WORLD SUMMIT
SMART ENERGY
RUSSIA

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

# Achieving savings through energy monitoring, forecasting and optimization: The European FEEdBACk project


**Marina Dorokhova**
**PhD Candidate**
**EPFL PV-LAB**


FEEdBACk®

# What is FEEdBACk?

**Fostering energy efficiency and behavioral change through ICT**

**New technologies**

- **Develop**
- **Integrate**
- **Test**

**Potential customers**

**Aggregator/ Retailer**

- Adjust energy consumption to market prices

**ESCO / Building owner**

- Install meters and sensors
- Minimize energy cost
- Reduce overall consumption

**DSO**

- Adjust energy consumption
- Enhance grid operation
- Provide ancillary services



FEEdBACk

# Work-Packages

- **Overall project structure:**

**WP1.**
**Project management**

**WP2.**
**Users' profiling and segmentation**

**WP3.**
**Energy monitoring, forecasting and optimization**

**WP4.**
**Digital marketplace and gamification**

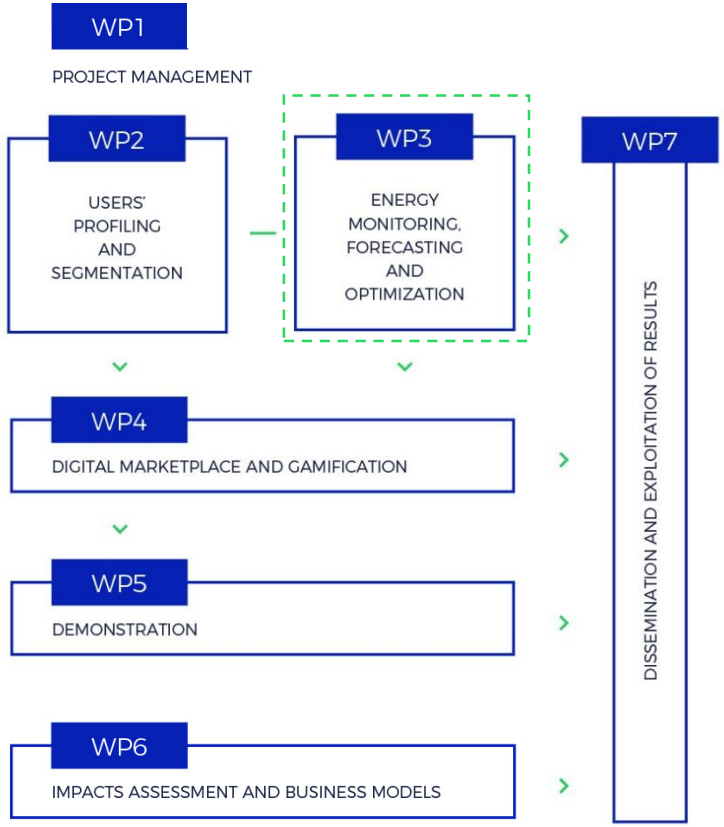
**WP5.**
**Demonstration**

**WP6.**
**Impacts assessment and Business Models**

**WP7.**
**Dissemination and exploitation results**

**Leader:** ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

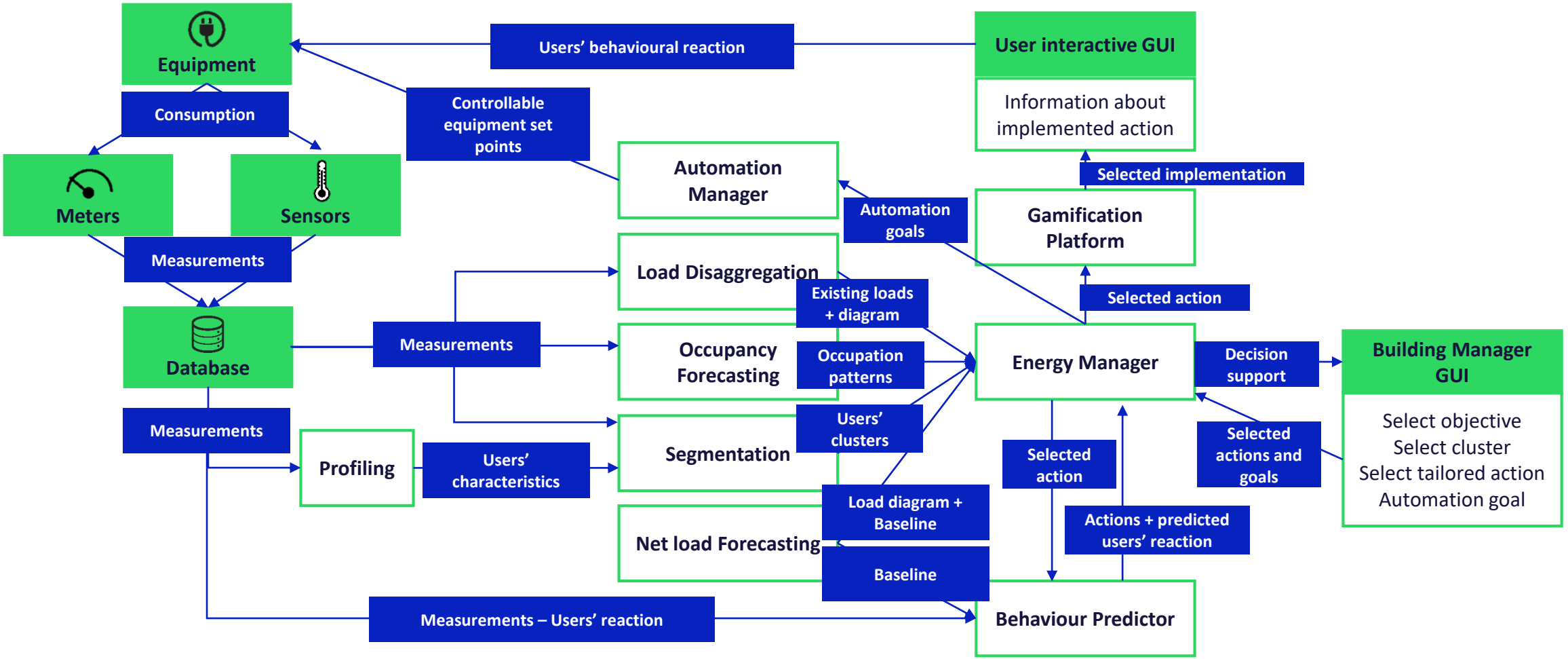
The main objective of this WP is to design and develop innovative ICT tools and applications that will be used to promote the interaction with the end users, thus motivating them to engage in behavioural changes towards energy efficiency goals.






FEEdBACK

# ICT-based Platform for Energy Efficiency






FEEdBACk

# Demonstrators

## PORTO – PORTUGAL

INESC TEC, Office
Oceanic climate

**ENERGY SAVINGS:**
15%

**BUILDING:**

- **Type:** Office / services
- **Area:** 4000 $m^2$
- **Floors:** 5
- **Consumption:** 630 MWh/y

## BARCELONA – SPAIN

El Prat de Llobregat, Public
Mediterranean climate

**ENERGY SAVINGS:**
12%

**BUILDING:**

- **Offices** x3
- **Cultural centers** x3
- **Education centers** x2
- **Sports centers** x2

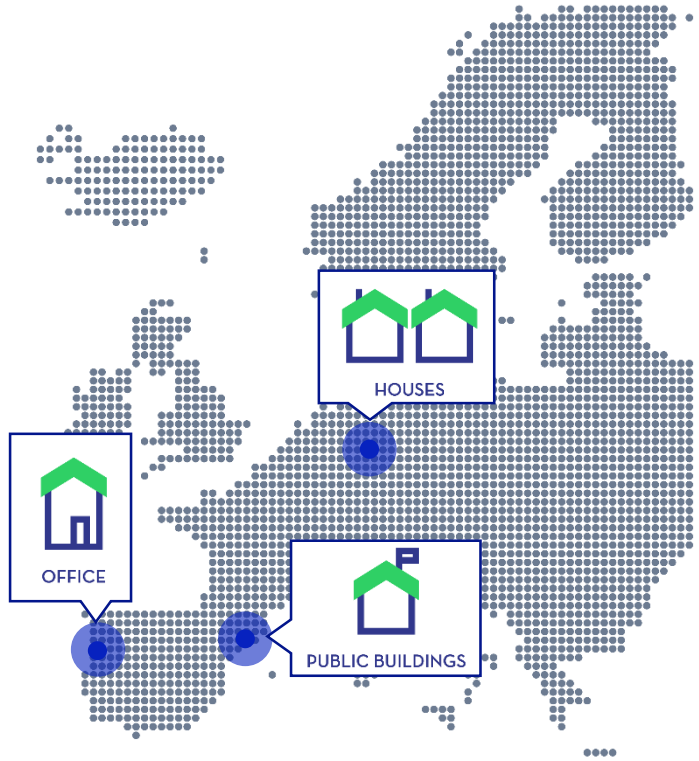
## LIPPE – GERMANY

Residential
Continental-oceanic climate

**ENERGY SAVINGS:**
12%

**BUILDING:**

- **Private houses** x25





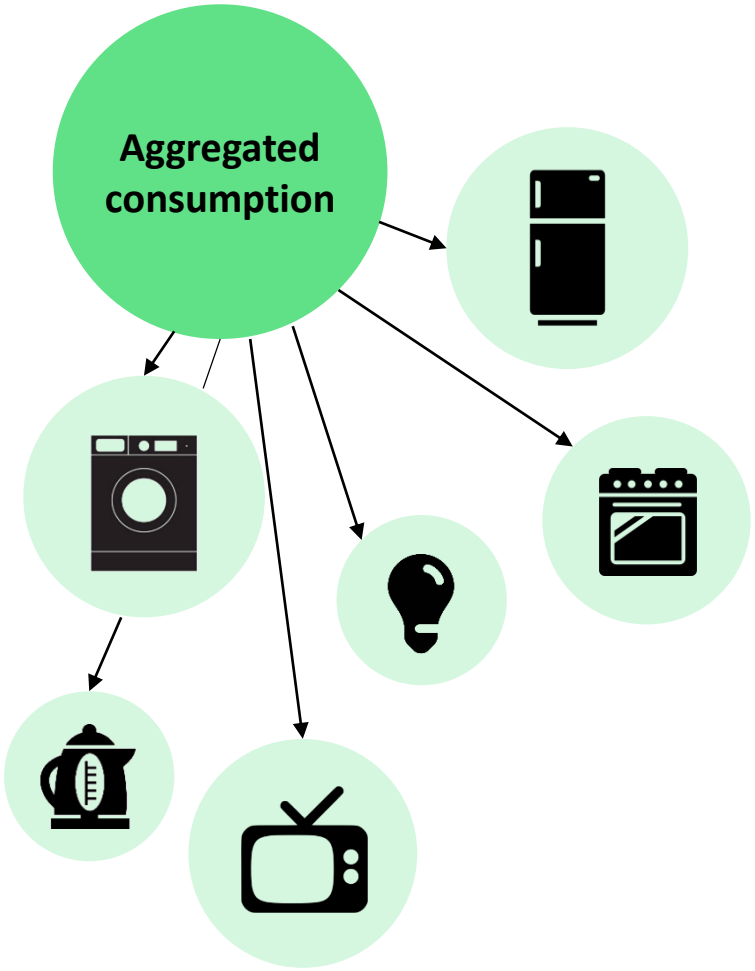

FEEdBACk

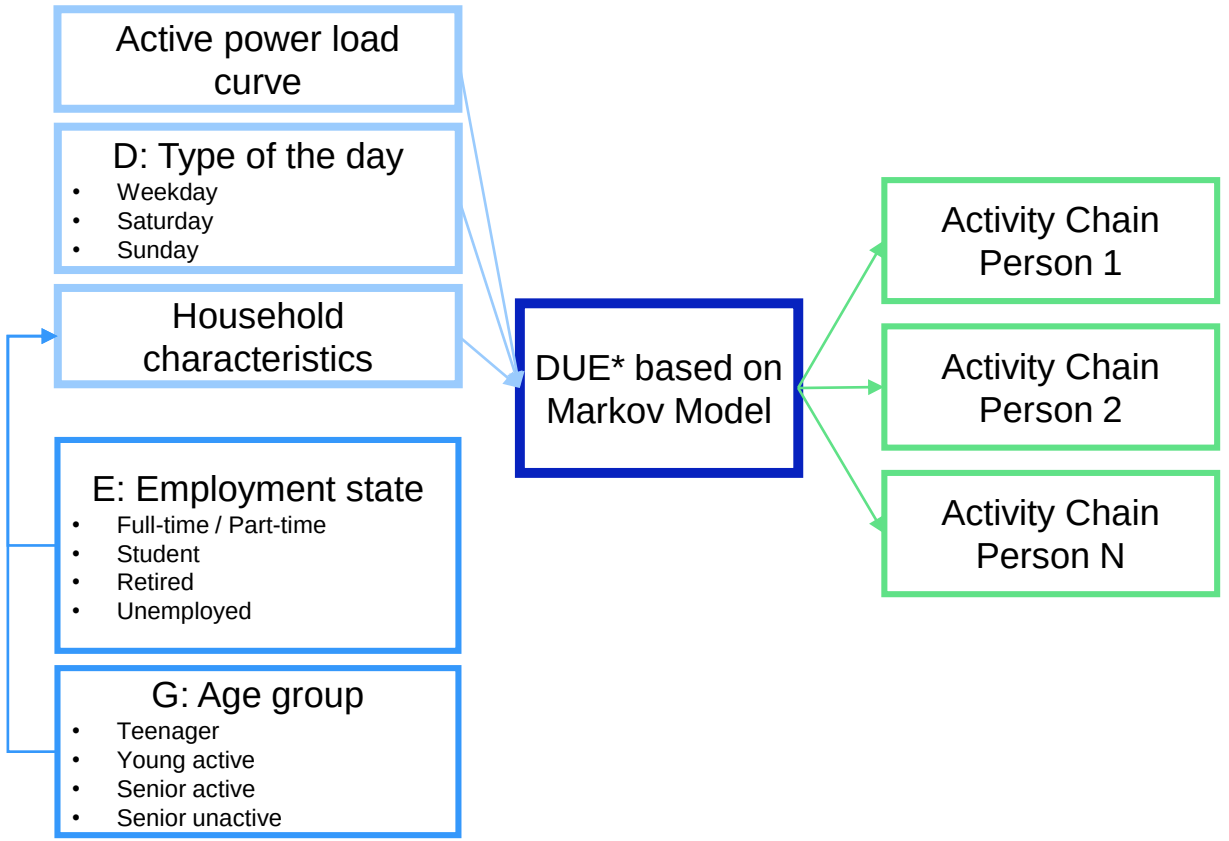
# Load disaggregation

## Towards inferring detailed electrical consumption

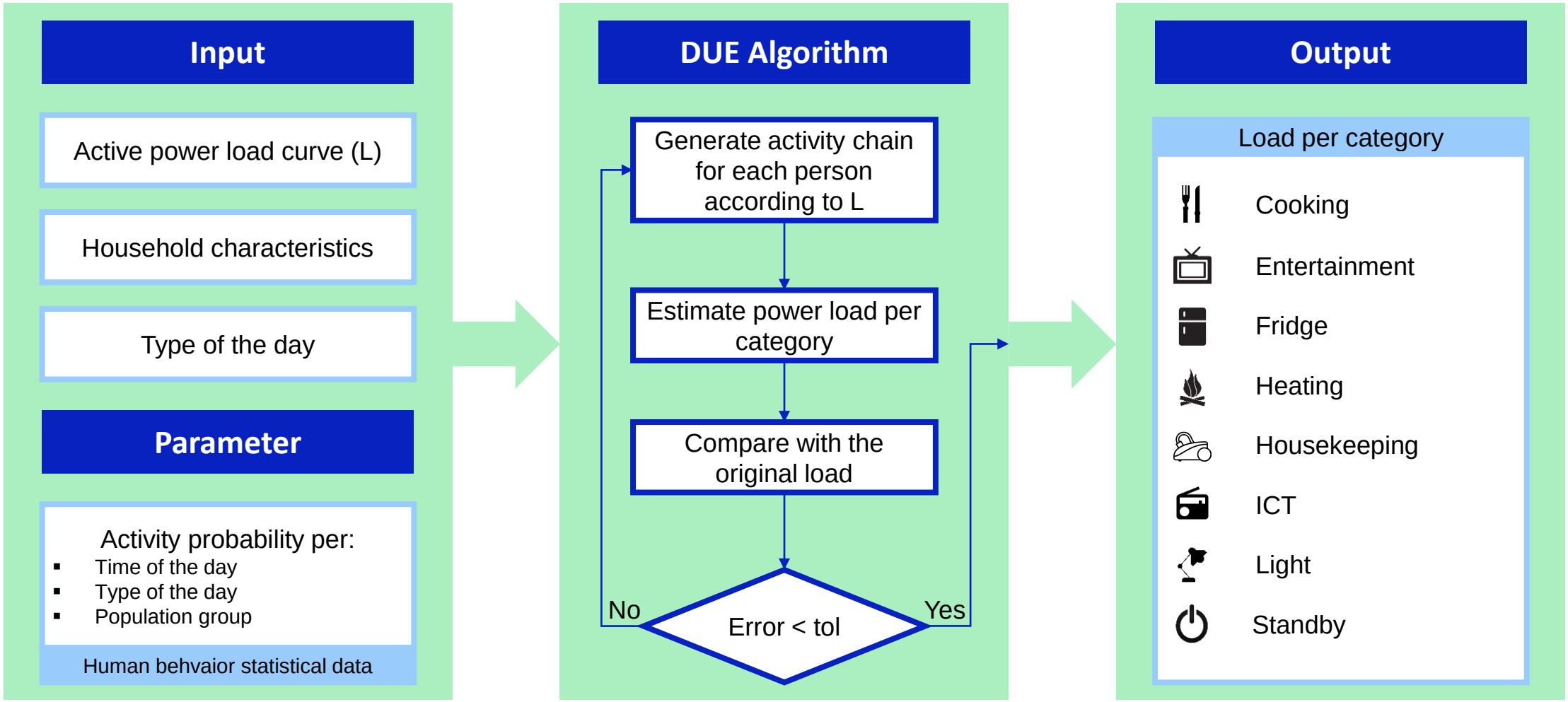
# Load disaggregation algorithm

*Device Usage Estimation



# Device Usage Estimation Algorithm



# Device Usage Estimation Algorithm

| Category | Appliances | Related activities |
|---|---|---|
| Cooking | Coffee maker, stove, oven, microwave, kettle | Cook, eat |
| ICT | Printer | Use computer, work, homework |
| Housekeeping | Washing machine, dishwasher, tumble dryer, vacuum cleaner | Clean, wash dishes, laundry |
| Entertainment | TV, stereo, PC, TV box, laptop, DVD, gaming console | All |
| Light | Lights | All |
| Fridge | Fridge, freezer | |
| Heating | Hairdryer, HP, boiler | Shower |
| Standby | Modem | |

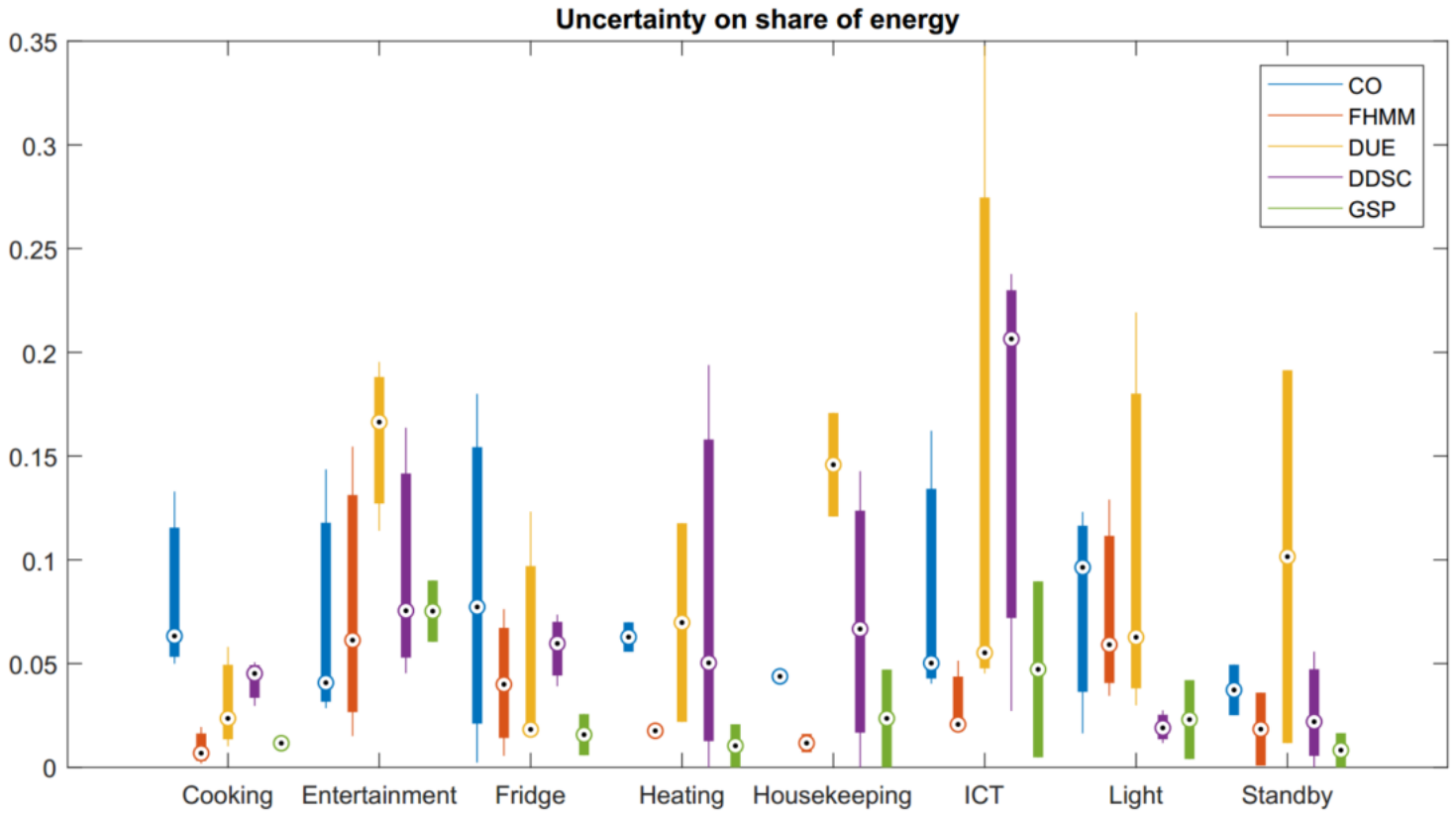
**Recognized activities:**

- Clean
- Use computer
- Cook
- Wash dishes
- Eat
- Homework
- Play game
- Laundry
- Music
- Watch TV
- Shower
- Work

**No appliances used:**

- Sleep
- Outdoor

# Device Usage Estimation Algorithm




**Comparison metrics:**

$$E_m = \frac{\sum_t \hat{P}_m^t}{\sum_t \sum_m \hat{P}_m^t} - \frac{\sum_t P_m^t}{\sum_t \sum_{m \in M} P_m^t}$$

**Comparison algorithms:**

- Combinatorial optimization
- Factorial Hidden Markov Model
- Discriminative Disaggregation via sparse coding
- Graph signal processing

**Comparison datasets:**

- ECO
- SMART-ENERGY.KOM
- UK-DALE

**8% average uncertainty on energy share**

**Unsupervised** | **Low sampling rate data** | **Efficient computing**

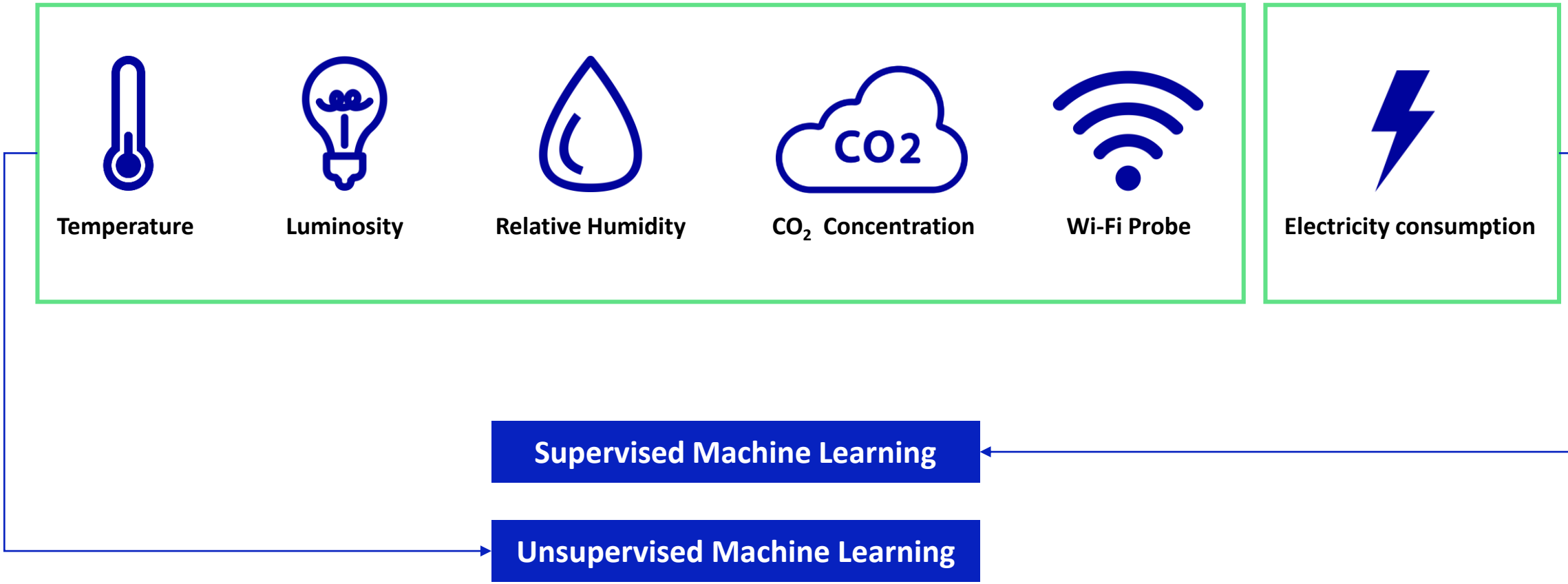


FEEdBACk

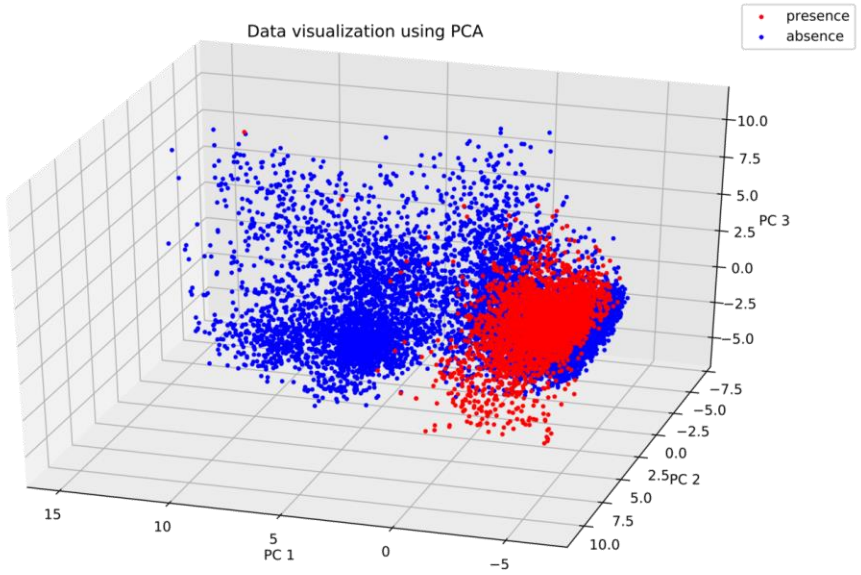
# Occupancy forecasting

## Enhancing automation strategies in intelligent buildings

# Occupancy forecasting



# Occupancy forecasting




X: 15-min power measurements

Y: 15-min binary occupancy data

Data pre-processing

**60+ manually engineered features**

Statistical features

Load curve shape features

Time-related features

One-Hot encoding

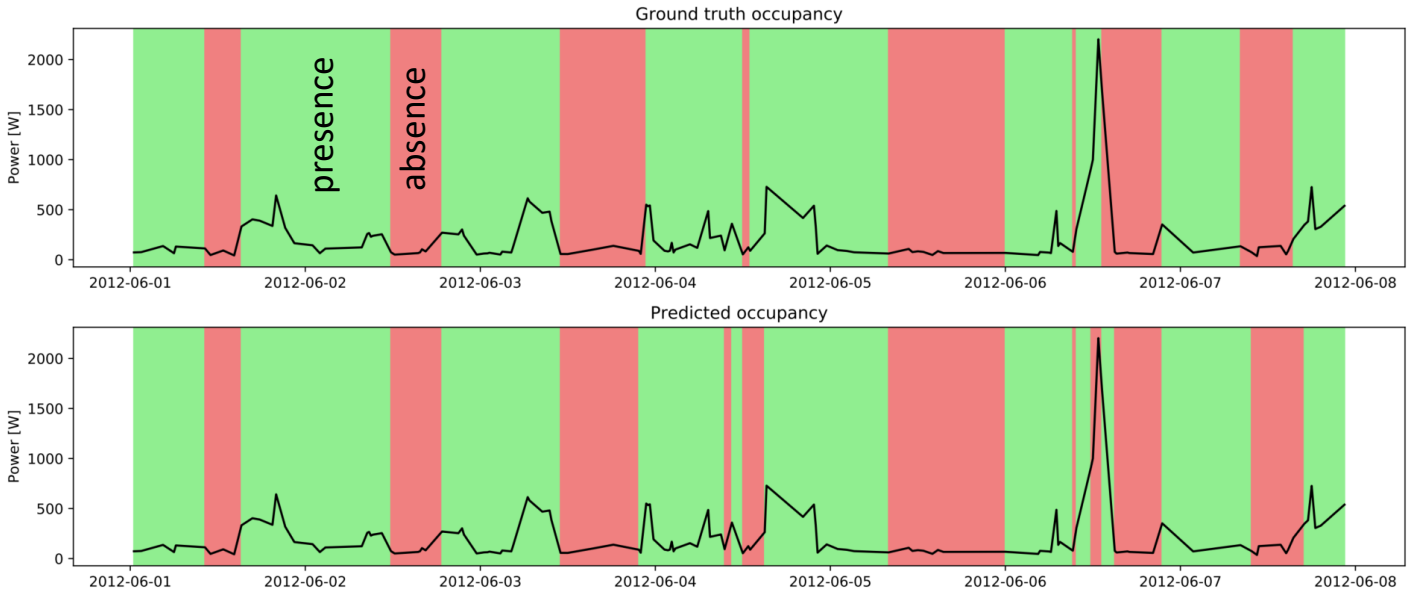
Feature selection

**Choice of model**

Optional grid search

Validation

# Occupancy forecasting

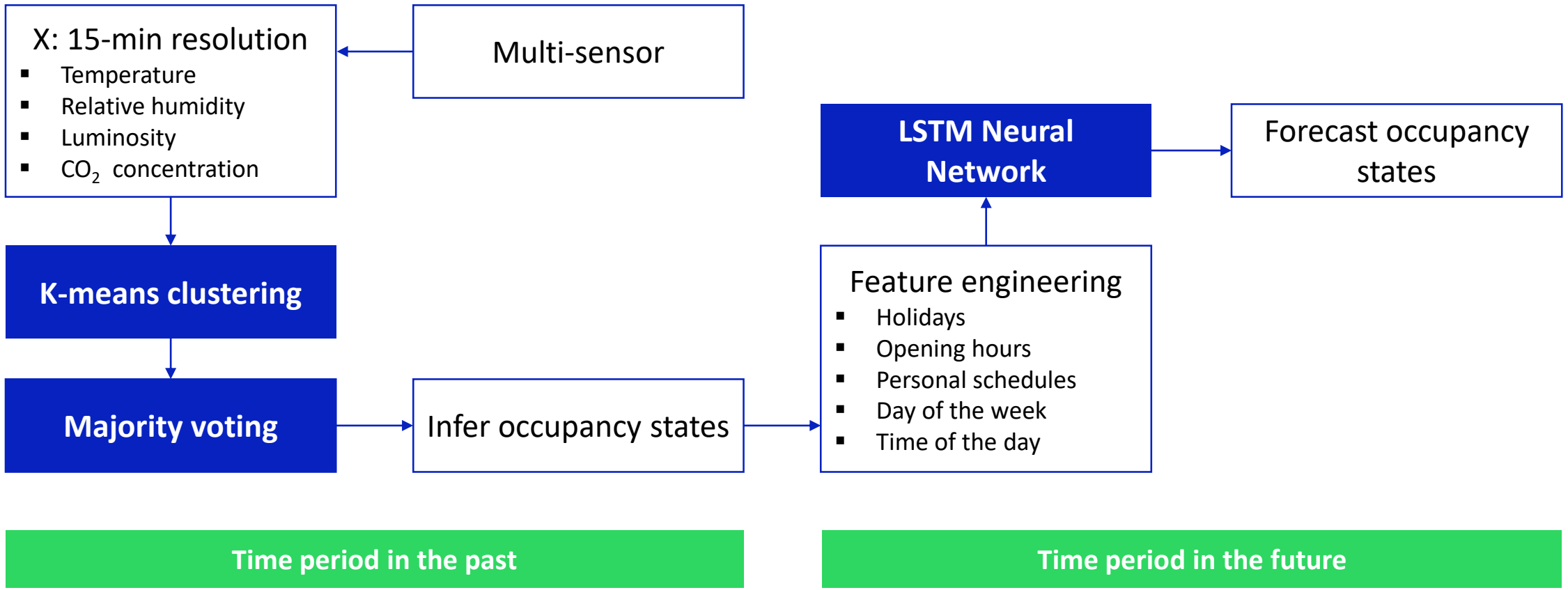



**Great potential for building automation – intelligent HVAC control**

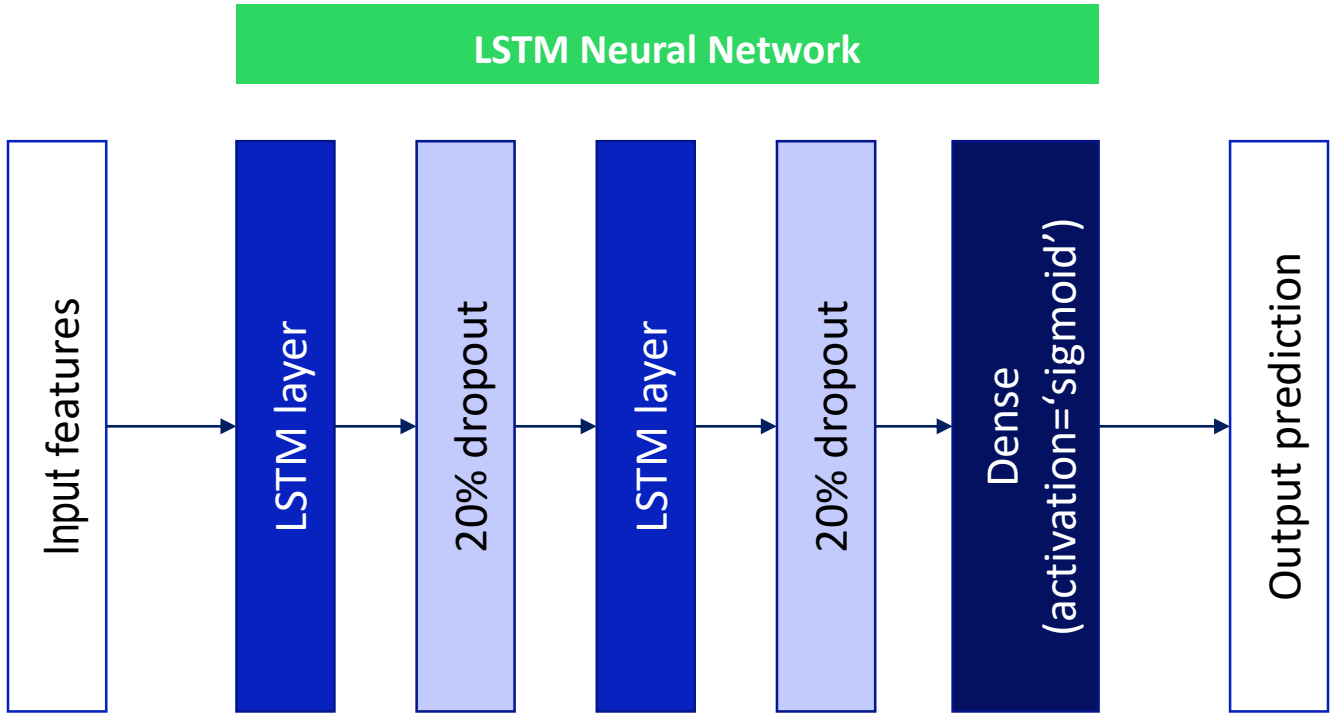
**Algorithm's testing in Porto demonstration site:**

| Model | Validation | Unseen |
|---|---|---|
| Baseline | 61.5% | 61.9% |
| Linear SVM | 94.8% (0.76%) | 94.2% |
| Optimized SVM | 97.5% (0.47%) | 97.1% |
| Bagging | 98.5% (0.72%) | 98.5% |
| AdaBoost | 95.5% (0.64%) | 95.0% |
| Neural Network | 95.8% (0.80%) | 96.9% |

# Occupancy forecasting

# Occupancy forecasting




| Model | Accuracy | Std |
|---|---|---|
| Baseline | 83.6% | 8.5% |
| LSTM | 92.4% | 9.5% |


# Acknowledgments

**EPFL, IMT Neuchâtel, PV-LAB**

**Prof. Christophe Ballif**

**Energy Systems Group:**

**Dr. Nicolas Wyrsch**

**Jordan Holweger**

**Lionel Bloch**

# FEEDBACK-PROJECT.EU

@FEEdBACkH2020

marina.dorokhova@epfl.ch
École polytechnique fédérale de Lausanne
PhD Candidate, PV-LAB

# THANK YOU

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 768935