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

Marina Dorokhova
PhD Candidate
EPFL PV-LAB
What is FEEdBACk?

Fostering energy efficiency and behavioral change through ICT

- 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
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: 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.
ICT-based Platform for Energy Efficiency

- **Equipment**
  - Consumption
  - Controllable equipment set points
- **Sensors**
  - Measurements
  - Automation Manager
    - Automation goals
  - Load Disaggregation
    - Existing loads + diagram
  - Occupation Forecasting
    - Occupation patterns
  - Segmentation
    - Users’ clusters
    - Load diagram + Baseline
  - Net load Forecasting
    - Baseline
    - Behaviour Predictor
- **Meters**
  - Measurements
  - Profiling
    - Users’ characteristics
- **Database**
  - Measurements
  - Measurements – Users’ reaction
  - User interactive GUI
    - Information about implemented action
  - Gamification Platform
    - Selected implementation
    - Selected action
  - Energy Manager
    - Decision support
    - Selected actions and goals
    - Actions + predicted users’ reaction
  - Building Manager GUI
    - Select objective
    - Select cluster
    - Select tailored action
    - Automation goal

- **Automation**
  - Manager
  - Managers
  - User interactive GUI
  - Gamification Platform
Demonstrators

PORTO – PORTUGAL
INESC TEC, Office
Oceanic climate

ENERGY SAVINGS: 15%

BUILDING:
- Type: Office / services
- Area: 4000 m²
- 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
Load disaggregation
Towards inferring detailed electrical consumption
Load disaggregation algorithm

- Active power load curve
- D: Type of the day
  - Weekday
  - Saturday
  - Sunday
- Household characteristics
- E: Employment state
  - Full-time / Part-time
  - Student
  - Retired
  - Unemployed
- G: Age group
  - Teenager
  - Young active
  - Senior active
  - Senior unactive

*Device Usage Estimation

Activity Chain Person 1
Activity Chain Person 2
Activity Chain Person N
Device Usage Estimation Algorithm

**Input**
- Active power load curve (L)
- Household characteristics
- Type of the day

**Parameter**
- Activity probability per:
  - Time of the day
  - Type of the day
  - Population group
- Human behavior statistical data

**DUE Algorithm**
- Generate activity chain for each person according to L
- Estimate power load per category
- Compare with the original load

**Output**
- Load per category:
  - Cooking
  - Entertainment
  - Fridge
  - Heating
  - Housekeeping
  - ICT
  - Light
  - Standby

Decision:
- Error < tol
- No
- Yes
# Device Usage Estimation Algorithm

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

**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:

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

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
Occupancy forecasting
Enhancing automation strategies in intelligent buildings
Occupancy forecasting

Temperature | Luminosity | Relative Humidity | CO$_2$ Concentration | Wi-Fi Probe | Electricity consumption

Supervised Machine Learning

Unsupervised Machine Learning
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

Feature selection

One-Hot encoding

Optional grid search

Validation

Choice of model
## Occupancy forecasting

Algorithm’s testing in Porto demonstration site:

<table>
<thead>
<tr>
<th>Model</th>
<th>Validation</th>
<th>Unseen</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>61.5%</td>
<td>61.9%</td>
</tr>
<tr>
<td>Linear SVM</td>
<td>94.8% (0.76%)</td>
<td>94.2%</td>
</tr>
<tr>
<td>Optimized SVM</td>
<td>97.5% (0.47%)</td>
<td>97.1%</td>
</tr>
<tr>
<td>Bagging</td>
<td>98.5% (0.72%)</td>
<td>98.5%</td>
</tr>
<tr>
<td>AdaBoost</td>
<td>95.5% (0.64%)</td>
<td>95.0%</td>
</tr>
<tr>
<td>Neural Network</td>
<td>95.8% (0.80%)</td>
<td>96.9%</td>
</tr>
</tbody>
</table>

Great potential for building automation – intelligent HVAC control.
Occupancy forecasting

X: 15-min resolution
- Temperature
- Relative humidity
- Luminosity
- CO₂ concentration

Multi-sensor

K-means clustering

Majority voting

Infer occupancy states

Feature engineering
- Holidays
- Opening hours
- Personal schedules
- Day of the week
- Time of the day

LSTM Neural Network

Forecast occupancy states

Time period in the past

Time period in the future
Occupancy forecasting

LSTM Neural Network

Input features → LSTM layer → 20% dropout → LSTM layer → 20% dropout → Dense (activation='sigmoid') → Output prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>83.6%</td>
<td>8.5%</td>
</tr>
<tr>
<td>LSTM</td>
<td>92.4%</td>
<td>9.5%</td>
</tr>
</tbody>
</table>
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