Differentially-Private Heat and Electricity Markets Coordination

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Abstract—Sector coordination between heat and electricity systems has been identified as an energy-efficient and cost-effective way to transition towards a more sustainable energy system. However, the coordination of sequential markets relies on the exchange of sensitive information between the market operators, namely time series of consumers’ loads. To address the privacy concerns arising from this exchange, this paper introduces a novel privacy-preserving Stackelberg mechanism (w-PPSM) which generates differentially-private data streams with high fidelity. The proposed w-PPSM enforces the feasibility and fidelity of the privacy-preserving data with respect to the original problem through a post-processing phase in order to achieve a close-to-optimal coordination between the markets. Multiple numerical simulations in a realistic energy system demonstrate the effectiveness of the w-PPSM, which achieves up to two orders of magnitude reduction in the cost of privacy compared to a traditional differentially-private mechanism.

I. INTRODUCTION

The development of market-based coordination mechanisms for heat and electricity systems has been identified as a crucial step towards an energy-efficient, cost-effective, and sustainable energy system [1], [2]. Recent advances in the literature have modelled the coordination between sequential and interdependent markets as a Stackelberg game [3]–[5]. In particular, the electricity-aware heat market (EAHM) developed in [3] provides a market-based mechanism for the coordination of heat and electricity systems. This market framework is modelled as a bilevel optimization problem and relies on the sharing of information between the electricity and heat market operators to achieve an optimal coordination.

Despite recent regulatory changes encouraging information exchange between system operators [6], users in the electricity market may be reluctant to exchange some information with the heat market operator due to privacy concerns. Revealing this sensitive data may provide a competitive advantage over other strategic agents, reveal identifying personal information, induce financial losses and security risks for the users, and even benefit external attackers [7], [8]. In particular, in the EAHM developed in [3] and used in this paper as a target application, we consider that the hourly electricity loads of individual consumers represent a sensitive data stream to be obfuscated before releasing to the heat market operator.

To address this privacy issue, Differential Privacy (DP) has emerged as a robust privacy framework for multiple applications [9]. DP relies on the injection of carefully calibrated noise to protect the disclosure of the individuals’ data, while allowing to extract information about the population. This framework can thus be used to obfuscate the sensitive data exchanged between the electricity and heat market operators in the EAHM. In particular, the w-privacy framework introduced in [10] provides an interesting framework to obfuscate time series of hourly data, such as electricity loads, within a predefined time window. However, the obfuscation of highly correlated and high-dimensional streams of data is particularly challenging due to the high level of noise required to maintain privacy goals [11]. When obfuscated data is used as input to optimization problems with strong techno-economic constraints, such as market clearing problems in energy systems, it may lead to severe fidelity and feasibility issues. To address this issue the authors in [12] developed an optimization-based fidelity-recovery phase to classic DP mechanisms. This approach has been adapted to the exchange of information in Stackelberg games, and applied to the coordination of electricity and natural gas markets in [13]. However, these recent advances in the literature are limited to classic definitions of DP. To the best of our knowledge, there is no existing mechanism to share differentially-private data streams with high fidelity in Stackelberg games.

Given the described research gaps, the contributions of this paper are threefold:

1) We introduce the novel w-PPSM which allows for the sharing of differentially-private data streams in Stackelberg games with high fidelity. This mechanism uses an optimization-based approach to
recover the fidelity and feasibility of the obfuscated data w.r.t. the original Stackelberg game. This mechanism is developed for the target application of the coordination between heat and electricity markets and the exchange of hourly electricity loads over a 24-hour window.

2) We show that the \(w\)-PPSM satisfies interesting theoretical properties. In particular, it achieves strong privacy goals while providing a bound on the error introduced on the obfuscated sensitive data.

3) Through multiple numerical simulations, we show the efficiency and robustness of the \(w\)-PPSM under varying privacy parameters and operating conditions. The numerical results show that the \(w\)-PPSM can achieve up to two orders of magnitude cost reduction compared to a standard differentially-private mechanism.

The remainder of this paper is organized as follows. Section II introduces the target application, Section III summarizes the background on DP, Section IV defines the proposed \(w\)-PPSM, Section V presents the numerical results, and Section VI concludes this paper.

**Nomenclature**

**A. Leader and follower’s data \((D^L, D^F)\)**

- \(\rho^E_j\): Electricity efficiency ratio of CHP \(j\) (-)
- \(\rho^H_j\): Heat efficiency ratio of CHP \(j\) (-)
- \(\text{COP}_j\): Coefficient of performance of HP \(j\) (-)
- \(E^\text{CH}_j\): Variable heat cost of supplier \(j\) at time \(t\) (\$/Wh)
- \(E^\text{CE}_j\): Variable electricity cost of supplier \(j\) at time \(t\) (\$/Wh)
- \(E^\text{max}_j\): Maximum electricity output of supplier \(j\) at time \(t\) (Wh)
- \(E^\text{min}_j\): Minimum electricity output of supplier \(j\) at time \(t\) (Wh)
- \(E^\text{max}_j\): Maximum fuel consumption of CHP \(j\) (Wh)
- \(H^\text{max}_j\): Maximum heat output of supplier \(j\) at time \(t\) (Wh)
- \(H^\text{min}_j\): Minimum heat output of supplier \(j\) at time \(t\) (Wh)
- \(L^E_j\): Electricity load \(l\) at time \(t\) (Wh)
- \(L^H_j\): Heat load \(l\) at time \(t\) (Wh)
- \(R^j\): Minimum power-to-heat ratio of CHP \(j\) (-)
- \(T^\text{max}_{z\rightarrow z'}\): Maximum transmission capacity from zone \(z\) to \(z'\) at time \(t\) (Wh)
- \(T^\text{min}_{z\rightarrow z'}\): Minimum transmission capacity from zone \(z\) to \(z'\) at time \(t\) (Wh)

**B. Leader and follower’s variables**

- \(A^E_{z\rightarrow t}\): Electricity market price in zone \(z\) at time \(t\) (Wh)
- \(e^\text{max}_j\): Maximum electricity output of CHP or HP \(j\) at time \(t\) (Wh)
- \(e^\text{min}_j\): Minimum electricity output of CHP or HP \(j\) at time \(t\) (Wh)
- \(e^l_j\): Electricity production of supplier \(j\) at time \(t\) (Wh)
- \(f^z\rightarrow z'\): Electricity flow from zone \(z\) to \(z'\) at time \(t\) (Wh)
- \(h^l_j\): Electricity production of supplier \(j\) at time \(t\) (Wh)

**II. HEAT AND ELECTRICITY MARKET COORDINATION**

**A. Interactions between Heat and Electricity Sectors**

In Nordic countries, heat and electricity systems are operated by sequential and independent competitive markets. The day-ahead heat market is traditionally cleared before the day-ahead electricity market. In each day-ahead energy market, suppliers place price-quantity bids for each hour of the following day that are dispatched based on a merit-order and least-cost principle. The sequential\(^1\) participation of combined heat and power plants (CHPs) and heat pumps (HPs) in both heat and electricity markets creates implicit interactions between the systems.

Firstly, the physical characteristics of CHPs and HPs induce a strong linkage between heat and electricity production. As a result, in the current day-ahead electricity market, the minimum and maximum electricity outputs of CHPs and HPs are defined by their day-ahead heat dispatch. This heat-driven approach limits the operational flexibility of these units in the electricity market, which may limit the penetration of renewable energy sources and increase electricity prices.

Additionally, the production costs of CHPs and HPs are intrinsically linked to their heat and electricity outputs. Indeed, the heat production cost \(\Gamma^H\) of HPs represents the cost of purchasing electricity in the day-ahead market. Similarly, the heat production cost of CHPs represents their total production cost minus revenues from electricity sales. However, the current market framework does not account for the impact of the heat production of CHPs and HPs on the electricity market prices, which in turn, impact the production costs in the heat market and may result in an inefficient dispatch.

**B. Electricity-Aware Heat Market Framework**

This paper provides an extension of the EAHM developed in [3]. This market framework aims at improving the coordination between heat and electricity sectors by better accounting for the interactions between them, while maintaining the sequential order of their decisions. This coordination framework is a classic Stackelberg game, in which the decisions of the first player (leader) impact the decisions of the second player (follower), which, in turn, impact the objective of the leader. As illustrated in the upper-part of Fig. 1, in the EAHM, the heat market operator (leader) tries to minimize heat production costs while anticipating the impact of the heat dispatch of CHPs and HPs on the electricity market outcomes, specifically on electricity prices, which in turn impact heat production costs. This EAHM can be modelled as a bilevel optimization problem, in which the upper-level problem, representing the heat market clearing, is constrained by the lower-level problem, representing the electricity market clearing for a given value of the heat market outcomes (namely the minimum and maximum electricity outputs of CHPs and HPs).

\(^1\)CHPs and HPs must place their bids in the heat market before the electricity market. And once the heat market has been cleared, they place their bids in the electricity market.
Hence, the lower-level problem $\mathcal{P}^F(e^{\min}_h, e^{\max}_h, D^F)$, is formulated as:

$$\begin{align*}
\min_{e^{\min}_h, e^{\max}_h, \lambda_t} \quad & \sum_{t \in T} \sum_{h \in \mathcal{H}} C^E_{h,t} e^F_{ht} \tag{1a} \\
\text{s.t.} \quad & \sum_{t \in T} L^E_{zt} = \sum_{j \in \mathcal{J}^{H}} e_{ht} + \sum_{v \in \mathcal{Z}^{E}} f^E_{zt} : \lambda^E_{zt}, \quad \forall z \in \mathcal{Z}^{E}, t \in T \tag{1b} \\
& \text{TE}^{\min}_{zt} \leq \lambda^E_{zt} \leq \text{TE}^{\max}_{zt}, \quad \forall z, t \in \mathcal{Z}^{E}, t \in T \tag{1c} \\
& e^{\min}_h \leq e^{F}_{ht} \leq e^{\max}_h, \quad \forall j \in \mathcal{J}, t \in T \tag{1d} \\
& e^{\min}_h \leq e^{F}_{ht} \leq e^{\max}_h, \quad \forall j \in \mathcal{J}^{CHP, HP}, t \in T \tag{1e}
\end{align*}$$

where (1a) represents the electricity production cost, (1b) is the electricity balance equation in each market zone, (1d) and (1e) represent the electricity production (or consumption) bounds of electricity-only producers, as well as CHPs and HPs, respectively. Note that the bounds in (1e) are decisions variables of the upper-level problem, and treated as input in the lower-level problem.

Additionally, the upper-level problem $\mathcal{P}^L (D^H, D^F)$ is formulated as:

$$\begin{align*}
\min_{D^H, D^F} \quad & \sum_{j \in \mathcal{J}^{H}} C^H_j h^F_{jit} - \sum_{j \in \mathcal{J}^{H}} (\lambda^E_j - C^E_j)e^F_{jit} \tag{2a} \\
& + \sum_{j \in \mathcal{J}^{CHP, HP}} \lambda^E_j \text{COP}^E_{jit} \tag{2a} \\
\text{s.t.} \quad & \sum_{j \in \mathcal{J}^{H}} h^F_{jit}, \quad \forall z \in \mathcal{Z}^{H}, t \in T \tag{2b} \\
& h^{H \min}_{jit} \leq h^F_{jit} \leq h^{H \max}_{jit}, \quad \forall j \in \mathcal{J}^{H}, t \in T \tag{2c} \\
& e^{\min}_h \leq e^{F}_{jit} \leq e^{\max}_h \frac{h^F_{jit}}{\text{COP}^E_j}, \quad \forall j \in \mathcal{J}^{CHP, HP}, t \in T \tag{2d} \\
& e^{\min}_h \leq e^{F}_{jit} \leq e^{\max}_h \frac{h^F_{jit}}{\text{COP}^E_j}, \quad \forall j \in \mathcal{J}^{CHP, HP}, t \in T \tag{2e} \\
& \{e^F_{jit}, \lambda^E_{jit}\} \in \text{sol. of } \mathcal{P}^F (e^{\min}_h, e^{\max}_h, D^F), \tag{2g}
\end{align*}$$

where (2a) represents the heat production cost as a function of electricity prices, (2b) is the heat balance equation in each market zone$^2$, (2c) represents the heat production bounds for all heat suppliers, (2d)-(2f) define the minimum and maximum electricity production (or consumption) of CHPs and HPs, and (2g) sets the electricity dispatch and prices as the optimal solutions of the lower-level problem. A detailed formulation of this bilevel optimization problem and its solution method is provided in [3].

$^2$Each heat market zone represents a geographically isolated district heating network.
given \( i < j \in [t] \), if \( L^E_i \neq L^E_j \) and \( L^E_i \neq L^E_i \), then it holds that \( j - i + 1 \leq w \).

In the context of the target application, a mechanism is said to satisfy \( w \)-event \( \varepsilon \)-differential privacy (\( w \)-privacy for short) if it satisfies the following definition:

**Definition 2** Let \( \mathcal{M} \) be a randomized algorithm that takes as input a stream prefix of arbitrary size and outputs an element from a set of possible output sequences \( S \). Algorithm \( \mathcal{M} \) satisfies \( w \)-privacy if, for all \( w \)-neighboring stream prefixes \( L^E[t] \sim_w L^E'[t] \), with \( t \in T^\infty \), and all sets \( S \subseteq S \), it satisfies:

\[
P \left( \mathcal{M}(L^E[t]) \in S \right) \leq \exp(\varepsilon)P \left( \mathcal{M}(L^E'[t]) \in S \right),
\]

where \( \varepsilon \in \mathbb{R}^+ \) is the privacy budget.

**C. Laplace Mechanism**

A commonly used method to achieve \( w \)-privacy for data streams is the so-called Laplace mechanism. In the target application of this work, the privacy goal is to protect a data stream of aggregate loads within a 24-hour window. Therefore, we consider the Laplace mechanism \( \mathcal{M}_{Lap} \) which takes as input a stream prefix \( L^E[t] \) and outputs the sequence \( \hat{L}^E[t] = [\hat{L}^E_1, \ldots, \hat{L}^E_t] \), such that \( \hat{L}^E_t = L^E_t + \xi_t \), where \( \xi_t \in \mathbb{R}^Z \) is drawn from the i.i.d. Laplace distribution \( \text{Lap}(\frac{\varepsilon}{w}) \) for \( i \in [t] \), with the time window parameter \( w \) = 24. It is a well-known result that this Laplace mechanism achieves \( w \)-privacy with \( w \) = 24 [11].

The main limitation of this mechanism is that the original data is highly perturbed and the outcome of the algorithm is a data stream that, used as input to an optimization problem, may lead to severe fidelity and feasibility issues [13]. The \( w \)-PPSM introduced in this paper specifically aims at mitigating this issue.

**IV. \( w \)-Privacy-Preserving Stackelberg Mechanism**

The PPSM developed in [13] allows the exchange of differentially private data of high fidelity between the agents of a Stackelberg game. This section describes an extension of the PPSM that achieves \( w \)-privacy for a data stream. Similarly to [13], this paper assumes that the leader and the follower each have access to their own accurate prediction models (\( \mathcal{M}^L \) and \( \mathcal{M}^F \)) that can privately forecast electricity market costs and prices. This assumption is realistic in energy systems, since prediction models are commonly used to efficiently bid in the markets.

**A. Steps**

The proposed \( w \)-PPSM (\( \mathcal{M}_{PPSM} \)) is performed each day, before the heat and electricity markets are cleared, to protect the sensitive data of the follower \( D^F \) for each hour of the following day. The outcome of this mechanism is the privacy-preserving data \( \hat{D}^F \) to be shared with the leader. The steps of this mechanism are schematically represented in Figure 1 and summarized below.

**1) Laplace-obfuscation:** Firstly, the follower obfuscates the sensitive data \( D^F \) according to the \( w \)-private Laplace mechanism \( \mathcal{M}_{Lap} \) described in Section III-C, before releasing it to the leader.

**2) Leader’s prediction:** Using publicly available data and the Laplace-obfuscated data \( \hat{D}^F \) obtained in step (1), the leader estimates the values of the minimum and maximum electricity outputs of CHPs and HPs (\( \hat{\lambda}_d^{\text{min}} \) and \( \hat{\lambda}_d^{\text{max}} \)) for the following day. To do so, it uses its prediction model \( \mathcal{M}^L \) to predict the electricity prices \( \hat{\lambda}_d^E \). The leader then solves a decoupled heat market \( \hat{P}(\hat{\lambda}_d^E, \hat{\lambda}_d^L) \), in which the follower’s variables \( \hat{\lambda}_d^L \) in the objective function (2a) are replaced by the predicted values \( \hat{\lambda}_d^E \), and the lower-level problem (2g) is replaced by constraint (1e) with \( e_{\hat{\lambda}_d} \) a free variable. Note that this optimization problem does not take the follower’s data \( D^F \) as input. The solutions of this optimization problem \( (\hat{\lambda}_d^{\text{max}}, \hat{\lambda}_d^{\text{min}}) \) are shared with the follower.

**3) Follower’s prediction:** With publicly available information, the Laplace-obfuscated data obtained in step (1), and the predicted values obtained in step (2), the follower predicts the electricity market costs \( \hat{\omega}_F \) and prices \( \hat{\lambda}_d^F \) using its prediction model \( \mathcal{M}^F \).

**4) Fidelity recovery:** Given its own available data, the obfuscated data obtained in step (1) and the predicted values computed in steps (2) and (3), the follower derives the new privacy-preserving data \( \hat{D}^F \). To do so, it uses an optimization-based approach to optimally redistribute the noise on the sensitive data introduced in step (1) while recovering feasibility and fidelity w.r.t to the solutions of the original Stackelberg game. This bilevel optimization problem, inspired by [13], is formulated as:

\[
\min_{\hat{\lambda}_d^F \in \hat{\lambda}_d^F} \| D^F - \hat{D}^F \|_2^2 \quad (4a)
\]

s.t.

\[
| \hat{\omega}_F - \omega_F | \leq \eta_F \quad (4b)
\]

\[
| \hat{\lambda}_d^F - \lambda_d^F | \leq \eta_d, \forall d \in Z, t \in T \quad (4c)
\]

\[
\hat{\lambda}_d^F = \text{sol. of } D^F \left( e_{\hat{\lambda}_d}^{\text{min}}, e_{\hat{\lambda}_d}^{\text{max}}, D^F, \hat{D}^F \right), \quad (4d)
\]
where the objective (4a) is to find a vector of privacy-preserving data \( \hat{D}^F \) that minimizes the distance w.r.t. the Laplace-obfuscated data \( D^F \), subject to fidelity constraints w.r.t. the predicted objective value \( \hat{\omega}^F \) (4b) and electricity prices \( \hat{\lambda}^E \) (4b), and feasibility constraints w.r.t. the follower’s problem \( P^F \left( \omega^{\text{min}}, \omega^{\text{max}}, D^E, D^F \right) \) in (4d). \( \eta_p \) and \( \eta_d \) are parameters specifying the desired fidelity levels. Note that since the dual variables of the follower directly impact the leader’s problem, (4c) indirectly enforces fidelity w.r.t. the leader’s objective value. Furthermore, the follower’s objective function \( \hat{\omega}^F \) and dual variables \( \hat{\lambda}^E \) are defined as the solutions to the lower-level problem (4d). The solutions to this optimization problem \( \hat{D}^F \) are shared with the leader.

After the w-PPSM has been performed, the leader uses the privacy-preserving data \( \hat{D}^F \) as input to solve its bilevel optimization problem \( P^L(D^L, \hat{D}^E, \hat{D}^F) \) described by (2a)-(2g).

B. Theoretical Properties

A direct extension of [13] ensures that the proposed w-PPSM satisfies important theoretical properties, among which, the most important are:

1) Privacy: For given positive real values of the parameters \( \alpha, \epsilon, \eta_p \) and \( \eta_d \), the proposed w-PPSM mechanism satisfies w-privacy.

2) Error on sensitive data: After the fidelity-recovery phase, the expected error induced by the w-PPSM on the original sensitive data is bounded by the inequality: \( \mathbb{E}[\| \hat{D}^F - D^F \|] \leq 4(\alpha \epsilon)^2 \).

The first property can intuitively be justified by the immunity to post-processing of the Laplace mechanism in step (1), and the fact that all subsequent steps (2)-(4) do not access the original sensitive data. The second property is derived using triangular inequalities.

V. Numerical Results

This numerical analysis evaluates the performance of the w-PPSM in comparison to the Laplace mechanism.

A. Case Study Setup

The case study considered is a simplified version of the one used in [4], which represents a modified version of the IEEE 24-bus system coupled with two 3-node district heating networks, in which network constraints are neglected. The overall system consists of four CHPs, two HPs, four heat-only generators, two heat storage units, twelve synchronous electricity generators, and six wind farms. Heat and electricity system parameters, as well as time series of heat and electricity loads and wind power generation for a given day are derived from [4], [15], [16] and available in the online appendix [17].

For this case study, the privacy budget \( \epsilon \) is fixed to 1, and the fidelity parameters \( \eta_p \) and \( \eta_d \) are fixed to 0.1% of the follower’s objective and 10.0% of the electricity prices, respectively. All the values displayed are average results over several instances.

B. Results

Table I reports the error on the original sensitive data, and the leader and follower’s costs of privacy, defined as the relative errors on the objective values of the leader and the follower, achieved by the Laplace mechanism and the w-PPSM for different values of the indistinguishability parameter \( \alpha \), which represents how much variation of load is protected. As expected, since the parameter \( \alpha \) determines the level of noise added to the original data, the errors on the sensitive data and the leader’s cost of privacy induced by the Laplace mechanism drastically increase as \( \alpha \) grows. On the contrary, the w-PPSM shows substantially better performances, and these errors remain stable with the increase of the parameter \( \alpha \). For larger values of \( \alpha \) (\( \geq 50 \)), the w-PPSM achieves up to one order of magnitude reduction in the error on the sensitive data, and two orders of magnitude reduction in the leader’s cost of privacy.

We also observe that the follower’s cost of privacy, for both mechanisms, slightly decreases with higher values of \( \alpha \). Intuitively, this can be explained by the interactions between the leader and the follower in the Stackelberg game. As the noise added to the electricity demand increases, the leader is less capable of anticipating the reaction of the follower, and of optimizing its own objective at the expense of the follower. Similar observations have been made related to the impact of DP on truthfulness in mechanism design [18]. Furthermore, the w-PPSM consistently achieves better performances compared to the Laplace mechanism, and up to two orders of magnitude reduction in the follower’s cost of privacy.

Table I

| \( M \) | \( \alpha \) | \( \Delta \eta_p \) (L1) | \( \Delta \eta_d \) (%) | \( \Delta \eta_E \) (%) |
|-------|-------|----------------|----------------|----------------|
| Laplace | 10.0 | 6139.88 | 0.764773 | 8.751309 |
| | 50.0 | 34131.08 | 47.556005 | 6.352331 |
| | 100.0 | 39131.19 | 58.455686 | 5.430761 |
| PPSM | 10.0 | 3723.66 | 0.842956 | 1.067518 |
| | 50.0 | 3843.56 | 0.606088 | 0.483239 |
| | 100.0 | 3296.58 | 0.302367 | 0.058785 |

Figure 2 presents heat maps of the leader and follower’s costs of privacy under varying operating conditions in both heat and electricity systems. These operating conditions in the heat (electricity) system are represented by the varying stress factors \( \eta_H^H (\eta_E^E) \) representing the multiplying factors applied to the heat (electricity) loads of the reference day previously considered. In this

\(^3\)The chosen values of \( \alpha \) guarantee a low privacy risk since the aggregate electricity demand ranges between 644.47MWh and 2498.54MWh.
Overall, this stress analysis underlines once more the robustness of the w-PPSM under various operating conditions. Indeed, the w-PPSM succeeds in keeping the leader and follower’s cost of privacy very low compared to the Laplace mechanism, for all the stress factor levels. Under certain operating conditions, the w-PPSM achieves up to two orders of magnitude reduction in the leader and follower’s costs of privacy.

We also notice that the highest costs of privacy for each mechanism are achieved under different combinations of stress factors. The Laplace mechanism performs especially poorly for the leader’s cost of privacy for high values of the electricity stress factor. Intuitively, this can be explained by the fact that, for higher electricity loads, the volatility of the electricity prices is increased, which in turn, impacts the merit order in the heat market and leads to a sub-optimal dispatch. However, this error is somehow reduced for corresponding higher values of the heat stress factor. Indeed, with higher heat loads, the relative share of HPs and CHPs in the heat dispatch, and therefore their impact on the leader’s objective value, decreases. Furthermore, the Laplace mechanism achieves the highest follower’s cost of privacy for the highest heat stress factor. Intuitively, this can be explained by the fact that, with higher heat loads, the heat dispatch of HPs and CHPs increases, which reduces their operational flexibility in the electricity market. These tightened interactions between heat and electricity markets result in higher errors on the electricity costs. This analysis identifies the system’s operating conditions that are the most vulnerable to perturbations and the ones resulting in a negligible cost of privacy when applying DP. This information can be leveraged to reduce the privacy budget [11].

VI. Conclusion

This paper introduces the w-PPSM which generates differentially-private data streams with high fidelity that can be used as input to the EAHM to coordinate the operation of heat and electricity systems. The w-PPSM was shown to enjoy strong theoretical properties. Furthermore, the numerical results show that the w-PPSM achieves up to two orders of magnitude reduction in the costs of privacy in both heat and electricity systems compared to the traditional Laplace mechanism.

Future work will aim at developing theoretical bounds on the costs of privacy, and accounting for potential correlations between the users’ data streams. Furthermore, focus will be placed on reducing the costs of privacy. Advanced obfuscation methods can be used to reduce the initial noise added to the data. And, the sparse vector technique can be adapted to privately identify the operating conditions resulting in negligible costs of privacy, and adapt the noise added under these conditions to reduce the privacy budget [11].

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