus providing value to the energy system [6].

There are several TES technologies that could be used in DH. In this paper, the focus lies on pit thermal energy storage (PTES). The pits are usually in the form of truncated pyramid stumps filled with water as storage medium, and the side and bottom of the pit are insulated. The top is insulated using a floating lid made from strongly insulating material [7]. PTES have several advantages such as relatively low investment expenditures that also decrease strongly with the size of the pit [8]. Additionally, their operation is relatively flexible, as changing between charging and discharging can be quite frequent. They can be used both for seasonal storage as well as relatively short-term (e.g. hours to days) balancing. PTES do not require particular geological formations [9], except space and suitable ground conditions to dig the pit. Introducing PTES in DH systems has been shown to reduce DH prices and increase the share of renewable energy sources in the system [8].

There is a wide range of reported efficiencies for PTES, ranging from 37% to 96% [4]. The difference, as evidenced in data from 2015 to 2017, can be partially explained by the difference in dispatch and the number of cycles per year. For example, the PTES in Marstal in Denmark reaches an efficiency of 39% to 66% with 0.7 to 1.1 cycles per year and the PTES in Dronninglund in Denmark reaches an efficiency of 90% to 96 % with 1.9 to 2.2 cycles per year [4, 5]. When modelling PTES, the efficiency, i.e. losses over time, could influence the results significantly. These losses over time are also called self-discharge rate. For PTES, the self-discharge rate depends on the heat transfer coefficient and the temperature difference between the storage and the ambient temperature. Thus, the self-discharge depends on the state of charge of the PTES. In simulation and monitoring it has been demonstrated that PTES loose most of the heat through the lid [10]. The bottom and sides of the truncated pyramids are usually well insulated and heat the surrounding soil gradually over the course of the first one to two years of operation. After that, the losses to the bottom and side reduce significantly [11].

This paper thus looks especially at the efficiency of PTES and thereby the different self-discharge rates for PTES in energy system modelling. Existing studies that analyze best practices for the modelling of PTES or other long-duration energy storage (e.g. [12]) do not investigate the effects of dispatch distortion of different self-discharge rates of TES. This analysis therefore brings a novel perspective to the existing literature and research on TES. To quantify the effect of the different self-discharge rates for TES found in the literature, the energy systems model *Enertile* is used to investigate changes in invest and dispatch of PTES under different assumptions.

The remainder of the paper is structured as follows: Section II describes the methodology of the *Enertile* model, PTES characteristics in the model and scenario design. The results are presented and discussed in section III. The conclusion is presented in section IV.

II. METHODOLOGY AND SCENARIO DESIGN

A. Energy system model Enertile

Enertile is a bottom-up energy system model, covering all EU member states with an hourly resolution and detailed potentials for renewable electricity and heat generation [3, 13]. The primary function of the linear optimization model is to minimize the total system cost for the supply, transmission and storage of energy. *Enertile* covers the energy carriers electricity, hydrogen and DH, whereas operation and capacity expansion are optimized at the same time [14]. A simplified version of the objective function of the linear optimization model is presented in the following (cf. [2]):

$$\min_{\vec{x}\vec{X}} \big[\mathrm{cost}_{\mathrm{el}}^{\mathrm{fix}}(\vec{X}) + \mathrm{cost}_{\mathrm{el}}^{\mathrm{var}}(\vec{x}) + \mathrm{cost}_{\mathrm{heat}}^{\mathrm{fix}}(\vec{X}) + \mathrm{cost}_{\mathrm{heat}}^{\mathrm{var}}(\vec{x}) + \mathrm{cost}_{\mathrm{el,chp}}^{\mathrm{var}}(\vec{x}) + \mathrm{cost}_{\mathrm{hydrogen}}^{\mathrm{fix}}(\vec{X}) + \mathrm{cost}_{\mathrm{hydrogen}}^{\mathrm{var}}(\vec{x})\big]$$

with:

$\vec{X}$: variables for installed capacity

$\vec{x}$: variables for installed generation

$\mathrm{cost}_{\mathrm{el}}^{\mathrm{fix}}$: fixed costs of electricity capacity expansion in €

$\mathrm{cost}_{\mathrm{el}}^{\mathrm{var}}$: variable costs of electricity generation in €

$\mathrm{cost}_{\mathrm{heat}}^{\mathrm{fix}}$: fixed costs of capacity expansion in DH in €

$\mathrm{cost}_{\mathrm{heat}}^{\mathrm{var}}$: variable costs of heat generation in DH in €

$\mathrm{cost}_{\mathrm{el,chp}}^{\mathrm{var}}$: variable costs of electricity generation from CHP in €

$\mathrm{cost}_{\mathrm{hydrogen}}^{\mathrm{fix}}$: fixed costs of hydrogen capacity expansion in €

$\mathrm{cost}_{\mathrm{hydrogen}}^{\mathrm{var}}$: variable costs of hydrogen generation in €

Demands are defined exogenously and can be met by the various technologies that are implemented in *Enertile*. As a key constraint in the formulation of the linear optimization, the hourly demand for each energy carrier has to be met for each model region [15]. The time horizon of the model is 2050. The supply of DH is modelled endogenously, based on an exogenously determined annual heat demand per region, which is then scaled to an hourly demand. This is done by using a daily DH time series that incorporate average daily outdoor temperature [6].

DH is further disaggregated to analyze different *DH types*, each with a multivalent generation mix (cf. methodology in [2, 7]). The *DH types* are based on a detailed analysis of 5815 DH areas in Europe, which are then clustered based on their predominant source for renewable heating potential [3]. The four *DH types* modelled in *Enertile* are:

- *DH type 1: River and lakes*
- *DH type 2: Geothermal*
- *DH type 3: Biomass*
- *DH type 4: Mixed*

The *DH types* represent DH networks with multiple sources: (1) ambient heat from rivers and lakes used with heat pumps, (2) ambient heat from wastewater treatment plants used with heat pumps, (3) industrial surplus heat used directly, (4) (deep) geothermal energy used directly, (5) biomass and biogas and (6) waste incineration. The *DH types* are named according to the heat source with the highest potential, i.e. in *DH type 1: Rivers and lakes*, large-scale heat pumps using rivers or lakes as a heat source could, for example, meet about 50% of the demand [6]. Further details on the *Enertile* model and in particular the modelling of DH in *Enertile* are presented in e.g. [3, 6].

A sector-coupled energy system model is best suited to capture the dynamic and operation of PTES in DH grids with high shares of heat-pumps. The detailed modeling of *DH types* in *Enertile* also enables a comparison between different DH networks with different generation mixes.

B. PTES characteristics

For this analysis, PTES is implemented as an option for thermal storage in DH in *Enertile.* Data on capital expenditures (CAPEX) and operational expenditures (OPEX) of PTES are taken from the technology dataset of the Danish Energy Agency (DEA) [16]. In the dataset, a value for losses per day is provided for the PTES technology, which is translated into losses per hour. These losses per day correspond to the so-called standing losses or self-discharge rate of the PTES and are applied every hour, in relation to the charging of the PTES. If the storage is charged more, the self-discharge is higher and vice versa. This approach accurately depicts the operation of PTES.

The self-discharge rate is thus applied to the DH generation formula in *Enertile* for every hour. D_t is the DH demand in hour t. To supply the demand, generation can either come from the various DH generation technologies $\mathrm{Gen}_{i,t}$ with $i = 1,..,n$ or from the PTES in hour t. The self-discharge rate λ is then applied to the state of charge of the PTES at hour t. Thus, if the difference between $(1-\lambda) * \mathrm{PTES}_t$ and PTES_{t+1} is positive, the PTES is discharged, and if it is negative, the PTES is charged, as shown in the following:

$$\mathrm{D}_t = \sum_{i=1}^{n} \mathrm{Gen}_{i,t} + \cdots + \mathrm{Gen}_{n,t} + (1-\lambda) \cdot \mathrm{PTES}_t - \mathrm{PTES}_{t+1}$$

with:

D_t: DH demand in hour t

$\mathrm{Gen}_{i,t}$: DH generation of DH technology i in hour t

$PTES_t$: state of charge of PTES in hour t

$PTES_{t+1}$: state of charge of PTES in hour $t+1$

λ: self-discharge rate of PTES

Therefore, the self-discharge rate is applied dynamically in *Enertile*, whereas losses per hour are higher if the storage level of the PTES is higher. The storage level at the beginning and the end of the optimization period (i.e. January 1st) is fixed to 80% to account for the fact that only one year is optimized under perfect foresight. For the purpose of this paper, PTES are the only TES option in DH grids modeled in the scenarios.

C. Scenario design

To capture the dispatch distortion of different self-discharge rates of PTES, the losses per hour are varied in the scenarios according to Table I. The aim of these scenarios is to quantify the effect of the dispatch distortion on the DH generation, storage capacity and storage dispatch. The scenarios are compared to a baseline scenario in which the losses are directly taken from the DEA dataset [16]. In the non-baseline scenarios, losses are increased/decreased by factors of two, five and ten.

TABLE I. SCENARIO DESIGN

Scenario name	**Losses per day, i.e. self-discharge rate**
Baseline	losses per day based on DEA
Losses/10	losses from Baseline divided by 10
Losses/5	losses from Baseline divided by 5
Losses/2	losses from Baseline divided by 2
Losses*2	losses from Baseline multiplied by 2
Losses*5	losses from Baseline multiplied by 5
Losses*10	losses from Baseline multiplied by 10

Since the approach of the paper is exploratory, the model is run only for Germany in a greenfield approach for the milestone year 2050 to save computation time and run more scenarios instead. The share of DH and all other relevant assumptions remains the same across all scenarios. All scenarios reach a climate neutral energy system in the year 2050.

To compare the results of the scenarios, the DH generation mix, the PTES capacity and the usage patterns of the PTES are analyzed, mainly by looking at the cycles per year. The correlation between PTES dispatch and electricity prices is then analyzed using the Spearman correlation coefficient monthly. With these comparisons, the effect of different self-discharge rates on the dispatch of the PTES and the DH generation in different *DH types* is shown.

III. RESULTS

A. DH generation mix in the baseline scenario

Figure 1 shows the DH generation mix for the *Baseline scenario* for each *DH type* in Germany in the year 2050. All *DH types* are multivalent networks with varying generation technologies due to the different renewable heat potentials [3]. *DH type 1: Rivers and Lakes* has the highest share of heat pumps and a relatively low share of dispatchable energy carriers like biomass and waste. In contrast, *DH type 2: Geothermal* has a very high share of geothermal energy and by far the lowest share of heat pumps. *DH type 3* and *DH type 4* have comparably similar results in terms of their generation mix.

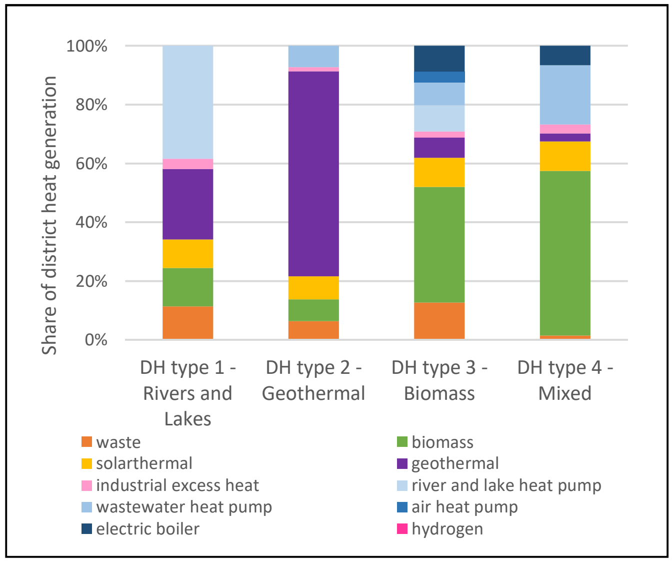

Figure 1: DH generation mix for each DH type in the *Baseline scenario*

B. Effects of variating losses of PTES in the scenarios

Figure 2 shows how the DH generation mix is affected by the variation of the self-discharge rate of the PTES. Here, only the two scenarios with the highest variation in both directions are shown, but the effect is consistent for all scenarios. If the self-discharge rate of the PTES is increased (cf. *Losses*10 scenario*), the model decides to rely more heavily on biomass generation in DH, as it is dispatchable, thus can be used at any time.

If losses are decreased (cf. *Losses/10 scenario*), the model can integrate more generation from heat pumps and electric boilers, as storage does allow heat pumps to operate more often at times of low electricity prices. This effect is consistent for all *DH types*, but most profound in DH *type 1*, with the highest share of heat pumps, and least in *DH type 2* with the lowest share of heat pumps. Air-sourced heat pumps and electrical boilers are more heavily impacted than those heat pumps that rely on a more constant source such as rivers and lakes or wastewater. In *DH type 3* and *4*, the effect is also not as pronounced as in *DH type 1*, since a lot of biomass generation decreases the need for PTES.

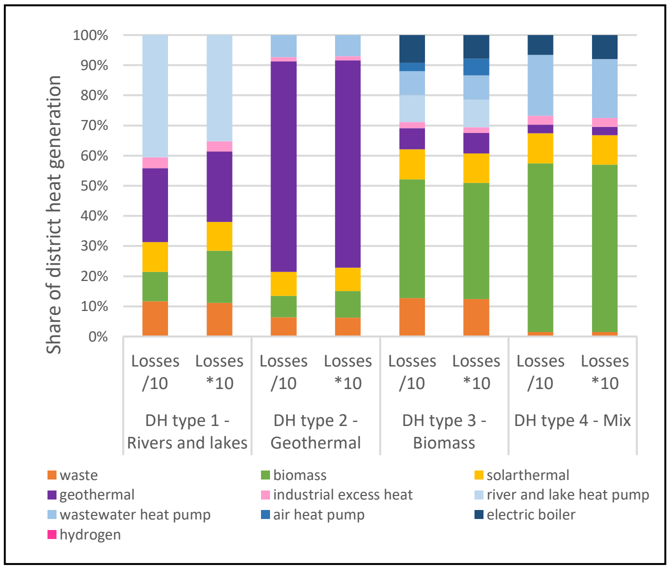

Figure 2: DH generation mix for each DH type for the *losses * 10* and *losses / 10* scenarios

A distinction between the *DH types* also occurs in terms of PTES capacity, and how the PTES is operated. Related results for *DH type 1* and *DH type 3* are shown in Figure 3. On the first axis, the installed capacity of the PTES in MWh and the total losses in MWh are shown. The second axis shows the cycles per year, which are calculated by dividing the total thermal energy that runs through the storage by the PTES capacity, are shown. Like the results for the generation mix, there is much less variation for *DH type 3*, which can be explained by the lower share of heat pumps and the significantly higher share of biomass.

In addition, the results show that the higher the losses per hour, the lower the installed capacity of the PTES and the higher the overall losses. However, total losses do not scale proportionally to the losses per hour, as the change in self-discharge rate also affects the dispatch of DH, including the dispatch of the PTES. This can be measured in cycles per year. For *DH type 1*, with the highest share of heat pumps and a relatively low share of biomass, the effect of the variation in self-discharge rate is by far the highest. Cycles per year change from 16.8 cycles per year in the baseline scenario to 9.3 cycles per year in the scenario with the lowest losses (cf. *Losses/10 scenario*). In contrast, the cycles increase to 19.8 cycles per year in the scenario with the highest losses (cf. *Losses*10 scenario)*. A storage with exactly one cycle per year would indicate a strict seasonal pattern, while 365 would indicate one charge/discharge per day.

In comparison, *DH type 3* shows much less variation for the different scenarios. The PTES capacity deviates much less, and the number of cycles per year also does not change as much as for *DH type 1*. The main driver of this seems to be the high share of biomass in *DH type 3*, which acts similarly to a storage system, since it is flexible. While the generation mix does change in *DH type 3*, the bigger change of PTES capacity, losses and cycles for *DH type 1* illustrates the link between DH generation mix and PTES: More capacity and better utilization of PTES enables the integration of more heat pumps. This effect is stronger in grids with less dispatchable DH generation technologies.

Additionally, we observe that the installed capacity of PTES does react to changes in self-discharge rate, especially in *DH type 1*. However, there seems to be both an upper and lower limit of how much installed PTES is cost optimal. This indicates that PTES are very valuable from a system perspective, which is why even with very high self-discharge rates, the installed capacity decreases only slightly compared to the baseline. Lowering the self-discharge rate does increase the cost-optimal capacity of PTES, but even the most extreme scenario sees only double the capacity of the *Baseline scenario*.

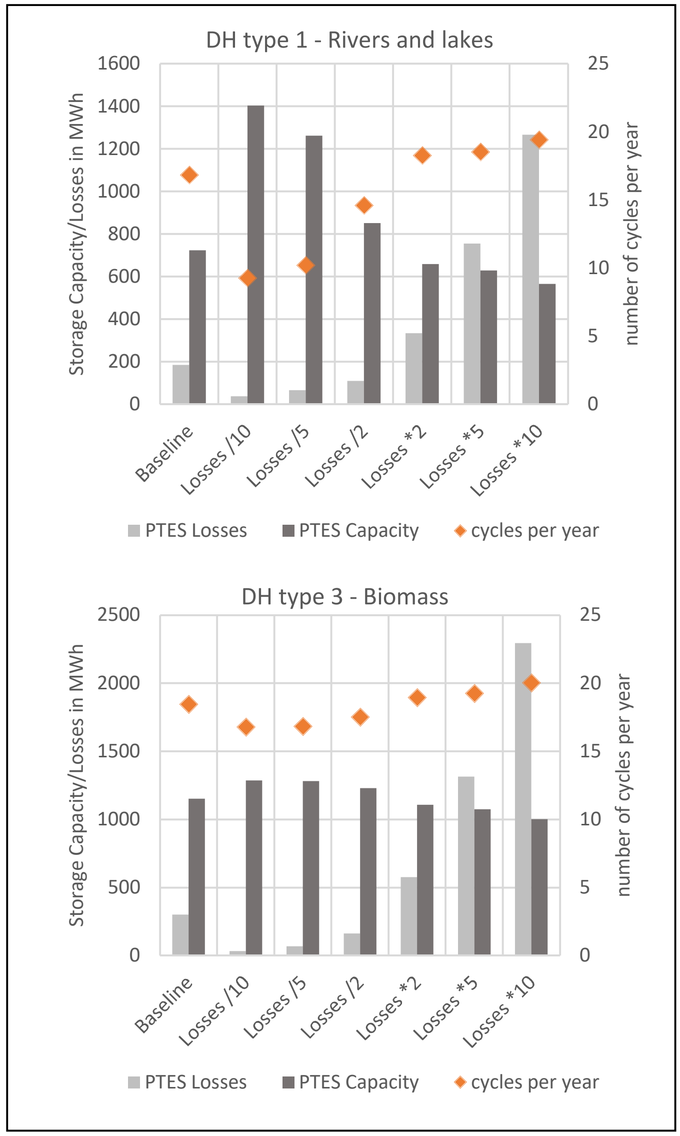

Figure 3: PTES capacity, losses and cycles per year across all scenarios for *DH type 1: Rivers and Lakes* (top) and *DH type 3: Biomass* (bottom)

The increase in self-discharge rate leads the optimization to decrease the time the storage is fully charged, while a decrease in losses per hour means that the storage can be fully charged with less negative consequences. Thus, we would expect the usage of the stored heat to shift more towards more valuable hours the lower the self-discharge rate, and vice versa. To test this, we calculate the correlation coefficient of the discharging of the PTES and the electricity price in monthly intervals. This is necessary due to the strong seasonality of both district heating demand and electricity prices, as has been demonstrated with *Enertile* before [6], which means correlation coefficients for the whole year tend to obfuscate the actual reaction of the model.

C. *Correlations between PTES dispatch and electricity prices*

Figure 4 shows the Spearman's rank correlation coefficient for *DH type 1* between the discharging of the PTES and electricity prices. Like the results in [7], the summer months are very noisy due to the very low DH demand and the very limited use of PTES. In contrast, the winter months clearly show that the PTES is discharged in times of high electricity prices and a relatively strong correlation between PTES discharging and electricity prices can be observed. In December this is not the case due to the constraint that the PTES needs to reach 80% at the end of the year. In the scenario with the highest self-discharge rate (i.e. *Losses*10 scenario*), this effect is less strong, and for the scenario with the lowest self-discharge rate (i.e. *Losses/10 scenario*), this effect is stronger than in the *Baseline scenario*. This effect is consistent across the analyzed scenarios.

This illustrates the effect of the dispatch distortion regarding the variation of the self-discharge rate of PTES in *Enertile*. If the self-discharge rate is lower, more storage capacity is installed, and the storage can be used more effectively to balance out times of high electricity prices. This results also in significantly lower cycles per year, meaning the storage operates in a more long-term manner compared to the baseline. Thus, the effect of the dispatch distortion affects DH networks with high shares of heat pumps and lower shares of dispatchable energy carriers more strongly (e.g. biomass).

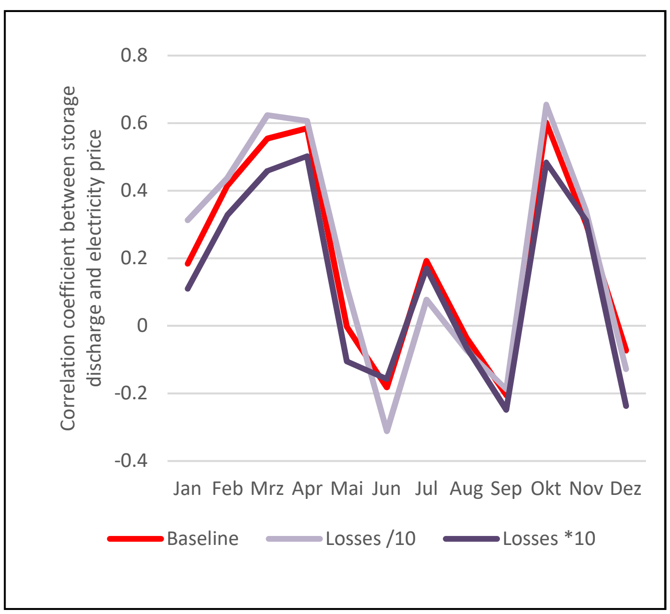

Figure 4: Monthly correlation coefficient of the PTES discharging and electricity price for *DH type 1*

D. *Discussion of results*

There are several limitations regarding our methodology here. Firstly, the model operates under perfect foresight and is thus able to optimize the dispatch of the PTES effectively, allowing it to reduce overall thermal losses by adjusting the dispatch of the PTES itself. In other words: If the self-discharge rate is implemented hourly as is demonstrated in this present paper, the dispatch has influence on the total losses, as more cycles per year generally lead to lower overall losses. This complicates the verification of PTES efficiencies found in the literature without knowledge about their dispatch. Moreover, the PTES would have to be charged without knowledge of when the discharge would be optimal, thus overall higher losses would be expected. Secondly, we did not investigate DH networks with very high shares of solar thermal energy, which exhibits a very strong seasonal profile and thus would push PTES to be operated much more seasonally. Thirdly, we did not compare the results from our method with the common practice in some models of applying a static efficiency to PTES, regardless of storage dispatch.

Compared to the existing literature, our analysis presents an exploratory investigation of the impact of different assumptions concerning the losses of PTES. The realized losses also seem plausible compared to real-life PTES projects like the one in Dronninglund [10]. The importance of the PTES operation on its efficiency has recently been discussed in a technology brief by the Danish Energy Agency [17]. The results of the novel approach of implementing the losses as hourly self-discharge rate emphasize the importance of the storage dispatch for the efficiency, and vice versa the importance of the dispatch on the efficiency of PTES.

IV. Conclusion

In this paper, the self-discharge rate of pit thermal energy storage (PTES) has been varied in the sector-coupled energy system model *Enertile* to investigate the effect of different hourly losses on the dispatch of district heating (DH) generation. It has been shown that the model does respond to a change in self-discharge rate by adjusting the dispatch of the PTES itself, which also leads to a change in DH generation. By analyzing different *DH type networks* with different underlying renewable heat generation potentials, it has been shown that this effect is strongest among DH networks with high shares of heat pumps and low shares of other dispatchable generators such as biomass or waste incineration plants.

The results illustrate the interdependency between self-discharge rate of PTES and their dispatch. With a higher self-discharge rate, the PTES do more cycles per year, thus focusing more on short-term storage and vice versa. This effect is, again, strongest in DH networks with high shares of heat pumps. This also influences the times during which the stored energy is used. With higher self-discharge rates, the storage is discharged less at times of high electricity prices. Therefore, many of the reported efficiencies of real-world PTES, are not very useful as input for energy system modelling, without information on the dispatch to achieve said efficiency. Further research should compare the modelling of the efficiency of PTES static and dynamic and compare different types of thermal storage technologies to each other.

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