Balancing Privacy and Access to Smart Meter Data

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Questions?

- Does the privacy concern prevent the consumers from sharing the data?
- What private information can be leaked by smart meter data? How is affected by other sources of data Do the consumers know? How does this affect consumer choice?
- What are the alternative approaches to protect privacy? How to choose?
- What are the costs of privacy protections (Infrastructure investment? impact on the utility of the data)?
- How to evaluate data under privacy protection?
- How to incentive data sharing by balancing privacy and utility?

Consumer Privacy Concerns

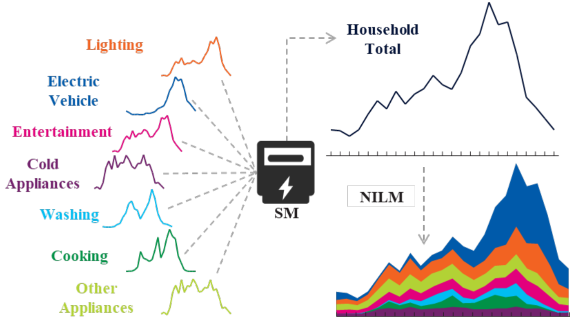
- Majority of consumers are willing to share their smart meter data, but it varies among customers
- Smart meter data is considered less sensitive than other types of personal data (financial, location, medical etc.)[1].
- Yet many consumers are not providing half-hourly data (49%) or simply do not know (37%) what their data sharing options[2]. WHY?
- **Are consumers currently making informed decisions?**
  - The options for data sharing
  - What are the implications of smart meter data sharing?

Willingness to Share: Customer-Facing Use Cases[3]

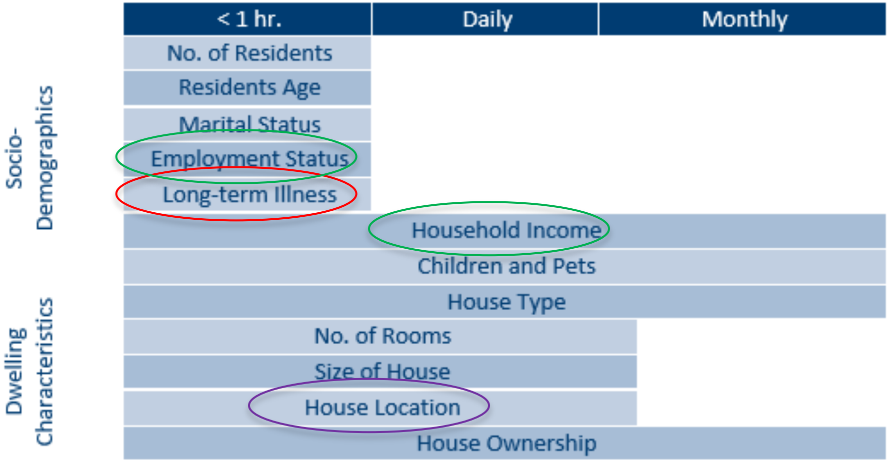
Willingness to Share: Market Operation Use Cases[3]

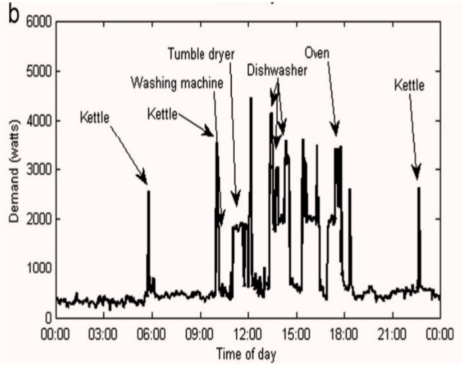
1. Skatova, A., McDonald, R. L., Ma, S., & Maple, C. (2019). Unpacking Privacy: Willingness to pay to protect personal data. https://doi.org/10.31234/osf.io/ahwe4
2. Citizen's Advice. (2019). *Clear and in control*.
3. Knight, A. (2018). *Consumer views on sharing half-hourly settlement data*. https://www.ofgem.gov.uk/publications-and-updates/consumer-research-datasets

Smart Meter Data – What information can be inferred?

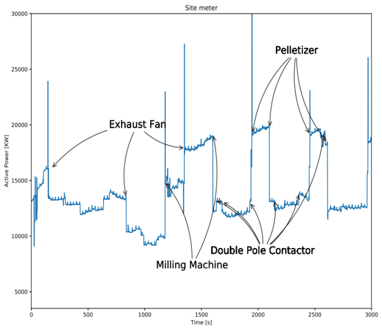


Medical
Financial
Location





Typical domestic load profile in the UK[2]



Typical load in a poultry feed factory[3]

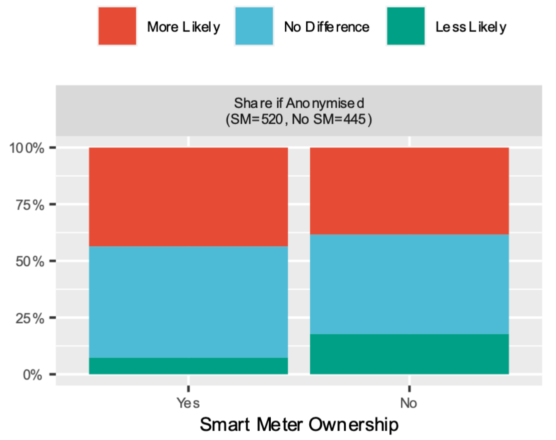
1. **Teng, F.**, Chhachhi, S., Ge, P., Prof, J. G., & Gunduz, D. (2022). Balancing privacy and access to smart meter data: an Energy Futures Lab briefing paper. *64*. https://doi.org/10.25561/96974
2. McKenna, E., Richardson, I., & Thomson, M. (2012). Smart meter data: Balancing consumer privacy concerns with legitimate applications. *Energy Policy*, *41*, 807–814. https://doi.org/10.1016/j.enpol.2011.11.049
3. Martins, P. B. et. al. (2018). Application of a Deep Learning Generative Model to Load Disaggregation for Industrial Machinery Power Consumption Monitoring. *2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 1–6. https://doi.org/10.1109/SmartGridComm.2018.8587415

Can we provide a truly privacy-preserving mechanism to promote energy data sharing?

Attitudes to Sharing Smart Meter Data - Options

- Majority are not fully aware of the information that can be inferred from smart meter data.
- When provided with information on the implications of data sharing concerns increase.
- Consumers would be more inclined to share smart meter data if it were privacy-preserved.

Contract decisions once privacy implications known[1]



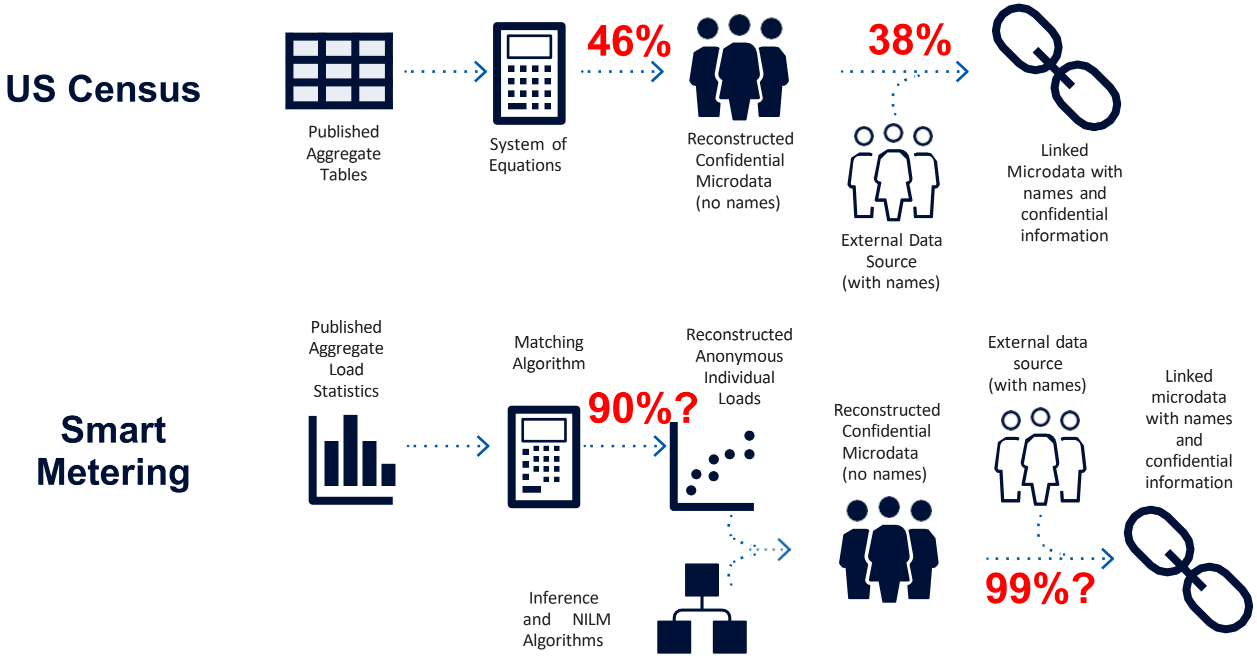
1. Jakobi, T., Patil, S., Randall, D., Stevens, G., & Wulf, V. (2019). It is about what they could do with the data: a user perspective on privacy in smart metering. ACM Transactions on Computer-Human Interaction, 26(1). https://doi.org/10.1145/3281444

Privacy-Preserving Technologies (PPTs)

- **Pseudonymisation**: Replacing identifiable features with consistent unique identifiers.
- **Aggregation:** Aggregating consumption data across multiple periods of time (temporal) or households(spatial).
- **Differential Privacy**: Carefully tuned noise addition to 'hide' individual contributions.
- **Homomorphic Encryption**: Perform arithmetic operations (e.g., addition, multiplication) on encrypted data without having to first decrypt it.
- **User Demand Shaping**: Altering actual consumption patterns using flexible assets to hide appliance characteristics.
- **Distributed Data Processing (Federated Learning)**: Distributed learning technique in which model parameters are shared but raw data kept locally.

Teng, F., Chhachhi, S., Ge, P., Prof, J. G., & Gunduz, D. (2022). Balancing privacy and access to smart meter data: an Energy Futures Lab briefing paper. *64*. https://doi.org/10.25561/96974

Vulnerabilities of Traditional Techniques



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Suitability

		Pseudo-nymisation	Aggregation	Homo-morphic Encryption	User Demand Shaping	Differential Privacy	Federated Learning
Privacy Guarantees	Anonymity	★	★	★		✓	
	Invulnerable to Linking					✓	
	Invulnerable to Inference				✓	✓	
	Minimise Impact of Data Breaches		★	✓	✓	✓	✓
Desirable Properties	Individual Level Data	✓			✓	★	★
	No Trusted Third-Party			✓	✓	✓	✓
	Easily Integrated	✓	✓			✓	
	Preserve Data Utility	✓	★	★	★		★
	Preference Heterogeneity	✓			✓	✓	✓

Orange stars indicate properties that the privacy-preserving technique is purported to have and which, in some cases, may have for practical purposes. However, these properties are not evidenced by theoretical guarantees.

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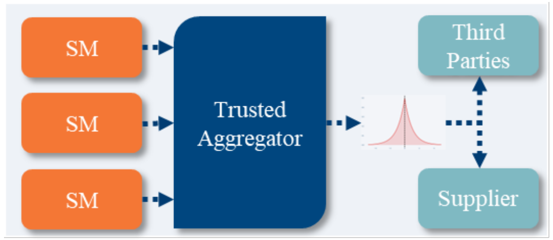
Is DP applicable for Energy Data? Energy Data is time series and is continuously released.

DP introduces a trade-off between privacy and accuracy. Implications for Energy Data?

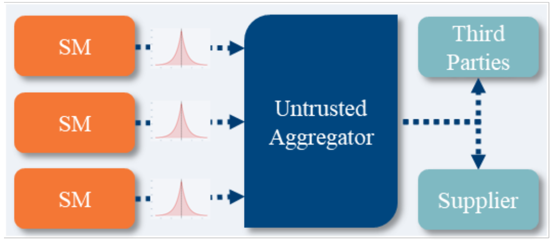
Centralised Framework – Differential Privacy

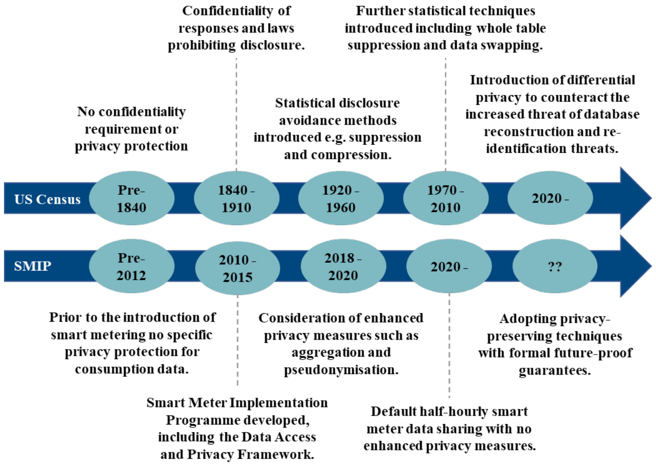
Differential Privacy (DP) – adding noise to mathematically ensure individuals cannot be identified from a dataset.

Global DP

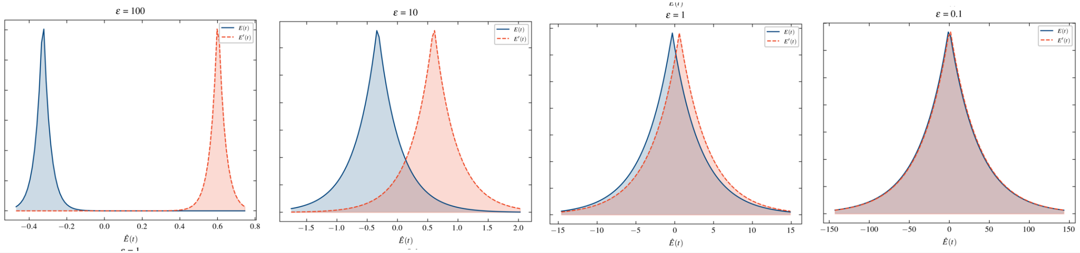


Local DP





$$\hat{E}(t)|E(t)$$
$$\hat{E}(t)|E'(t)$$



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What is the right level of DP for each individual?

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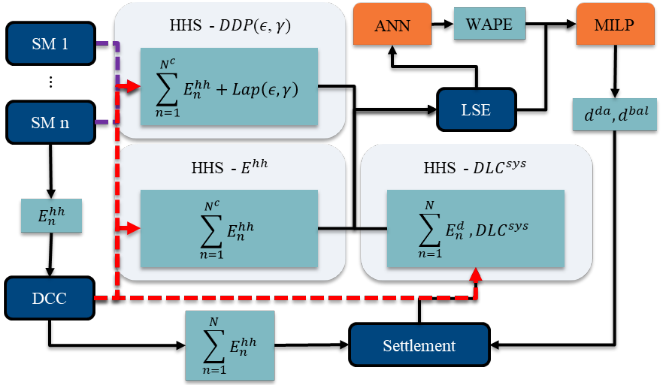
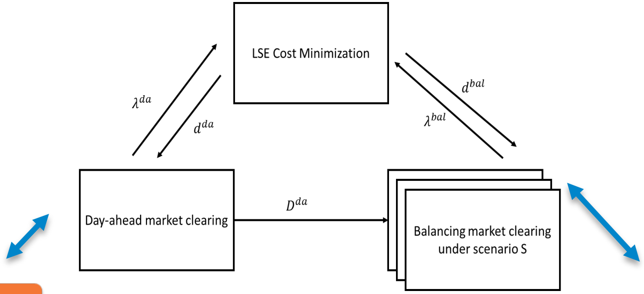
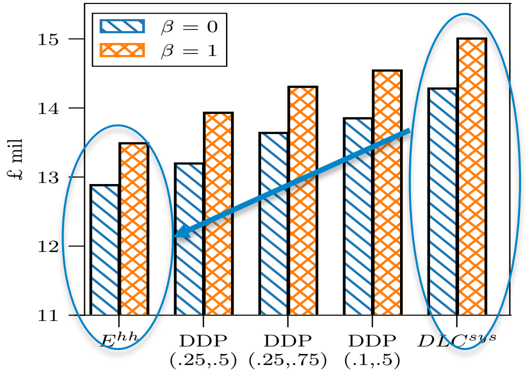
Differentially Private Load Forecasting and Energy Procurement

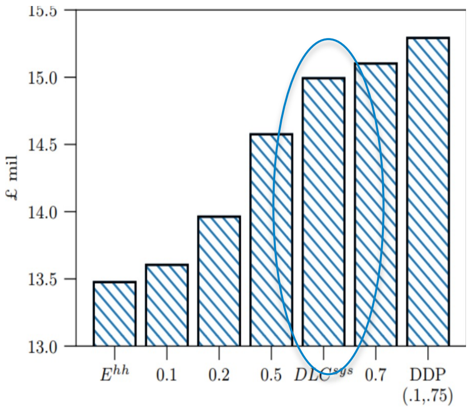
Project "Consumer-centric privacy protection scheme for energy consumption data", Supergen Energy Networks







Leveraging Preference Heterogeneity?



Chhachhi, S., & **Teng, F.** (2021). *Market Value of Differentially-Private Smart Meter Data*. 1–5. https://doi.org/10.1109/isgt49243.2021.9372228

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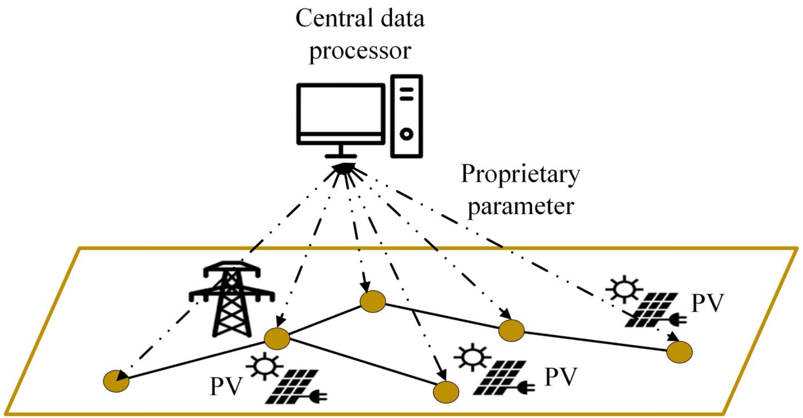
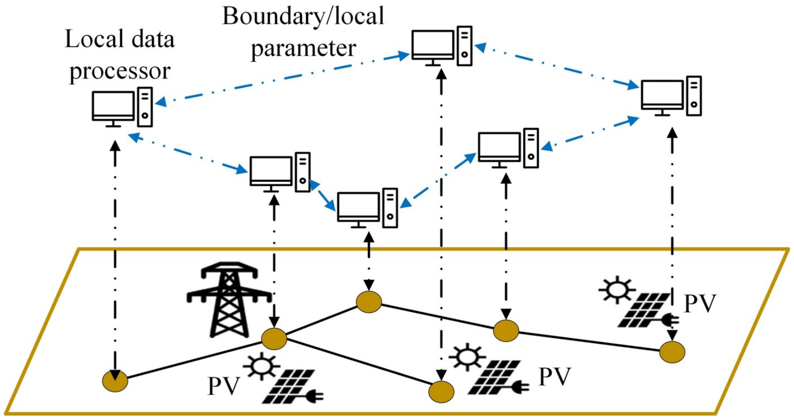
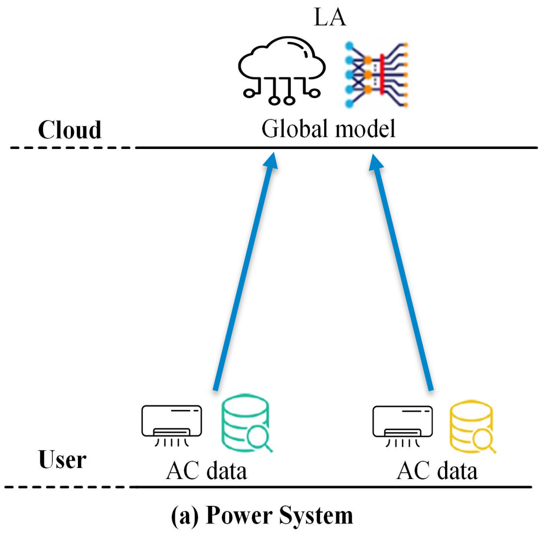
Distributed Data Processing Framework for Energy Systems by Utilizing Edge-device





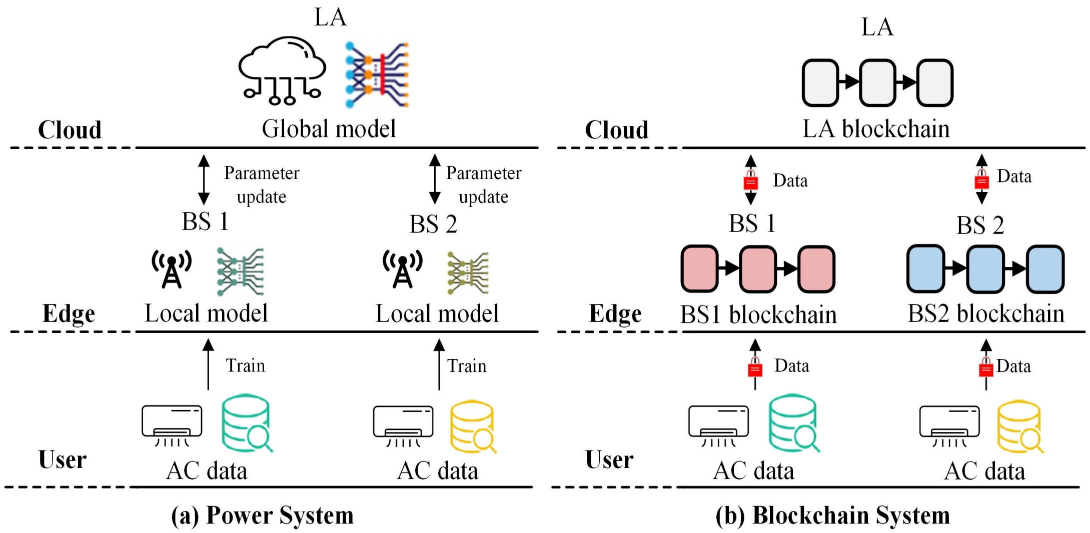
Federated Learning



Project "Blockchain-enabled cloud-edge coordination for demand side management", EPSRC-SIEMENS

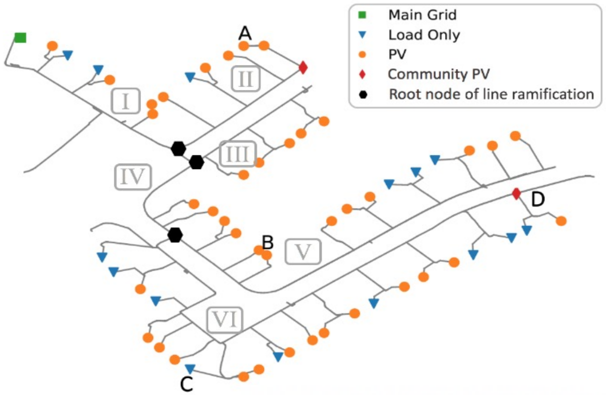
Wang, Y., Bennani, I. L., Liu, X., Sun, M., & Zhou, Y. (2021). Electricity Consumer Characteristics Identification: A Federated Learning Approach. *IEEE Transactions on Smart Grid*, *12*(4), 3637–3647. https://doi.org/10.1109/TSG.2021.3066577

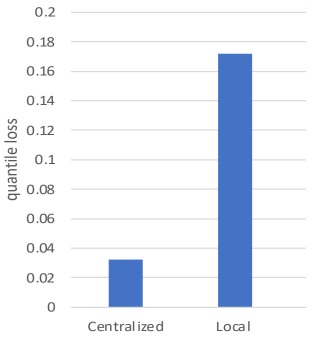
Federated Learning

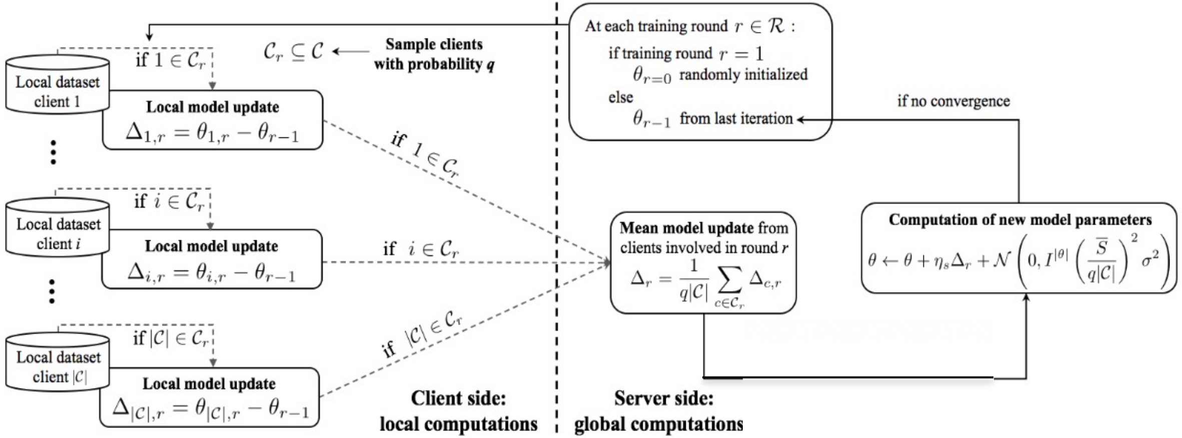


Project "Blockchain-enabled cloud-edge coordination for demand side management", EPSRC-SIEMENS

Federated Learning in Voltage Forecasting



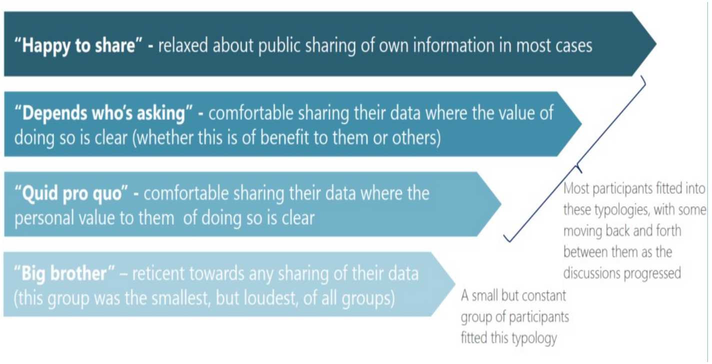


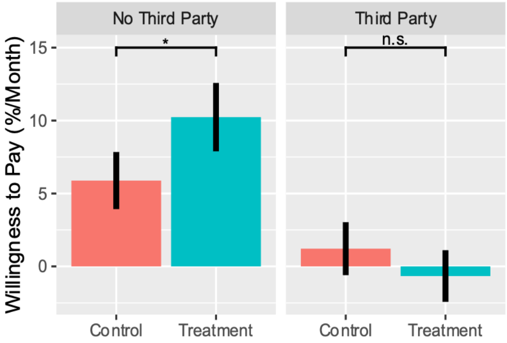


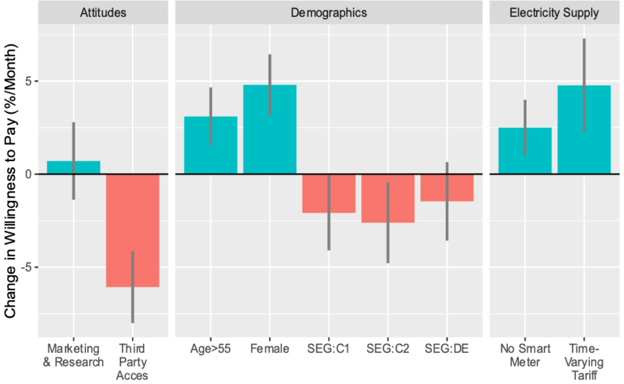
JF Toubeau, **F. Teng,** T. Morstyn, L. Krannichfeldt and Y. Wang "Privacy-Preserving Probabilistic Voltage Forecasting in Local Energy Communities", ArXiv

Attitudes to Sharing Smart Meter Data - Incentives

- A big portion of consumers were happy to share their data only if details on how it may benefit the system as well as benefit them personally is provided[1].
- Consumers are aware that their data has value and demand compensation for it (when given the choice).
- This increases when consumers are aware of the inferable information embedded within smart meter data.
- Significant heterogeneity across socio-demographic, contractual and attitudinal characteristics.







1. Dickman, A., & Aslaksen, A. P. (2017). *Consumer attitudes to DNO access to half hourly electricity consumption data*. https://www.ipsos.com/ipsos-mori/en-uk/data-privacy-and-smart-meters

Markets for Differentially-Private Energy Data

Data Valuation Mechanism

- Data value dependent on:
  - Task: model, evaluation metric
  - Context: other (public) data
  - Quality: noise and quantity
- Privacy concerns and ownership rights warrant valuation prior to data access.
- Data re-used repeatedly and for different tasks motivating a model agnostic ‘intrinsic’ valuation mechanism.

Data Market Mechanism

- Budget Feasibility: Data owners should be compensated commensurate with data value
- Individual rationality: Compensation should cover owners' own perceptions of value.
- Incentive compatibility: Privacy concerns and owners’ valuations should be truthful.
- Dependent Privacy: Payment-dependent privacy preferences.

Joint Energy & Data Market

- Data has direct effect on uncertainty in the energy markets (load, flexibility, prices).
- Inherent coupling and decision-dependent structure requires joint optimisation across energy and data markets.
- To ensure budget feasibility gains in energy market must cover improvements in, for example, procurement costs.

How do we value data in a model agnostic manner while preserving privacy i.e. without first accessing it?

✓ - shown,
✓ - possible with minimal extension

Data Valuation – Overview

1. **Model Error/Performance:** Reduction in, for example, mean square error for linear regression[1].
2. **Dual Variables/Shadow Prices:** Sensitivity of an optimization problem to a particular input/constraint (e.g. dual variables of Wasserstein DRO[2]).
3. **Regression Coefficients:** Regression performed with regularization determined by data owners' willingness-to-sell. (e.g. LASSO penalty parameters[3])
4. **Composite metrics + Transfer functions:** Metrics which incorporate quality and quantity metrics (e.g. Shannon entropy x non-noise ratio[4]) are fitted to model evaluation metrics using (synthetic) data.
5. **Statistical distances:** Measures which compute the similarity between two distributions (e.g. Kullback-Liebler Divergence or Wasserstein Distance[5]).

	Model Agnostic	No Data Access	Efficient Calculation	DP Effect
1				✓ (possible with minimal extension)
2			✓	✓
3			✓	
4		✓		✓ (possible with minimal extension)
5	✓	✓	✓	✓

1. Goncalves, C, et.al. (2021). Towards Data Markets in Renewable Energy Forecasting. *IEEE Transactions on Sustainable Energy*, *12*(1), 533–542. https://doi.org/10.1109/TSTE.2020.3009615
2. Mieth, R., et. al. (2023). *Data Valuation from Data-Driven Optimization*. http://arxiv.org/abs/2305.01775
3. Han, L, et. al.. (2021). *Trading Data for Wind Power Forecasting: A Regression Market with Lasso Regularization*. http://arxiv.org/abs/2110.07432
4. Chen, L., et. al. (2021). Toward Future Information Market: An Information Valuation Paradigm. *2021 IEEE Power & Energy Society General Meeting (PESGM)*, 1–5. https://doi.org/10.1109/PESGM46819.2021.9638205
5. Zhao, Y, et. Al.. (2018). *Federated Learning with Non-IID Data*. https://doi.org/10.48550/arXiv.1806.00582

Statistical Distances- Wasserstein Metric Valuation

- Which distance to use?
  - The Wasserstein distance between two distributions is:

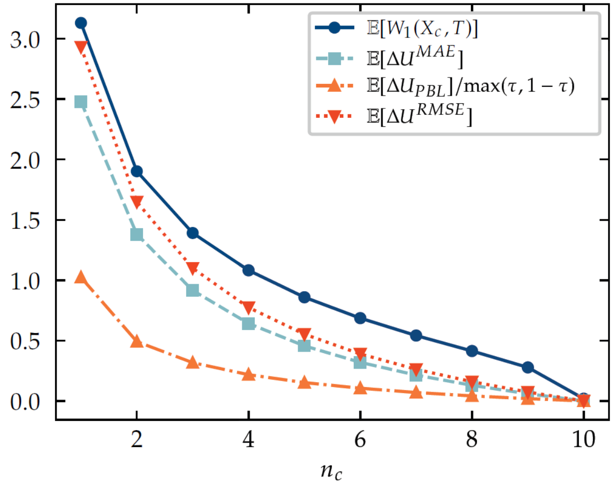
$$W_p(X,Y) = \inf_{X\sim\mu, Y\sim\nu} (E\|X-Y\|^p)^{1/p}$$

  - Wasserstein metric/distance has a number of advantages:
    - Continuous, well defined even when distributions do not overlap.
    - Has metric properties.
    - Calculated efficiently and privately in the case p = 1 [1,2].
    - Effect of differential privacy can be bounded[1]:

$$W_1(X_1 + X_L, X_2) \leq W_1(X_1, X_2) + \frac{\Delta}{\epsilon}, where\ X_L \sim Lap\left(0, \frac{\Delta}{\epsilon}\right)$$

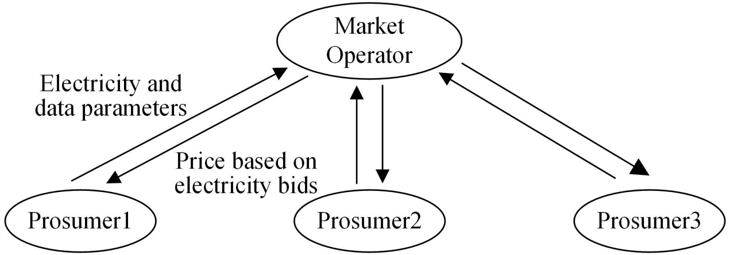
- How does it relate to model performance/error?
  - Lipschitz bound: *Given a K-Lipschitz loss function $l(x_i)$ and its expected value $U(X_i) = \mathbb{E}[l(x_i)]$, the difference between the loss obtained with X_1 or X_2 is bounded by the 1-Wasserstein distance between them*[3]*:*

$$|U(X) - U(Y)| \leq L \cdot W_1(X,Y)$$



1. Chhachhi, S., & **Teng, F**. (2023). *On the 1-Wasserstein Distance between Location-Scale Distributions and the Effect of Differential Privacy*. http://arxiv.org/abs/2304.14869
2. Blanco-Justicia, A., & Domingo-Ferrer, J. (2020). Privacy-Preserving Computation of the Earth Mover's Distance. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12472 LNCS*, 409–423.
3. Ghorbani, A., Kim, M. P., & Zou, J. (2020). *A Distributional Framework for Data Valuation*. http://arxiv.org/abs/2002.12334

A Joint Energy and Data Market - Case study



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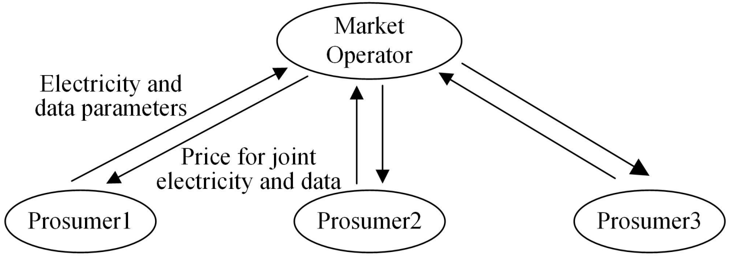
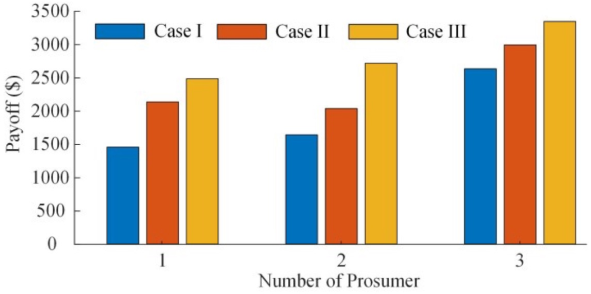
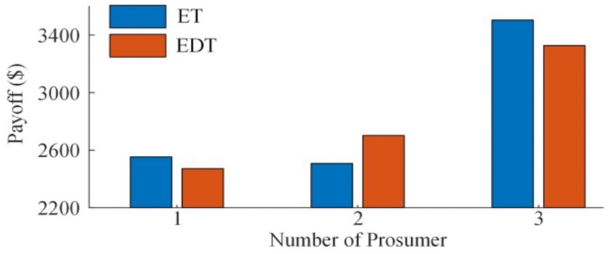


(b)





M. Yan and **F .Teng*** “Towards Joint Electricity and Data Trading: A Scalable Cooperative Game Theoretic Approach”, *Arxiv*

Summary

- Some of the data has embedded within significant amounts of personal or commercially sensitive information, particularly if combined with other data sources
- The majority of consumers are unaware but when informed have significant privacy concerns. Privacy concerns are heterogonous among consumers.
- Privacy-preserving techniques can ensure protection while providing access
  - DP is appliable for energy system data but needs to understand the trade-offs
  - A distributed framework for control, optimization and learning plays a critical role in energy digitalization
  - A hybrid centralized/decentralised data processing framework may be eventually needed
- A joint energy and data trading mechanism is needed for the future market