HeatFlex: Machine learning based data-driven flexibility prediction for individual heat pumps

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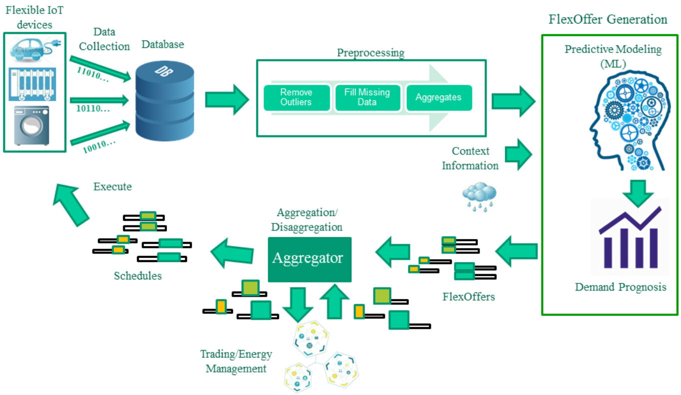
Introduction

- Significant advancements were made in smart grids
- Majority of current research focuses on flexibility based demand-response mechanisms

- With heating constituting the largest part of energy demand, heat pumps are key sources of flexibility



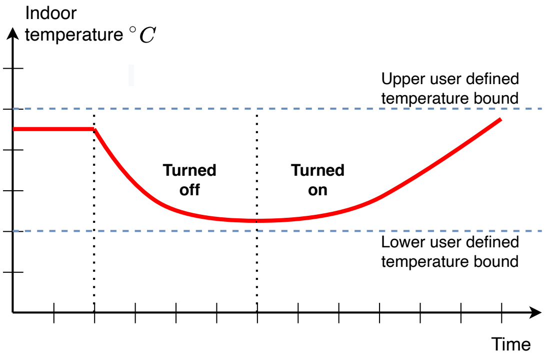
Flexibility lifecycle [Pe2018]

Heat pump flexibility

- Allow deviation in indoor temperature within user defined temperature bounds
- Increase or decrease heat pump power while maintaining temperature within set bounds

- Two key elements are required to extract flexibility from heat pumps:

  1. Remote control mechanism to change heat pump operation and, subsequently, energy consumption
  2. Predictive models to accurately estimate temperature changes, to not violate set temperature bounds



Heat pump operation within user defined temperature bounds

Heat pump remote control

- SG-Ready smart heat pump interface specification developed to enable flexible heat pump operation
- SG-Ready defines 4 heat-pump operation modes that can be selected using a remote signal
- Only *Off* and *ForcedOn* define deterministic, implementation-agnostic heat pump behaviour

SG-Ready heat pump operating modes

Mode	Operation
Off	Switched off (max 2h)
Normal	Default
RecommendedOn	Prefers switch on
ForcedOn	Actively switched on

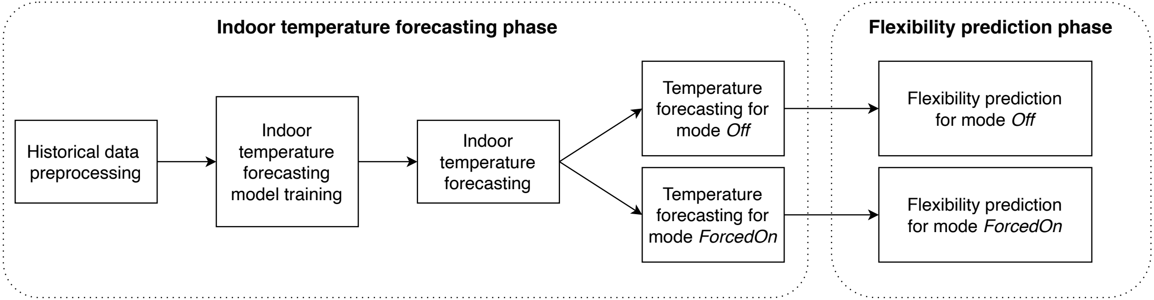
Heat pump predictive models

- Previous work uses physical modelling and significant amounts of monitored variables [Pa2013, Ne2017]
  - Requires a tailor-made model for each individual heat-pump deployment
  - Requires significant amounts of high quality, high frequency data
  - Requires a lot of installed sensors in deployment sites
- No previous data-driven, scalable methods for heat pump flexibility prediction are known

- Our work fills the gap in literature by proposing the first fully data-driven method for heat pump flexibility prediction - **HeatFlex**
- **HeatFlex** uses only 3 widely available monitored variables for prediction: indoor temperature, outdoor temperature, heat pump power consumption

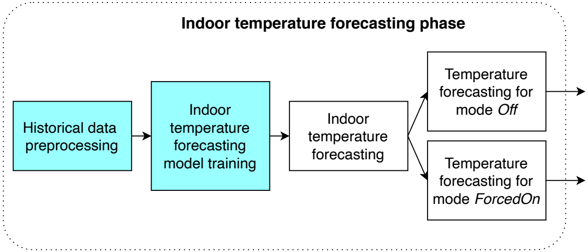
HeatFlex overview

- HeatFlex can be split into two parts: **Indoor temperature forecasting** and **Flexibility prediction**



HeatFlex overview

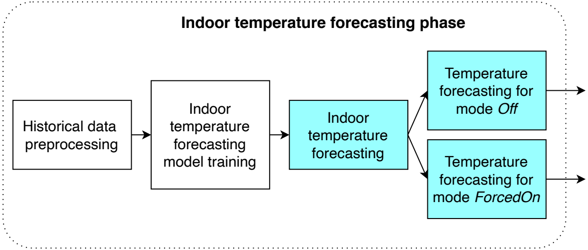
HeatFlex overview: indoor temperature forecasting (1)



HeatFlex indoor temperature forecasting

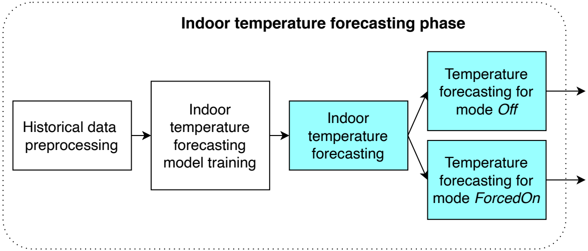
- Historical data used for training:
  1. Indoor temperature
  2. Outdoor temperature
  3. Heat pump power consumption
- Model hyperparameters are selected, including:
  - Memory (m) – how many past data points will be used for forecasting
  - Horizon (h) – how long in the future will the models forecast

HeatFlex overview: indoor temperature forecasting (2)



HeatFlex indoor temperature forecasting

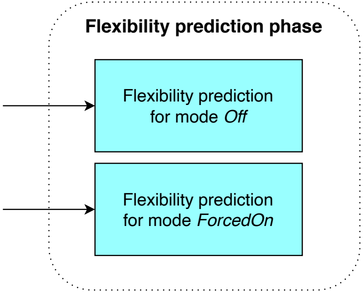
- Once models are trained using historical data, they are used to forecast indoor temperature
- Models are used to generate two forecasts:
  1. Assuming the heat pump will operate in mode *Off*
  2. Assuming the heat pump will operate in mode *ForcedOn*

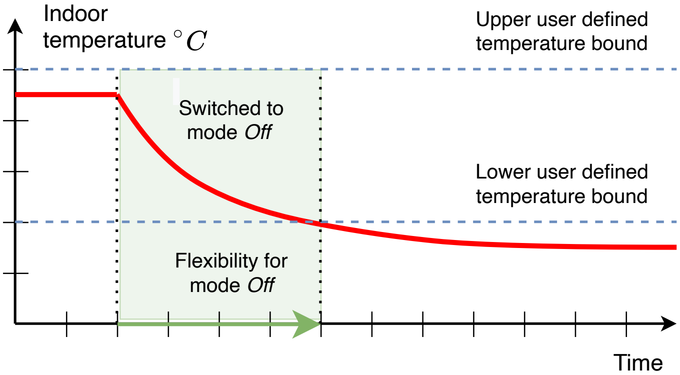


HeatFlex indoor temperature forecasting

- Model inputs (*m* records of):
  1. Past indoor temperature (T_{ind})
  2. Past outdoor temperature (T_{out})
  3. Past power consumption (P_{hp})
  4. Preset power consumption (U) (corresponding to mode *Off* or *ForcedOn*)
  5. Date, time and day of the week (DT)
- Model outputs (*h* records of):
  - Forecasted indoor temperature (T_{ind})

HeatFlex overview: flexibility prediction (1)

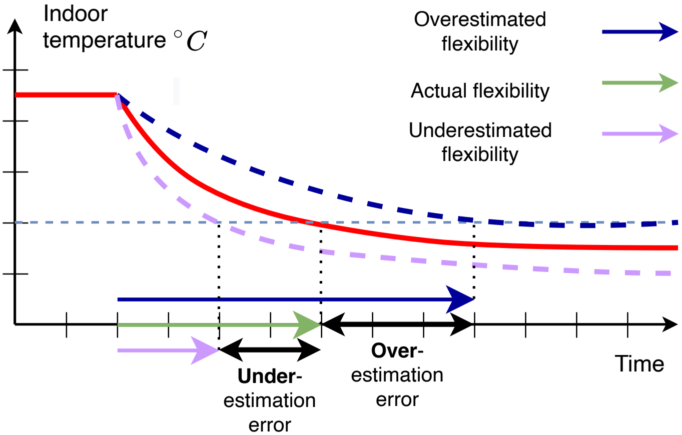




- Use indoor temperature forecast to calculate time before violation of predefined user temperature bounds for modes *Off* and *ForcedOn*
- **Flexibility** – the amount of time heat pump can operate in a given mode before violating user temperature bounds

HeatFlex overview: flexibility prediction (2)

- Two types of non-overlapping errors are possible:
  - **Overestimation**: when predicted flexibility exceeds actual flexibility
  - **Underestimation**: when actual flexibility exceeds predicted flexibility



HeatFlex overview: flexibility prediction (3)

- In this paper we introduce metrics to numerically quantify HeatFlex flexibility prediction performance
  - *MAFE*, *MAUFE*, *MAOFE* measure flexibility prediction error
  - *EPFR* – percentage of accurately predicted potential flexibility

$$MAOFE(Z, \hat{Z}) = \frac{1}{n} \sum_{i=1}^{n} |min(Z_i - \hat{Z}_i, 0)|$$

$$MAUFE(Z, \hat{Z}) = \frac{1}{n} \sum_{i=1}^{n} |max(Z_i - \hat{Z}_i, 0)|$$

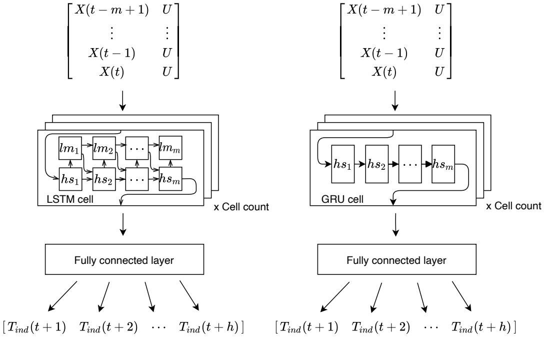
$$MAFE = MAUFE + MAOFE$$

$$EPFR(Z, \hat{Z}) = \frac{\sum_{i=1}^{n} max(Z_i - \hat{Z}_i, 0)}{\sum_{i=1}^{n} Z_i}$$

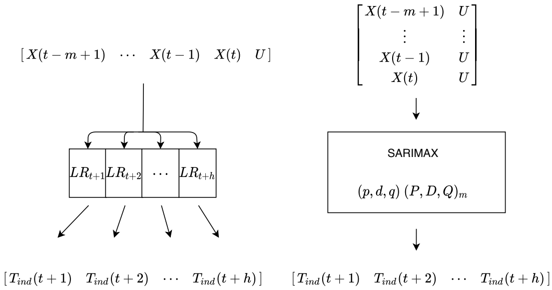
Indoor temperature forecasting models (1)

- LSTM and GRU recurrent neural networks were used to build indoor temperature forecasting models
- Commonly used for deep learning based sequence modelling and forecasting

- Cell count (c) – how many LSTM or GRU cells will be used to form the hidden layer



LSTM and GRU indoor temperature forecasting model architectures



Multivariate linear regression and SARIMAX baseline forecasting models

- Multivariate Linear Regression (LR) and SARIMAX were chosen as model baselines
- Commonly used as data-driven predictive models for timeseries forecasting and regression tasks

Experiment setup

- Experiments utilized data from 3 real heat pump deployments
  - Deployments: NIST, NYSERDA S40, NYSERDA S44
  - Sourced from 2 open access datasets: NIST Net-Zero and NYSERDA
  - Around 12 months of timestamped data

- Data cleaned, preprocessed, normalized
  - Removed false readings, extreme outliers
  - Resampled at 15 minute granularity
  - Split into three subsets: training, validation, test

- Memory $m \in \langle 16, 32, 48, 96 \rangle$ and cell count $c \in \langle 16, 32, 48, 80 \rangle$ (for LSTM and GRU)
- Temperature forecast horizon $h = 4$ (hour ahead)
- Model training was repeated 3 times, second-best result used in analysis

- Models were implemented and trained using PyTorch and Pmdarima

Indoor temperature forecasting results (1)

- Trained models successfully learned to capture how indoor temperature changes w.r.t. heat pump operation
- LSTM models showed overall best performance across all 3 deployments

Trained model RMSE error on all datasets

	Dataset		
	NIST	**S40**	**S44**
LSTM (c=16, m=16)	0.3240	**0.2352**	**0.3084**
LSTM (c=32, m=96)	**0.0833**	0.2408	0.3106
GRU (c=16, m=16)	0.3200	0.2513	0.3171
GRU (c=16, m=96)	0.1262	0.2458	0.3283
LR (m=32)	0.2620	0.2852	0.4066
LR (m=16)	0.3274	0.2604	0.4119
SARIMAX	0.1424	0.9086	2.2577

Indoor temperature forecasting results (2)

- LSTM outperformed GRU by around 9%
- LSTM and GRU models on average outperformed LR and SARIMAX models by around 32%
- Baseline model performance varied heavily across different deployments

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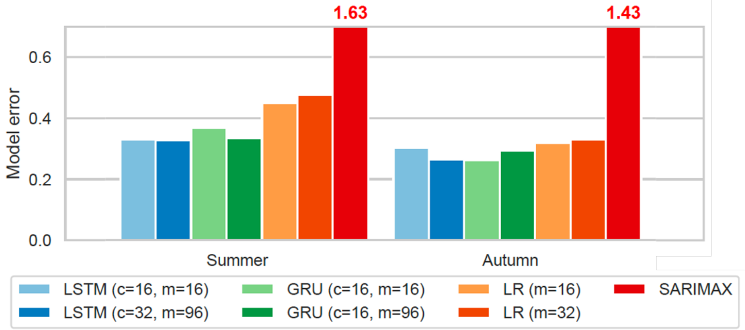
Indoor temperature forecasting results (3)

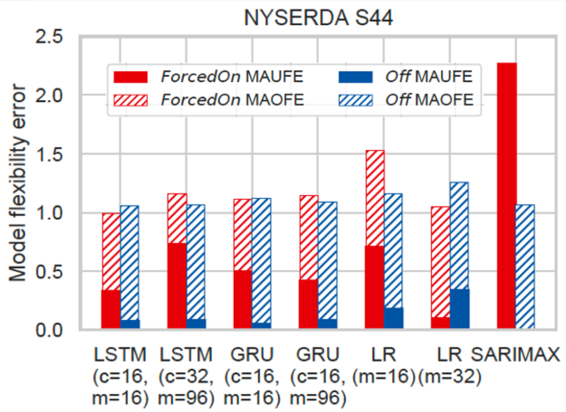
- Seasonal analysis revealed that LSTM and GRU have consistent accuracy throughout the year
- Baseline models LR and SARIMAX fluctuate through different seasons



Temperature forecasting error for summer and autumn seasons on NYSERDA S44

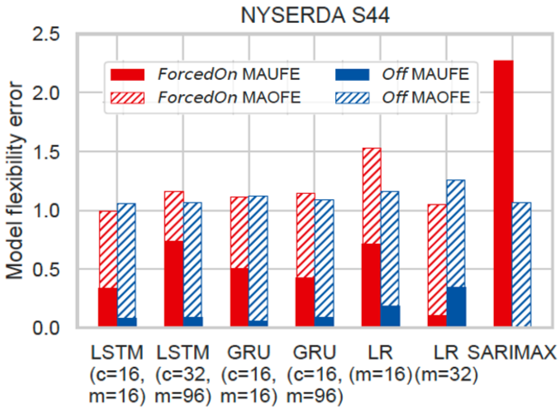
Flexibility prediction results (1)

- Flexibility prediction experiments were performed using best performing indoor temperature forecasting models
- User temperature bounds were set to $\pm 0.5^{\circ}C$ from starting temperature



Flexibility prediction error

- Flexibility error results followed very similar trends to indoor forecasting error
- LSTM and GRU outperformed LR and, especially, SARIMAX

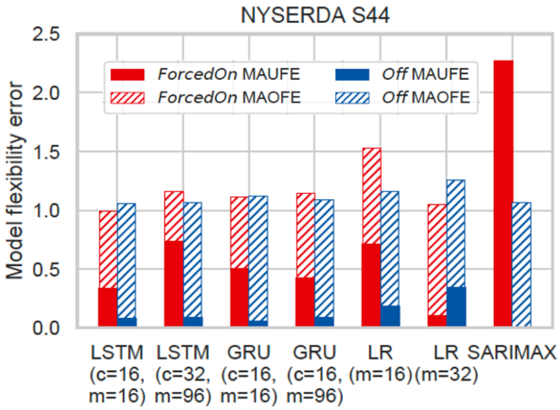


Flexibility prediction error

Flexibility prediction results (3)

- Best performing model was GRU(c=16, m=16)
  - Lower forecasting error does not always result in lower flexibility error

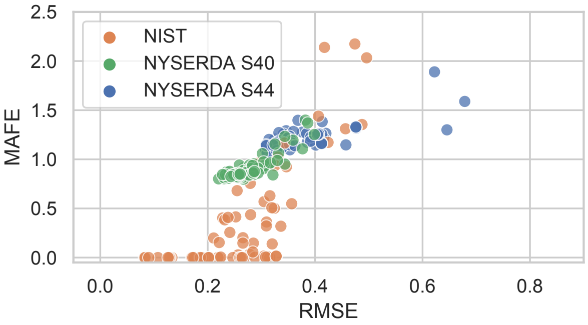
- Dominant type of flexibility error differed across different deployments



Flexibility prediction error

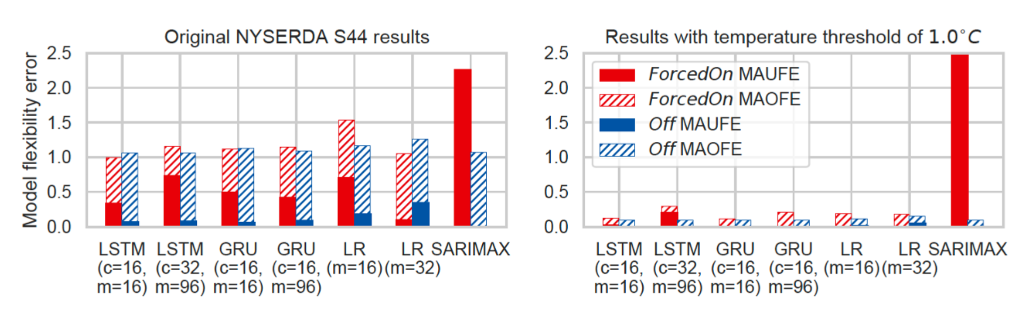
Flexibility prediction results (4)

- Non-linear positive relationship exists between temperature and flexibility errors
- On average, reducing temperature forecasting error reduces flexibility error



Correlation between prediction errors

Flexibility prediction results (5)



- Increasing bounds can increase prediction accuracy

Conclusions and Future work

- Novel fully data-driven flexibility prediction method for heat-pumps **HeatFlex** can effectively predict flexibility using only 3 monitored variables
- LSTM and GRU indoor temperature forecasting models have 32% lower forecasting error than baseline models
- Future work: Use additional real or simulated data, develop flexibility prediction methods for other devices, develop probabilistic prediction methods

Flexible energy (kWh) and EPFR of best performing models

Operation mode	*Off*	*ForcedOn*
Flexible Energy	4108 kWh	1929 kWh
EPFR	92.90%	90.00%

This work was supported by the FEVER (Flexible Energy Production, Demand and Storage-based Virtual Power Plants for Electricity Markets and Resilient DSO Operation) project under the Horizon 2020 programme