Machine Learning

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Digitalisation and the Rebound Effect seminar, HS2020, ETH Zürich
Motivation

Final energy consumption in the residential sector by use, EU-27, 2018

- Space heating: 63.6%
- Water heating: 14.8%
- Cooking: 6.1%
- Lighting and appliances: 14.1%
- Other and uses: 1.0%
- Space cooling: 0.4%

Source: Eurostat (online data code: nrg_bal_c)

How can we improve space heating?

Improve the building
  • Have a better isolation
  • Buy solar panels
  • Improve heat pump
How can we improve space heating

Improve the building
• Have a better isolation
• Buy solar panels
• Improve heat pump

Improve how we use heating
• Machine Learning to decide when to heat
Supervised Machine Learning

- Linear Regression
- Logistic Regression
- SVM
- KNN
- Ensemble Method
- Neural Network

Source: https://elearningindustry.com/machine-learning-process-and-scenarios
1. Predict demand of electricity to reduce the lost

• Short term: optimal day-to-day operational efficiency of electrical power delivery

• Medium term: to schedule fuel supply and timely maintenance operations

A high precision is required

LSTM-RNN

Figure 3. Proposed forecasting methodology.
Figure 5. Box Plot of Electric load (a) Yearly (b) Quarterly.

Features selection

Results

- The predictions with the LSTM-RNN have a better accuracy than the ones with the other algorithms.
- The accuracy does not change over the time.

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE Extra Trees</td>
<td>513.8</td>
<td>90.9</td>
</tr>
<tr>
<td>RMSE LSTM</td>
<td>378</td>
<td>59.8</td>
</tr>
<tr>
<td>CV (RMSE) % Extra Trees</td>
<td>1.95</td>
<td>0.3</td>
</tr>
<tr>
<td>CV (RMSE) % LSTM</td>
<td>1.31</td>
<td>0.2</td>
</tr>
<tr>
<td>MAE Extra Trees</td>
<td>344</td>
<td>55.8</td>
</tr>
<tr>
<td>MAE LSTM</td>
<td>270.4</td>
<td>45.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Forecasting Horizon</th>
<th>MAE</th>
<th>RMSE</th>
<th>CV (RMSE) %</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 Weeks</td>
<td>251</td>
<td>339</td>
<td>0.61</td>
</tr>
<tr>
<td>Between 2–4 Weeks</td>
<td>214</td>
<td>258</td>
<td>0.56</td>
</tr>
<tr>
<td>Between 2–3 Months</td>
<td>225</td>
<td>294</td>
<td>0.63</td>
</tr>
<tr>
<td>Between 3–4 Months</td>
<td>208</td>
<td>275</td>
<td>0.50</td>
</tr>
<tr>
<td>Mean-Medium term</td>
<td>215.6</td>
<td>275.6</td>
<td>0.56</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>8.6</td>
<td>18</td>
<td>0.06</td>
</tr>
</tbody>
</table>
2. Optimize heating depending on electricity cost and productivity

1. Predict the inside temperature
2. Find the best optimization for heating

• Irish study. They used an Irish house as reference
• 205m²
• Solar panels of 6 kWp
• Space heating of 12kW
• Electricity price depend on the hour of the day

1. Predict the inside temperature

**Heat on**
- Outside temperature
- Wind speed
- Inside temperature
- PV production
- Storage tank temperature
- Circulation pump electricity consumption

**Heat off**
- Outside temperature
- Wind speed
- Inside temperature
- PV production
- Storage tank temperature
- Circulation pump electricity consumption

Feature Selection with Pearson correlation linear coefficient

Tree model
MP5

1. Predict the inside temperature

**Heat on**
- Outside temperature
- Inside temperature
- Storage tank temperature
- Circulation pump electricity consumption

**Heat off**
- Outside temperature
- Inside temperature
- PV production

Feature Selection with Pearson correlation linear coefficient

2. Optimal strategy search

Minimize electricity expenditure and consumption

Optimization for the next 2 hours (15 minutes step)

Fig. 10. Electricity consumption profiles for the month of January 2014.
Results

Fig. 12. Total heating electricity consumption for (January 2014).

Fig. 15. (a) Electricity generation cost and (b) Cumulative carbon emissions for January 2014.

## Results

<table>
<thead>
<tr>
<th></th>
<th>Smart algorithm</th>
<th>Baseline algorithm</th>
<th>Rule-based algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity consumption</td>
<td>39%</td>
<td>22.90%</td>
<td></td>
</tr>
<tr>
<td>Costs</td>
<td>42%-49%</td>
<td>27%-40%</td>
<td></td>
</tr>
<tr>
<td>Environmental</td>
<td>38%</td>
<td>20%</td>
<td></td>
</tr>
<tr>
<td>Return of Investment</td>
<td>5-10 years</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. Optimize heating depending on the home presence

Heating planning

Building temperature:
- 20° when it’s occupied
- 10° when it’s unoccupied

3476 households
75 weeks, every 30 minutes, between July 2009 and Decembre 2010

75.4 % of occupation

Results

9% of overall saving

14% savings for the employed singles

Problems

• Privacy

• Discomfort

• Irrelevant in the future with global warning and more efficient building
Problem of distribution

We have seen that with smart heating you can make more energy savings with a person leaving alone in a large house with poor isolation.

Should we favour such a person rather than a family living in a small house?
Data Center

From previous presentation, we have seen that data center consume a lot. For now, it’s 1% of the world consumption of energy.

Google used Google DeepMind

- Weather
- Interaction between env. and equipment
- Data center specification

Neural Network trained on PUE

40% of reduction of cooling.
15% less PUE

Google DeepMind graph showing results of machine learning test on power usage effectiveness in Google data centers

Rebound effects

• Higher comfort temperature in the dwelling or to buy a newer or larger heating devices

• People may increase their energy consumption in other areas of the daily life
Conclusion

With Machine Learning, we can:
• Save electricity and energy
• Save money
• Without lose of comfort

We may imagine more automation ...
Other applications to save energy

• Automate the temperature in each room separately (man and woman)
• For cooling

Google wanted to use their algorithm to:
• Improving power plant conversion efficiency
• Reducing semiconductor manufacturing energy and water usage,

Thank you for your attention
3 different applications of Machine Learning

1. **Optimize heating in function of electricity cost and productivity**
   

2. **Predict demand of electricity to reduce the lost**
   

3. **Optimize heating in function of home presence**
   
Figure 6. Box Plot of Electric Load Consumption Weekend vs. Weekday.
To classify occupation

• Based on the use of electricity
• Hidden Markov Model
• Unsupervised algorithm
• To be able to deal with data without a ground truth of the occupancy

### Average floor space per occupant by period of construction, 2019

<table>
<thead>
<tr>
<th>Period of construction</th>
<th>Floor space per occupant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>46m²</td>
</tr>
<tr>
<td>before 1919</td>
<td>47m²</td>
</tr>
<tr>
<td>1919 - 1945</td>
<td>44m²</td>
</tr>
<tr>
<td>1946 - 1960</td>
<td>41m²</td>
</tr>
<tr>
<td>1961 - 1970</td>
<td>41m²</td>
</tr>
<tr>
<td>1971 - 1980</td>
<td>46m²</td>
</tr>
<tr>
<td>1981 - 1990</td>
<td>49m²</td>
</tr>
<tr>
<td>1991 - 2000</td>
<td>49m²</td>
</tr>
<tr>
<td>2001 - 2005</td>
<td>49m²</td>
</tr>
<tr>
<td>2006 - 2010</td>
<td>48m²</td>
</tr>
<tr>
<td>2011 - 2015</td>
<td>48m²</td>
</tr>
<tr>
<td>2016 - 2019</td>
<td>47m²</td>
</tr>
</tbody>
</table>

Source: FSO - Buildings and dwellings statistics