FDA-HeatFlex: Scalable Privacy-Preserving Temperature and Flexibility Prediction for Heat Pumps using Federated Domain Adaptation

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Background and Motivation (1/3)

- Decarbonization and use of renewable energy for improving energy efficiency [1].
- Heat pumps as the most energy-efficient technology for residential heating [1].
- Flexibility in energy systems by heat pumps [1,2].
- Example: Heat pumps utilize electricity when renewable energy is abundant [1,2].

Table 1: SG-Ready heat pump operating modes

Operating mode	Definition
Off	Heat pump operation actively switched off, using minimal power (limited to 2 hours a day)
Normal	Heat pump operation is normal
RecommendedOn	Heat pump operation is set to prefer switching on (interpreted as a recommendation)
ForcedOn	Heat pump (and auxiliary heaters, if applicable) operation actively switched on, using maximum power

[1] Liu, Shuo, et al. "Field study of heat pump-assisted hybrid desiccant cooling system for thermal environment control and energy consumption under different load patterns." Case Studies in Thermal Engineering 36 (2022): 102170.
[2] Brusokas, Jonas, et al. "HeatFlex: Machine learning based data-driven flexibility prediction for individual heat pumps." Proceedings of the Twelfth ACM International Conference on Future Energy Systems. 2021.

Background and Motivation (2/3)

- Dependency on varying indoor temperature for flexible operation of heat pumps [2].
- Indoor temperature prediction required for heat pump flexibility prediction [2].
- Example: Controlling the heat pump electricity consumption either to increase or decrease while ensuring that the indoor temperature remains within the specified comfort range [2].
- Using Traditional Machine Learning (ML) models to learn the pattern of varying indoor temperature [2,3].

[3] Masini, Ricardo P., Marcelo C. Medeiros, and Eduardo F. Mendes. "Machine learning advances for time series forecasting." Journal of economic surveys 37.1 (2023): 76-111.

Background and Motivation (3/3)

- Problems with Traditional ML approaches [4,5,6]:

Insufficient model training data resulting poor prediction

- Leading to wrong and sub-optimal heat pump control.

Data shift problem/ Generalization issues

- Due to unique insulation levels and temperature responses of buildings.

Privacy concerns

Federated Learning

Domain Adaptation

[4] Farahani, Abolfazl, et al. "A brief review of domain adaptation." Advances in Data Science and Information Engineering: Proceedings from ICDATA 2020 and IKE 2020 (2021): 877-894.
[5] Jin, Xiaoyong, et al. "Domain adaptation for time series forecasting via attention sharing." International Conference on Machine Learning. PMLR, 2022.
[6] Shi, Yuan, and Xianze Xu. "Deep federated adaptation: An adaptative residential load forecasting approach with federated learning." Sensors 22.9 (2022): 3264.

Related Works and Contributions (1/2)

- Related Works:
  - Conventional ML approaches have been used for predicting the load demand and energy consumption of buildings [7].
  - Transfer Learning techniques adopted in the energy sector to address the data scarcity problem for energy consumption prediction [8].
  - Federated Transfer Learning techniques to address both data scarcity and privacy issues for energy consumption and load forecasting [9].

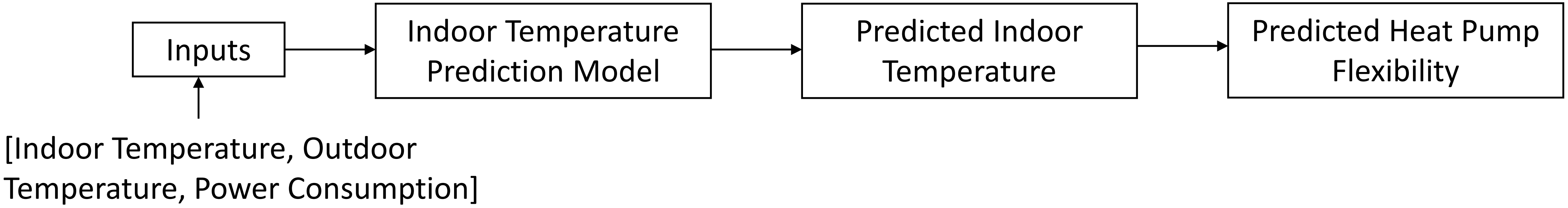
- Closely Related Work:
  - HeatFlex uses simple Deep learning approaches to train an indoor temperature and flexibility prediction model, leading to data shift and privacy issues [2].

[7] Wang, Jiangyu, et al. "Energy consumption prediction for water-source heat pump system using pattern recognition-based algorithms." *Applied Thermal Engineering* 136 (2018): 755-766.
[8] Gao, Nan, et al. "Transfer learning for thermal comfort prediction in multiple cities." Building and Environment 195 (2021): 107725.
[9] Li, Junyang, et al. "Federated learning-based short-term building energy consumption prediction method for solving the data silos problem." Building Simulation . Vol. 15.No. 6. Beijing: Tsinghua University Press, 2022.

Related Works and Contributions (2/2)

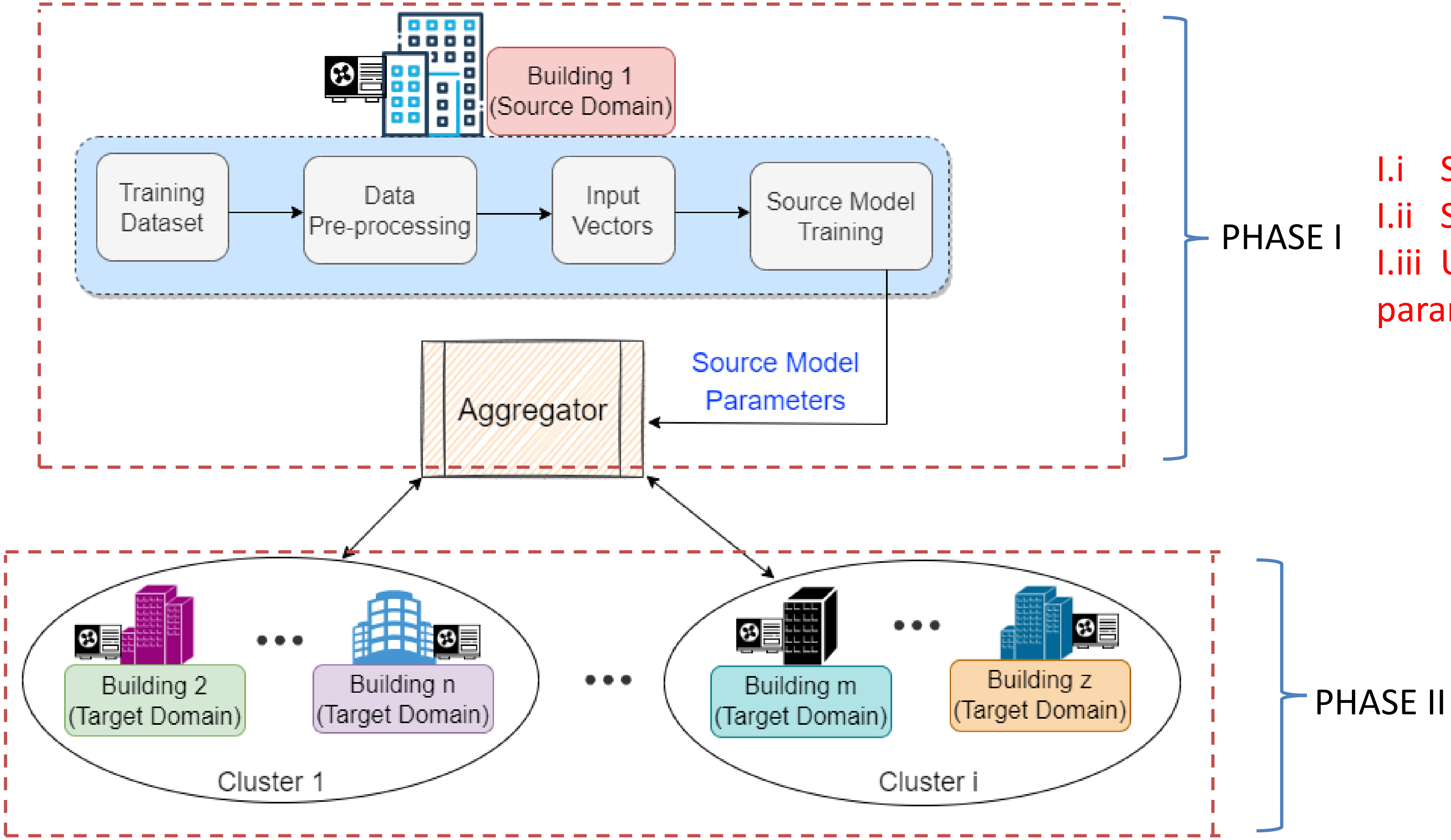
- Our Proposal: FDA-HeatFlex (Federated Domain Adaptation for Heat Pump Flexibility) combines domain adaptation and federated learning, to solve the problems of data shift and privacy, respectively.

- Example Scenario:



Methods	Data Shift Problem	Privacy Concerns	Sufficient Data
HeatFlex	Yes	Yes	Required
FDA-HeatFlex	No	No	Not Required

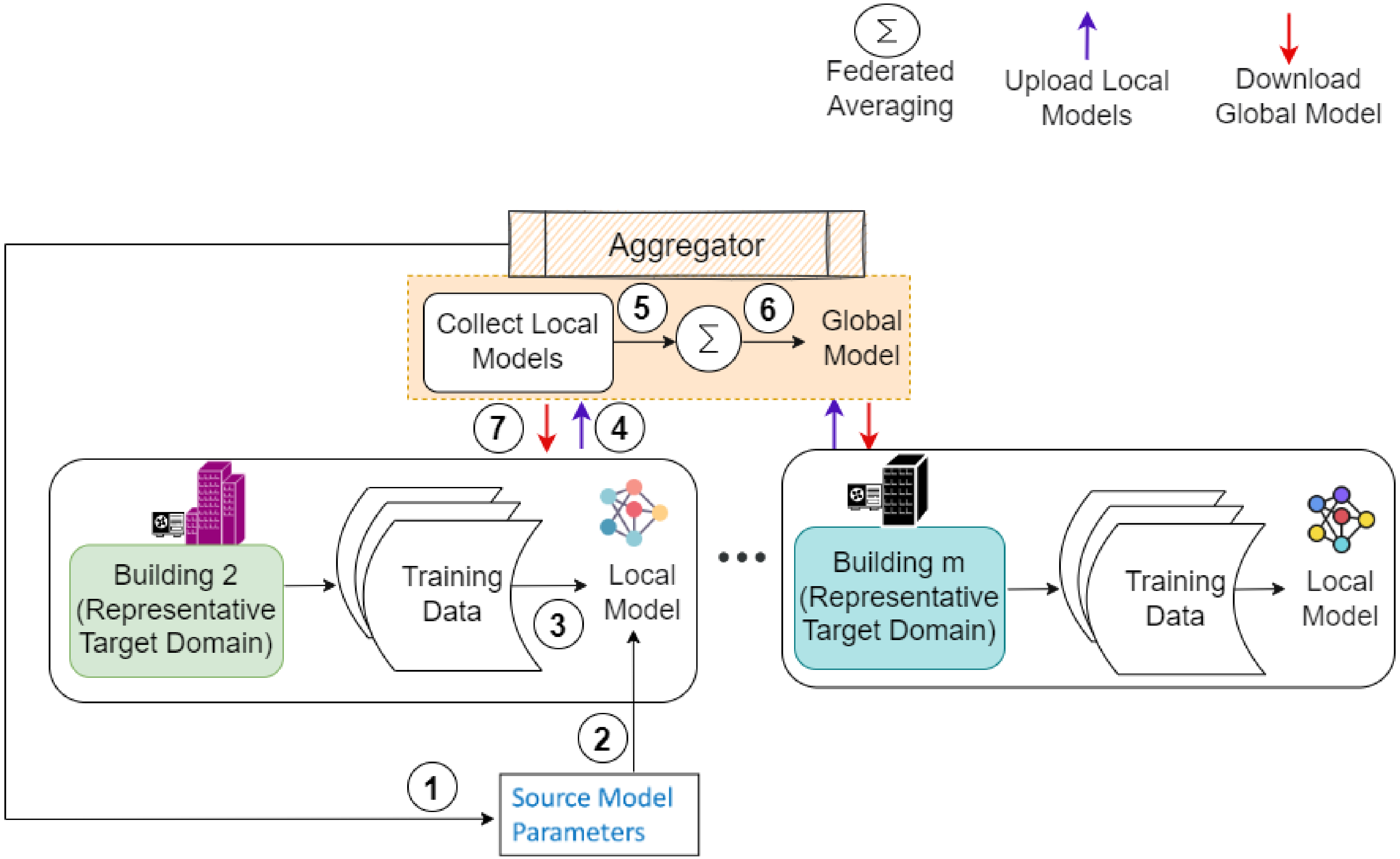
Overview of FDA-HeatFlex



I.i Selection of Source Domain
I.ii Source Model Training
I.iii Uploading source model parameters

II.i Selection of Target Domains
II.ii Clustering of Target Domains
…

FDA for Indoor Temperature Prediction (1/2)



- Multiple steps of Phase II

  II.i Selection of Target Domains
  II.ii Clustering of Target Domains
  II.iii Local Model Training
  II.iv Update Global Model
  - a. Federated Averaging
  - b. Re-weighting

FDA for Indoor Temperature Prediction (2/2)

❑ Re-weighting Global Model

- Correlation Alignment (CORAL) function [10]:

$$d(\omega^i, \omega^j) = \frac{1}{4m^2} \| D_{cv_i} - D_{cv_j} \|^2, \quad (7)$$

where ω^i and ω^j are the local model parameters of target domains i and j, m is the size of time window; denoting dimension of features, and D_{cv_i} and D_{cv_j} are the covariance matrices of the local model parameters.

- Adaptive boosting (AdaBoost) [11]:

$$\alpha_{r+1} = \begin{cases} \alpha_r \times U; & \text{if } d(\omega^i, \omega^j)_r \geq d(\omega^i, \omega^j)_{r-1} \\ \alpha_r; & \text{otherwise,} \end{cases} \quad (8)$$

where $\alpha_r = \frac{1}{|\hat{\mathcal{B}}'|}$, and U is the updating function computed as

$$U = 1 + \sigma(d(\omega^i, \omega^j)_r - d(\omega^i, \omega^j)_{r-1}), \quad (9)$$

where σ is the sigmoid function.

Algorithm 1 Indoor Temperature Prediction Using Federated DA

Input:
  $\tilde{\mathcal{B}}'$: the set of selected target domains;
Output:
  $\mathcal{M}_G$: final global model;
Initialization:
  initialize local models using source model parameter ω_0^s;
while $\mathcal{M}_G$ is not converged **do**
  for each communication round $r = 1, 2, \ldots$ **do**
    for $k \in \tilde{\mathcal{B}}'$ **in parallel do**
      $\omega_{r+1}^k \leftarrow \omega_{r+1}^k - \eta \nabla \ell(\omega_r^g)$; ▷ Local training
    end for
    $\omega_{r+1}^g \leftarrow \sum_{k=1}^{|\tilde{\mathcal{B}}'|} \frac{n_k}{D} \omega_{r+1}^k$; ▷ Federated averaging
    $\alpha_r \leftarrow \frac{1}{|\tilde{\mathcal{B}}'|}$; ▷ Compute value of alpha
    $d(\omega_r^i, \omega_r^j) \leftarrow$ solve Eq. (7); ▷ Compute distance
    if $d(\omega_r^i, \omega_r^j) \geq d(\omega_{r-1}^i, \omega_{r-1}^j)$ **then**
      $\alpha_{r+1} \leftarrow$ solve Eq. (8); ▷ Update value of alpha
    else
      $\alpha_{r+1} = \alpha_r$;
    end if
    $\omega_{r+1}^g \leftarrow \alpha_{r+1} \times \omega_{r+1}^g$; ▷ Re-weighting global model
  end for
end while

[10] Du, Yuntao, et al. "Adarnn: Adaptive learning and forecasting of time series." *Proceedings of the 30th ACM international conference on information & knowledge management*. 2021.
[11] Zheng, Zhedong, and Yi Yang. "Adaptive boosting for domain adaptation: Toward robust predictions in scene segmentation." IEEE Transactions on Image Processing 31 (2022): 5371-5382.

Heat pump Flexibility Prediction (1/2)

- **Heat pump flexibility** [2]: It reflects the number of hours/time periods that the heat pump can be in mode ForcedOn or Off before breaching the user-specified comfort intervals.

- Predicting the heat pump flexibility for mode ForcedOn [2]:

1

$$\hat{Y}^{\text{on}} = \mathcal{M}_G(\mathcal{X}^{\text{on}}; \omega),$$

2

$$I_i^{\text{on}} = \begin{cases} 1, & \text{if } T_\ell \le \hat{Y}_i^{\text{on}} \le T_u \\ 0, & \text{otherwise,} \end{cases}$$

- Predicting the heat pump flexibility for mode Off [2]:

1

$$\hat{Y}^{\text{off}} = \mathcal{M}_G(\mathcal{X}^{\text{off}}; \omega),$$

2

$$I_i^{\text{off}} = \begin{cases} 1, & \text{if } T_\ell \le \hat{Y}_i^{\text{off}} \le T_u \\ 0, & \text{otherwise,} \end{cases}$$

Summary of Notations Used
$\hat{Y}^{on}$, $\hat{Y}^{off}$: Predicted Indoor Temperature
M_G : Global Model
X^{on}, X^{off}: Past Observations
I_i^{on}, I_i^{off}: Indication function
T_ℓ: User-defined lower comfort bound
T_u : User-defined upper comfort bound
$\hat{Y}_i^{on}$, $\hat{Y}_i^{off}$: i_{th} element of $\hat{Y}^{on}$ and $\hat{Y}^{off}$

Heat pump Flexibility Prediction (2/2)

- Heat pump flexibility example for mode ForcedOn:

1

$$\boxed{\hat{Y}^{on} = \mathcal{M}_G(\mathcal{X}^{on}; \omega),}$$

- $\hat{Y}^{on}$ = [22°C, 23°C, 23.5°C, 24°C, 24.5°C, 24°C] for h = 6.

2

$$\boxed{I_i^{on} = \begin{cases} 1, & \text{if } T_\ell \leq \hat{Y}_i^{on} \leq T_u \\ 0, & \text{otherwise,} \end{cases}}$$

- T_ℓ = 20°C, and T_u = 24°C.
- I_i^{on} = [1,1,1,1,0,1]
- Thus, F^{on} = 4.

Summary of Notations Used
$\hat{Y}^{on}$: Predicted Indoor Temperature
h: Prediction horizon
M_G : Global Model
X^{on}: Past Observations
I_i^{on}: Indication function
T_ℓ : User-defined lower comfort bound
T_u : User-defined upper comfort bound
$\hat{Y}_i^{on}$: i_{th} element of $\hat{Y}^{on}$
F^{on} : Predicted heat pump flexibility

Experimental Results (1/3)

- **Datasets:**

1. New York State Energy Research and Development Authority (NYSERDA) [12]
2. Net-Zero Energy Residential Test Facility (NIST) [13]

- **Baselines:**

➢ Indoor Temperature Prediction:

1. Local Model Training Only (Localized Training)
2. Source Model Training Only (Source Training)
3. Decentralized Parallel Stochastic Gradient Descent (D-PSGD)
4. Single Domain Adaptation (Single DA)

➢ Heat pump Flexibility Prediction:

1. HeatFlex [2]

[12] https://data.ny.gov/Energy-Environment/Water-Furnace-Geothermal-Heat-Pumps-Symphony-Time-/48yz-n8mx/data
[13] https://pages.nist.gov/netzero/data.html

Experimental Results (2/3)

- FDA-HeatFlex outperforms the state-of-the-art training approaches for indoor temperature prediction with 66.91% (on average) improvement.

Performance Evaluation Metric:

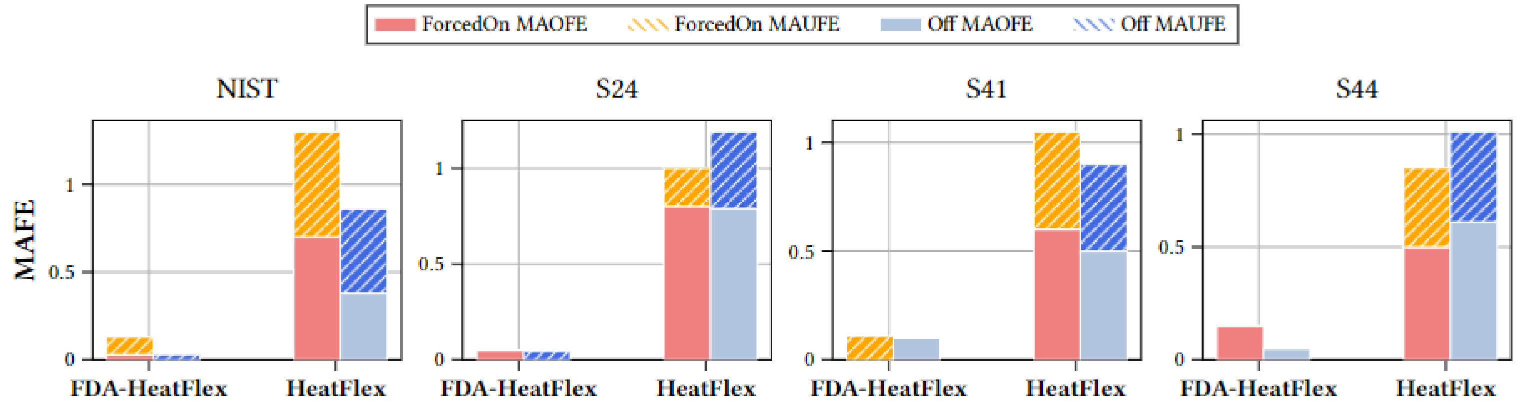
- RMSE: Root Mean Square Error
- MAE: Mean Absolute Error

Table 2: Indoor Temperature prediction error of FDA-HeatFlex compared to the baselines

Methods	Test Target Domains							
	NIST		S24		S41		S44	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Localized Training	0.158	0.143	0.240	0.229	0.455	0.431	0.270	0.253
HeatFlex	0.321	0.317	0.255	0.235	0.219	0.201	0.322	0.290
Source Training	0.331	0.256	0.131	0.122	0.185	0.172	0.170	0.159
D-PSGD	0.089	0.065	0.094	0.075	0.091	0.08	0.087	0.068
Single DA	0.072	0.057	0.078	0.063	0.089	0.071	0.096	0.083
FDA-HeatFlex	**0.044**	**0.027**	**0.038**	**0.026**	**0.04**	**0.031**	**0.042**	**0.036**

Experimental Results (3/3)

- FDA-HeatFlex outperforms the state-of-the-art baseline for heat pump flexibility with 91.8% (on average) improvement.



The flexibility prediction error of FDA-HeatFlex compared to the baseline HeatFlex.

Performance Evaluation Metric:

- MAFE: Mean Absolute Flexibility Error
  1. Mean Absolute Overestimated Flexibility Error (MAOFE)
  2. Mean Absolute Underestimated Flexibility Error (MAUFE)
- MAFE = MAOFE + MAUFE

Conclusion and Future Works

- Motivation:
  - The performance of ML models suffers severely due to limited data, leading to data shift issue.
  - ML models are also prone to privacy issues.

- Our Contributions:
  - FDA-HeatFlex framework combines domain adaptation and federated learning techniques to solve the data shift and privacy issues, respectively.
  - FDA-HeatFlex outperforms the baselines for the indoor temperature prediction, and the current state-of-the-art baseline on flexibility prediction by 66.91% and 91.8% improvement on average, respectively.

- Future Work:
  - In the future, we will focus on implementing the framework in a real-world setting to validate its effectiveness in a practical application.