Machine Learning

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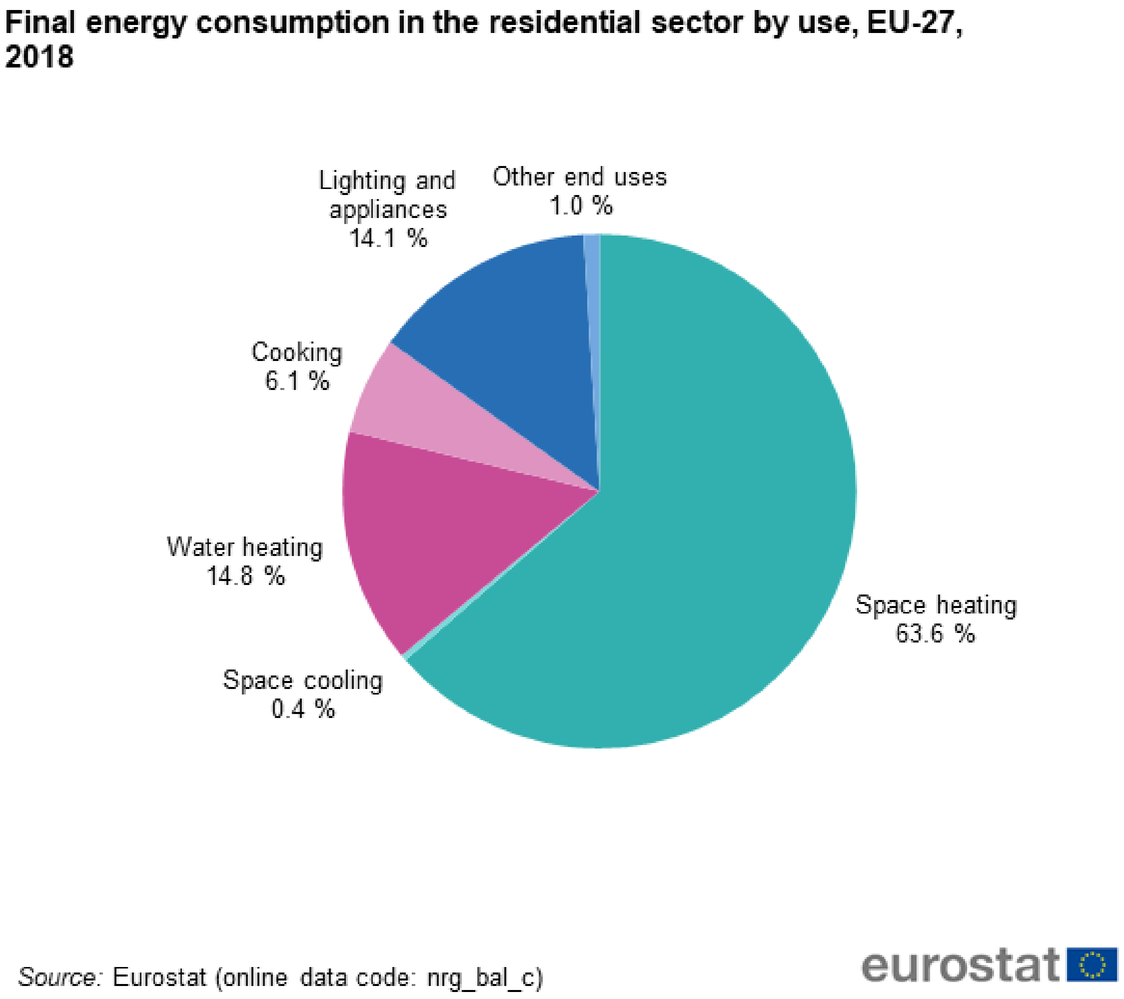
Digitalisation and the Rebound Effect seminar, HS2020, ETH Zürich


ALPHAGO
00:00:49
AlphaGo
Google DeepMind
LEE SEDOL
00:01:00


Autonomous Mode
48
mph


SAVE THE WATER

Motivation

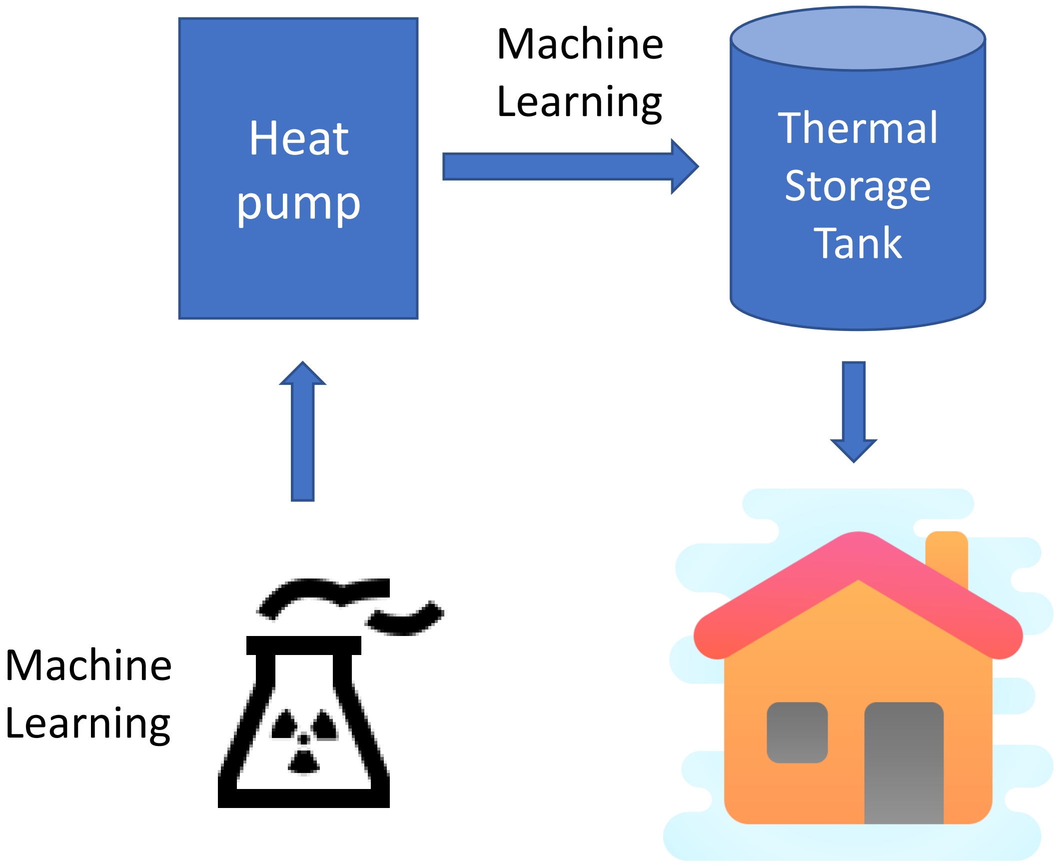


Source: Eurostat, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_consumption_in_households#Energy_products_used_in_the_residential_sector

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
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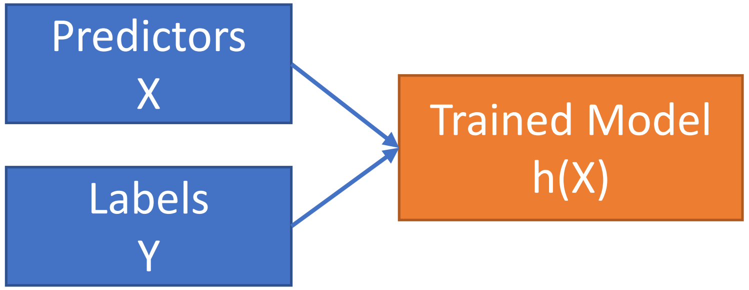
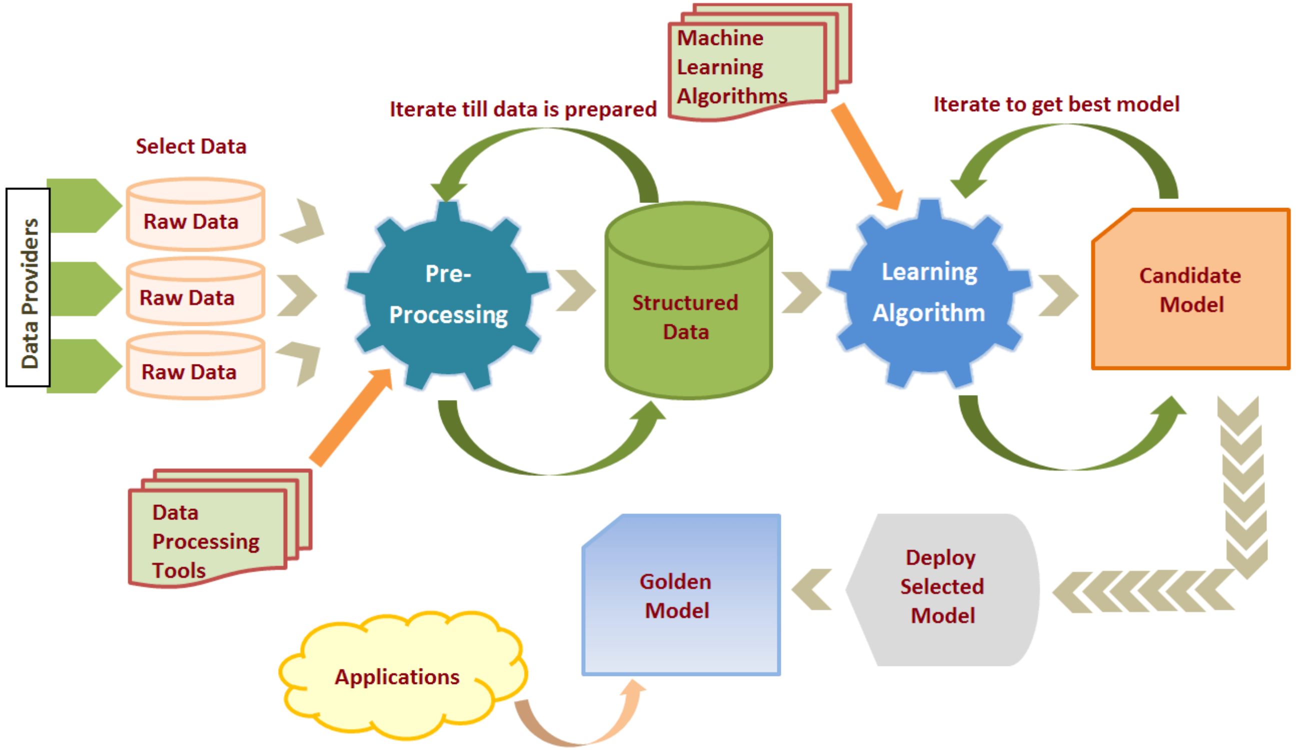
- Improve heat pump

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

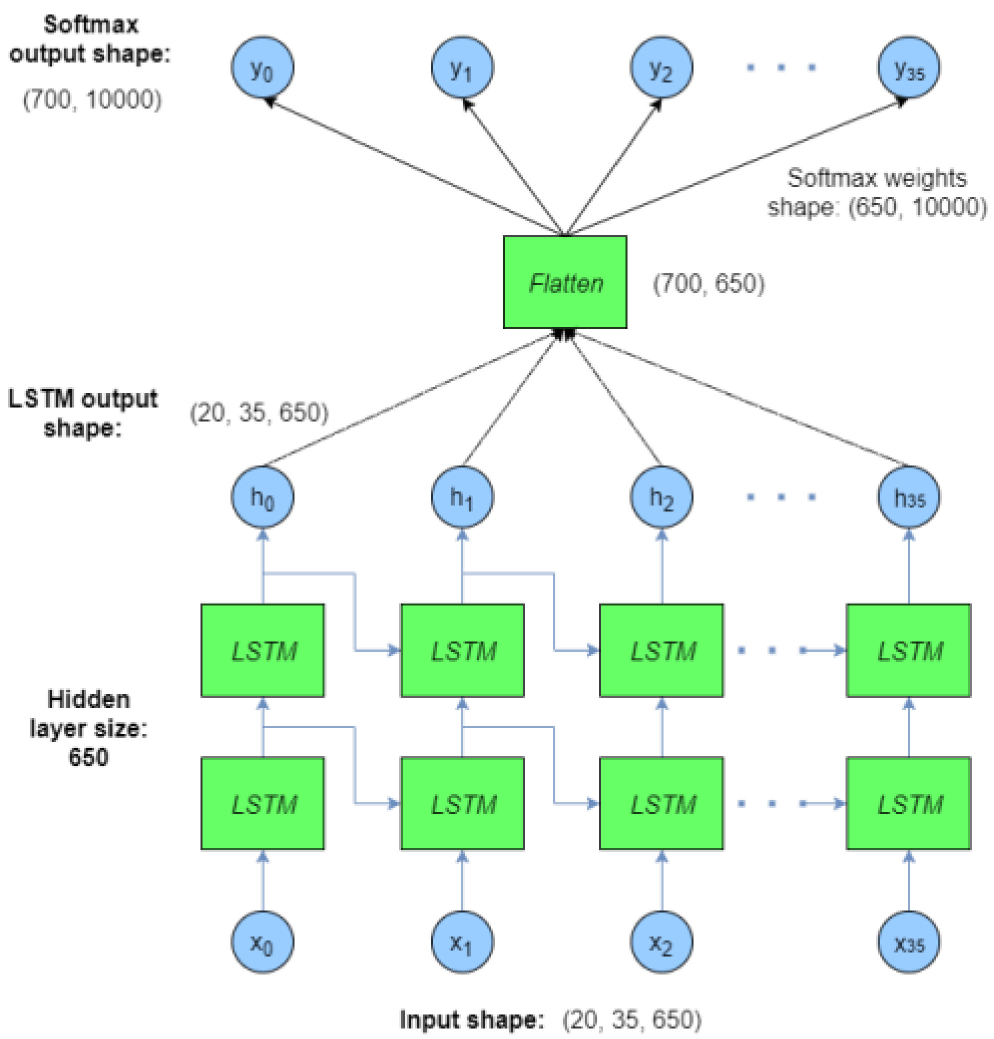
- Short term: optimal day-to-day operational efficiency of electrical power delivery

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

A high precision is required

Source: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

LSTM-RNN



Source: https://adventuresinmachinelearning.com/recurrent-neural-networks-lstm-tutorial-tensorflow/

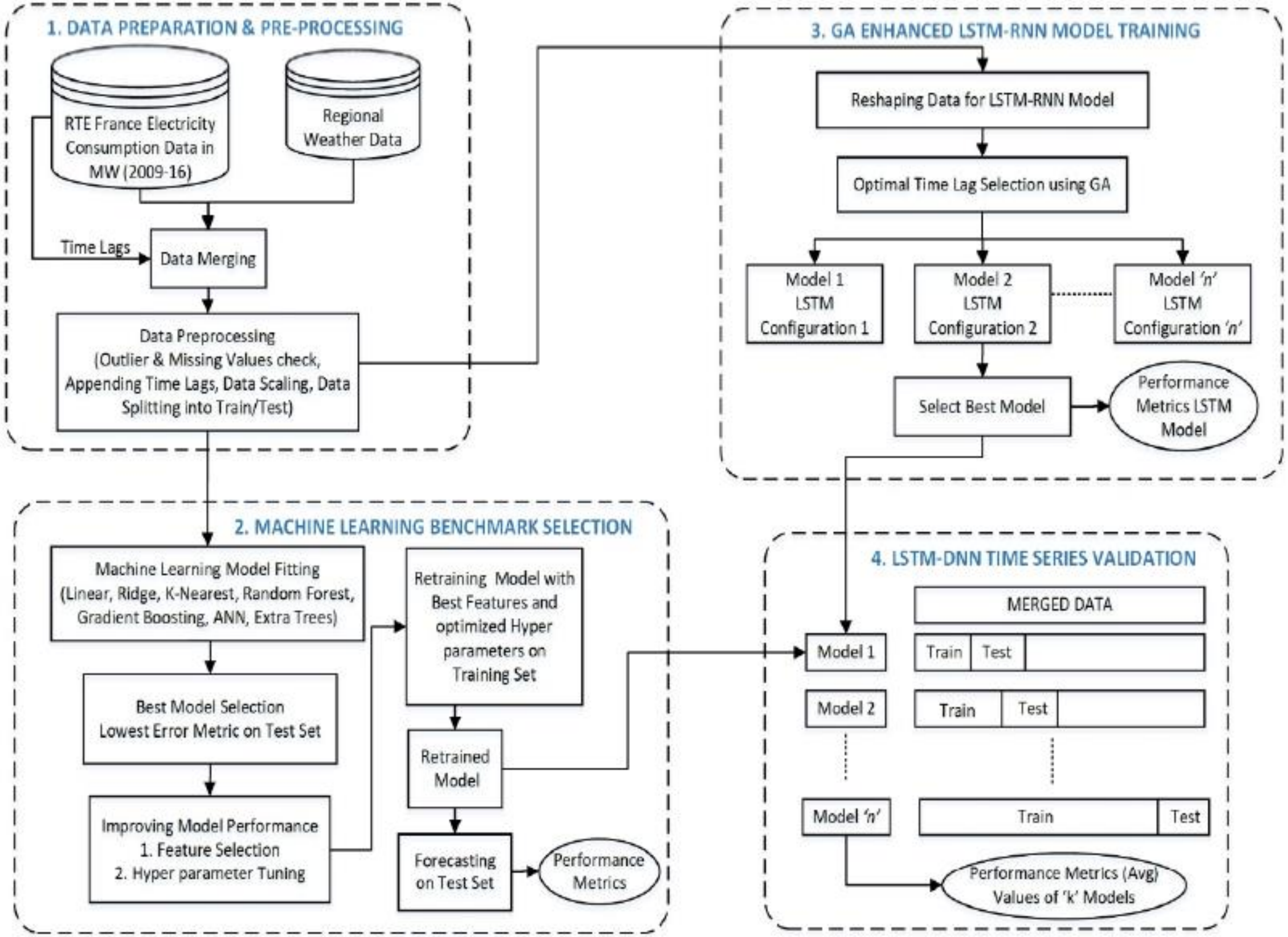


Figure 3. Proposed forecasting methodology.

Source: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

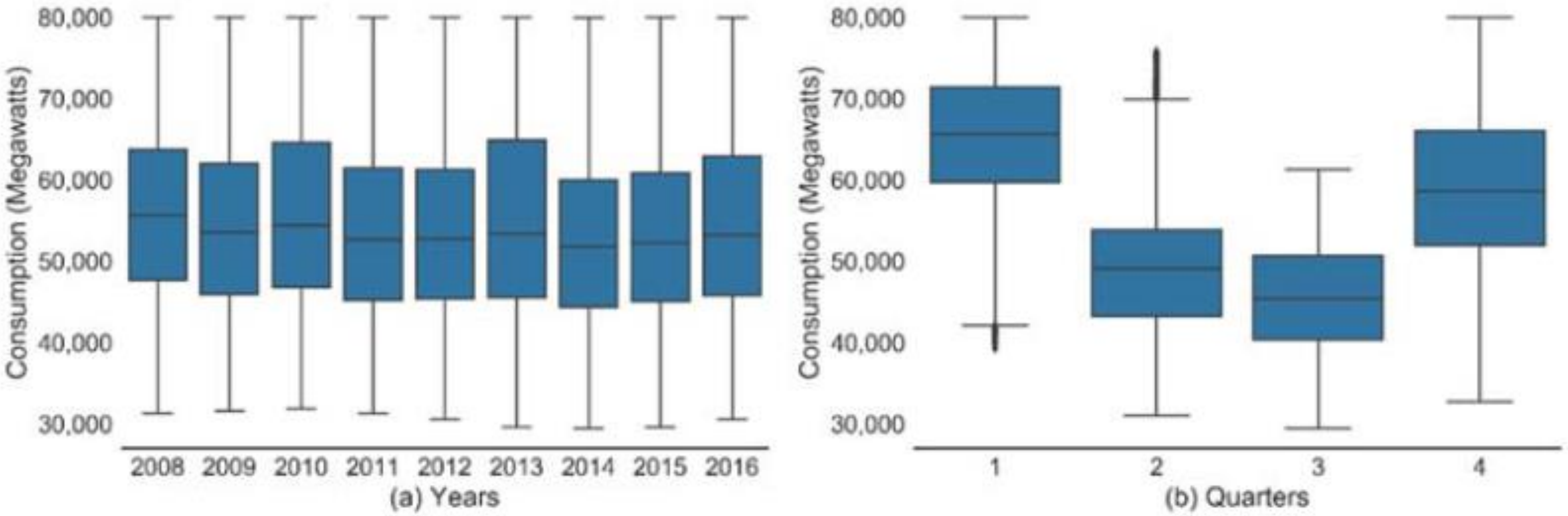


Figure 5. Box Plot of Electric load (**a**) Yearly (**b**) Quarterly.

Source: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

Features selection

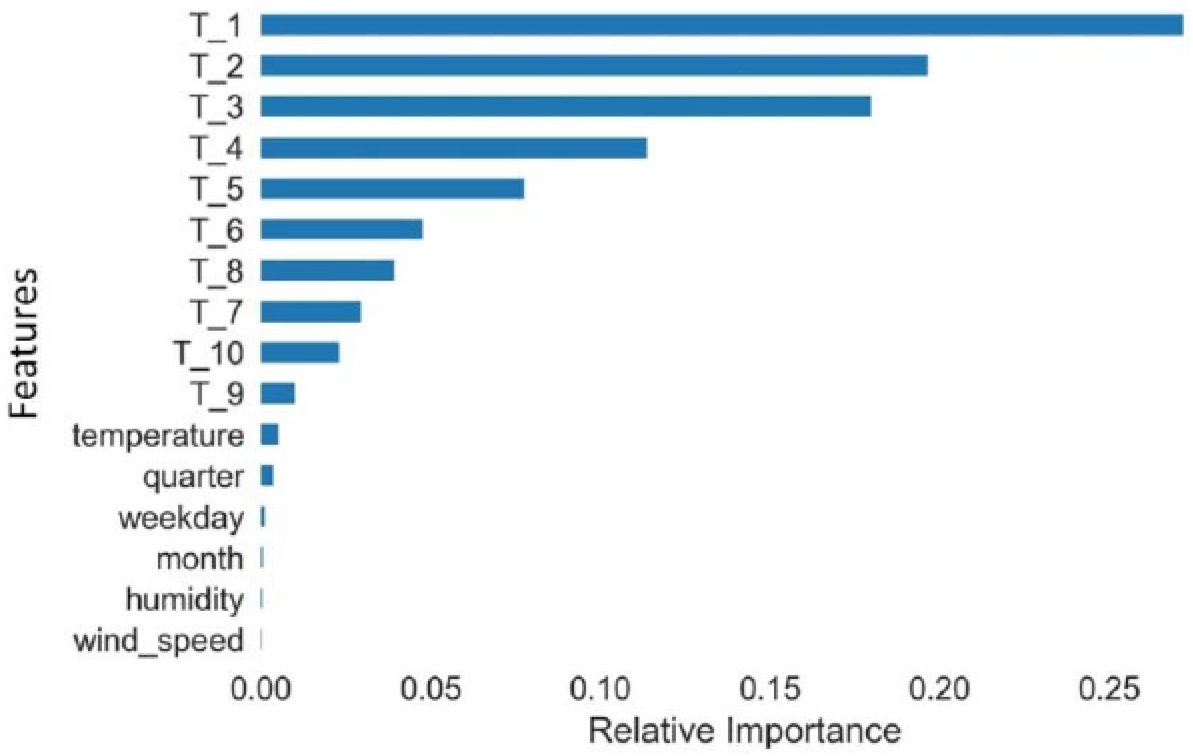


Figure 8. Feature importance plot.

Source: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

Results

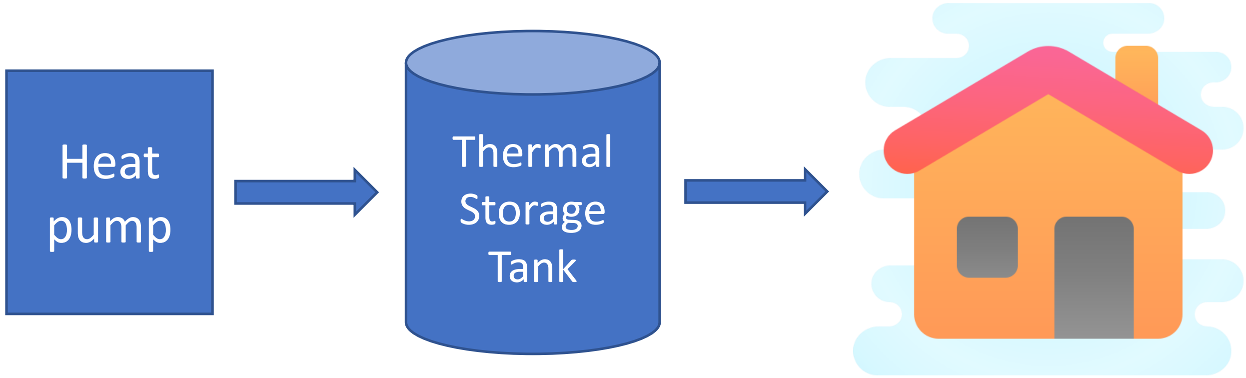
Model	Mean	Std. Deviation
RMSE Extra Trees	513.8	90.9
RMSE LSTM	378	59.8
CV (RMSE) % Extra Trees	1.95	0.3
CV (RMSE) % LSTM	1.31	0.2
MAE Extra Trees	344	55.8
MAE LSTM	270.4	45.4

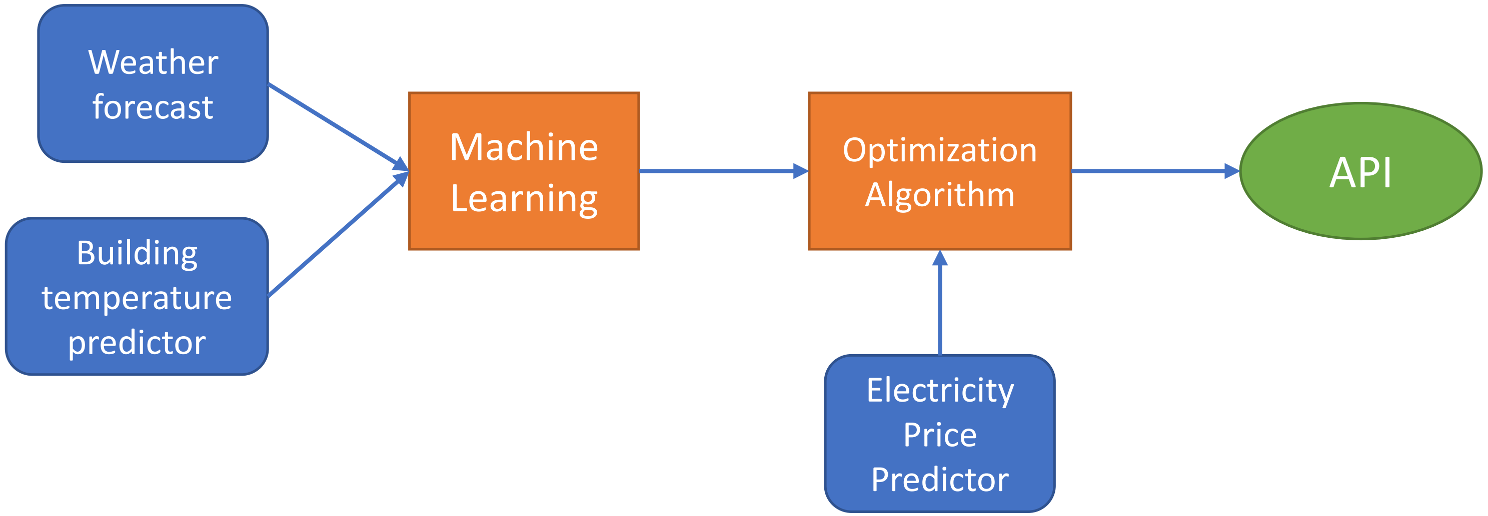
Forecasting Horizon	MAE	RMSE	CV (RMSE) %
2 Weeks	251	339	0.61
Between 2–4 Weeks	214	258	0.56
Between 2–3 Months	225	294	0.63
Between 3–4 Months	208	275	0.50
Mean-Medium term	215.6	275.6	0.56
Std. Dev.	8.6	18	0.06

- 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.

Source: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

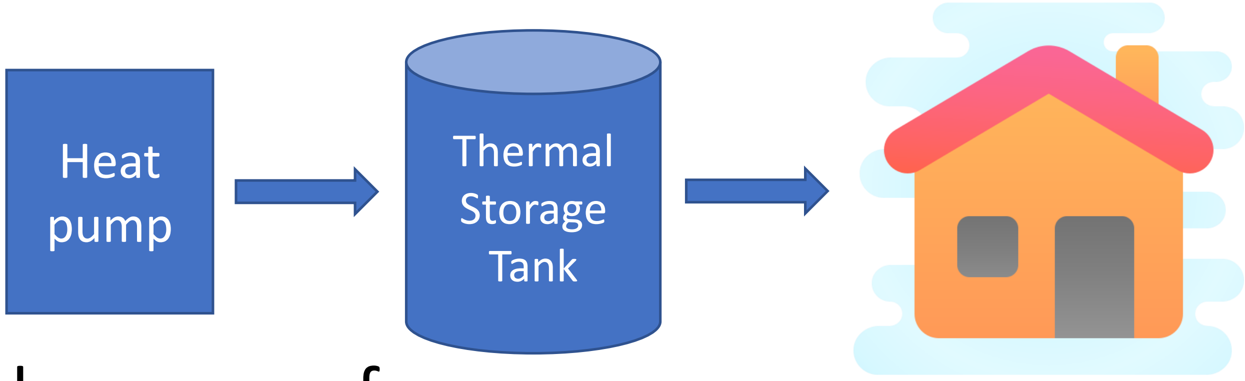
2. Optimize heating depending on electricity cost and productivity





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

Source: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019



- Irish study. They used an Irish house as reference
- 205m^2
- Solar panels of 6 kWp
- Space heating of 12kW
- Electricity price depend on the hour of the day

Table 1
Time of use electricity tariffs (€/kWh).

	Weekdays						Weekends					
	A	B	C	D	Flat	SMP (avg)	A	B	C	D	Flat	SMP (avg)
00:00–08:00	0.12	0.11	0.1	0.09	0.135	0.046	0.12	0.11	0.1	0.09	0.135	0.044
08:00–17:00	0.14	0.135	0.13	0.125	0.135	0.065	0.14	0.135	0.13	0.125	0.135	0.062
17:00–19:00	0.2	0.26	0.32	0.38	0.135	0.097	0.14	0.135	0.13	0.125	0.135	0.088
19:00–23:00	0.14	0.135	0.13	0.125	0.135	0.071	0.14	0.135	0.13	0.125	0.135	0.067
23:00–00:00	0.12	0.11	0.1	0.09	0.135	0.053	0.12	0.11	0.1	0.09	0.135	0.053

Source: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019

1. Predict the inside temperature

Heat on

Outside temperature

Wind speed

Inside temperature

PV production

Storage tank temperature

Circulation pump electricity consumption

Tree model
MP5

Feature Selection with Pearson correlation linear coefficient

Heat off

Outside temperature

Wind speed

Inside temperature

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2. Optimal strategy search

Minimize electricity expenditure and consumption

Optimization for the next 2 hours (15 minutes step)

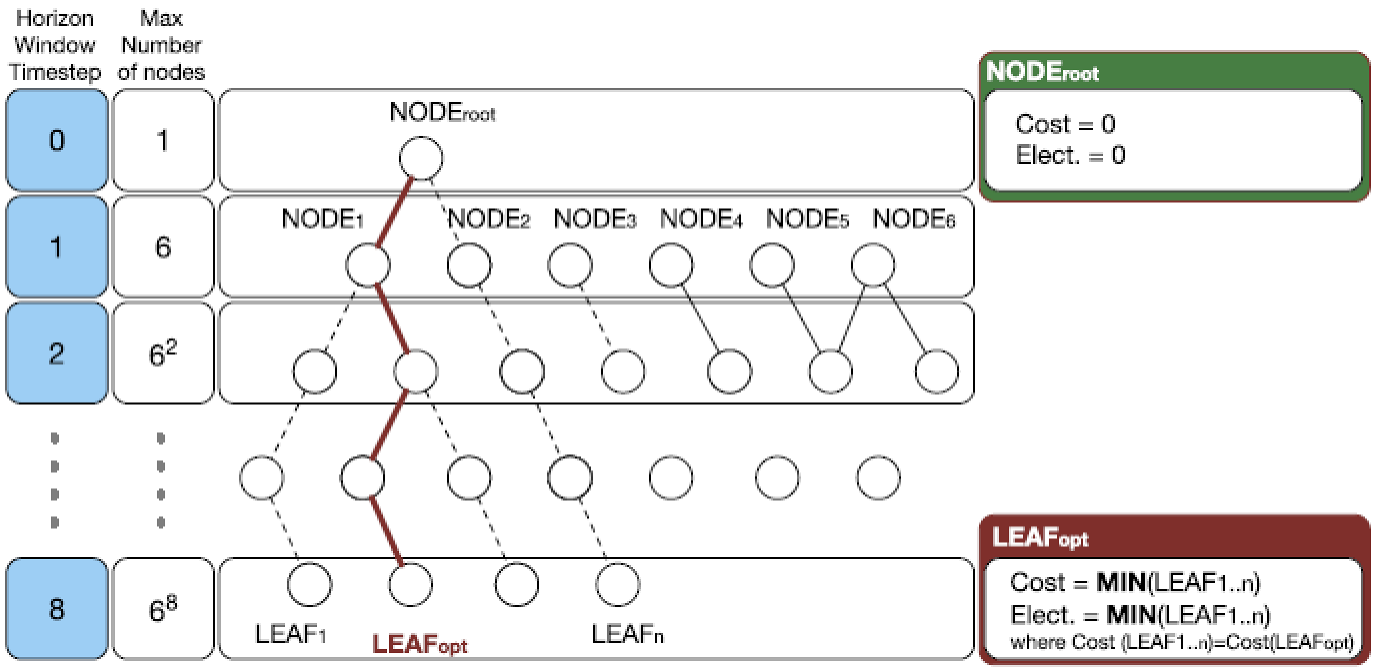


Fig. 8. Optimal strategy search on solution tree.

Source: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019

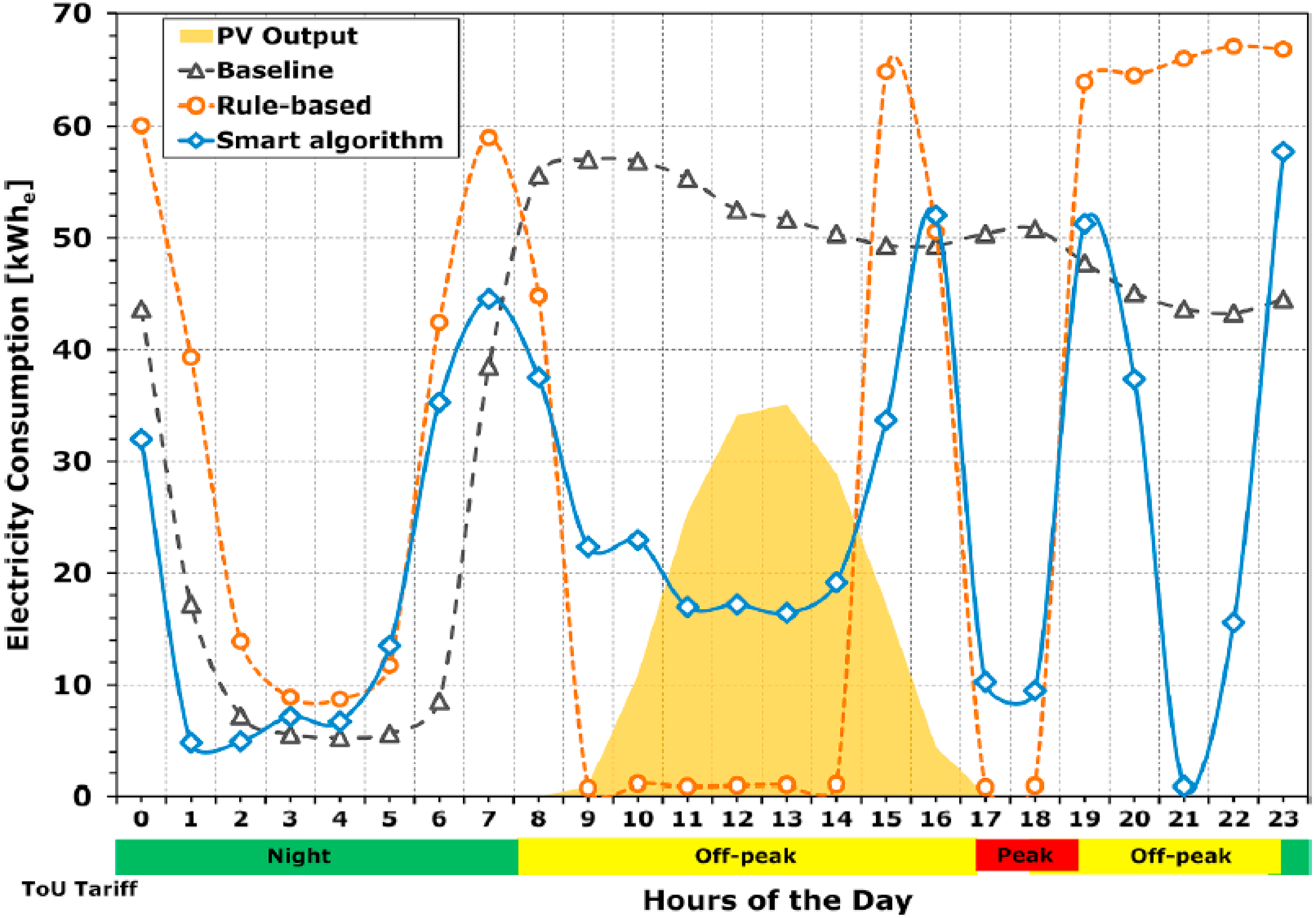


Fig. 10. Electricity consumption profiles for the month of January 2014.

Source: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019

Results

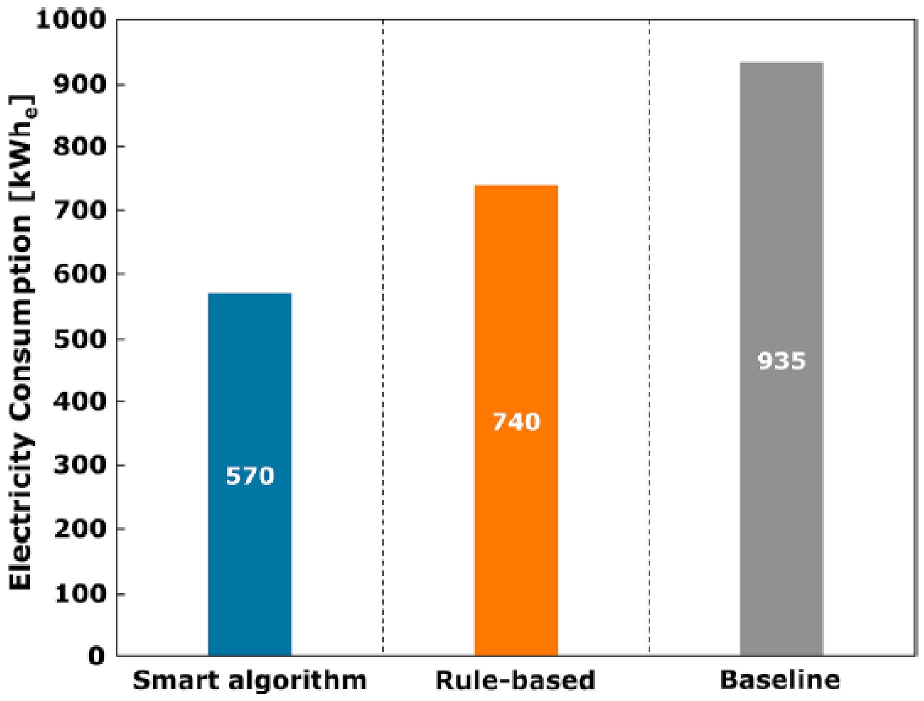


Fig. 12. Total heating electricity consumption for (January 2014).

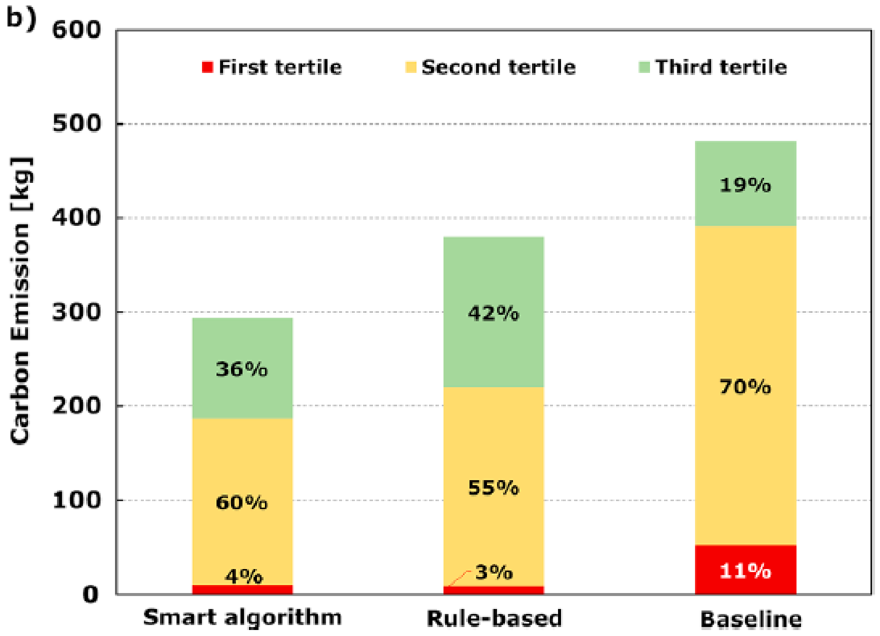


Fig. 15. (a) Electricity generation cost and (b) Cumulative carbon emissions for January 2014.

Source: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019

Results

Smart algorithm	Baseline algorithm	Rule-based algorithm
Electricity consumption	39%	22,90%
Costs	42%-49%	27%-40%
Environmental	38%	20%
Return of Investment	5-10 years	

Source: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019

3. Optimize heating depending on the home presence

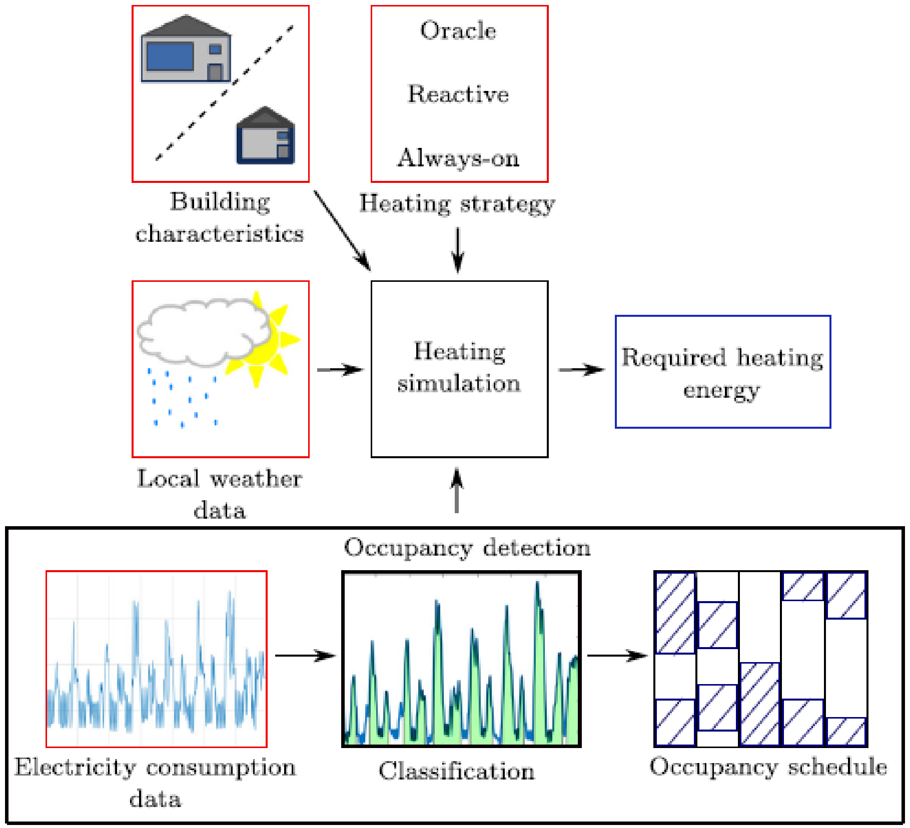


Fig. 1 An overview of our approach to determine the savings potential with inputs marked in red

Source: Vincent Becker, Wilhelm Kleiminger, Vlad C. Coroamă, Friedemann Mattern. Estimating the savings potential of occupancy-based heating strategies, Energy Informatics 1, 2018

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

Source: Vincent Becker, Wilhelm Kleiminger, Vlad C. Coroamă, Friedemann Mattern. Estimating the savings potential of occupancy-based heating strategies, Energy Informatics 1, 2018

Results

9% of overall saving

14% savings for the employed singles

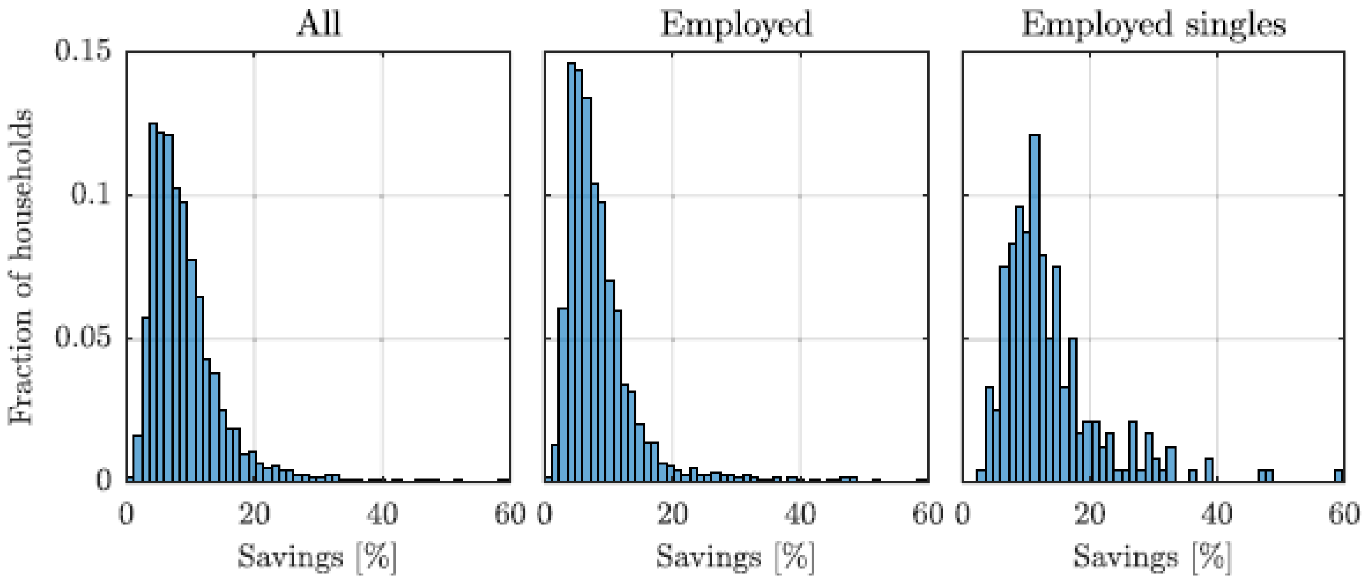
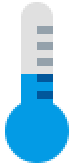


Fig. 5 Histograms of the relative savings for the oracle strategy

Source: Vincent Becker, Wilhelm Kleiminger, Vlad C. Coroamă, Friedemann Mattern. Estimating the savings potential of occupancy-based heating strategies, Energy Informatics 1, 2018

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

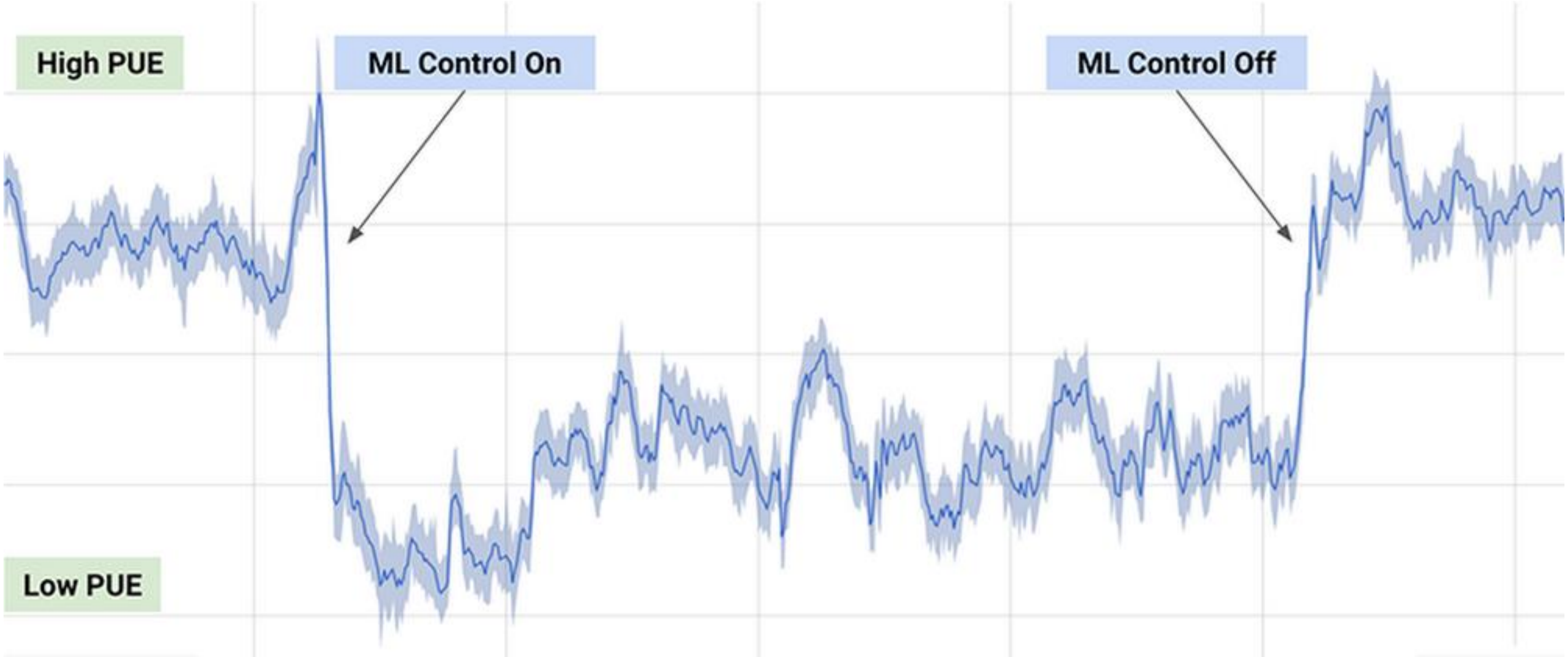
→

40% of reduction of cooling.
15% less PUE

Source: Rich Evans and Jim Gao. DeepMind AI reduces energy used for cooling Google data centers by 40%, report, 2016

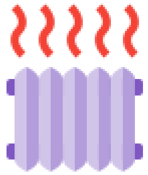
Google DeepMind graph showing results of machine learning test on power usage effectiveness in Google data centers

Source: Rich Evans and Jim Gao. DeepMind AI reduces energy used for cooling Google data centers by 40%, report, 2016



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,

Source: Rich Evans and Jim Gao. DeepMind AI reduces energy used for cooling Google data centers by 40%, report, 2016

Thank you for your attention

3 different applications of Machine Learning

1. Optimize heating in function of electricity cost and productivity
   title: Fabiano Pallonetto, Mattia De Rosa, Federico Milano, Donal P. Finn. Demand response algorithms for smart-grid ready residential buildings using machine learning models, Applied Energy 239, pp. 1265-1282, 2019

2. Predict demand of electricity to reduce the lost
   title: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

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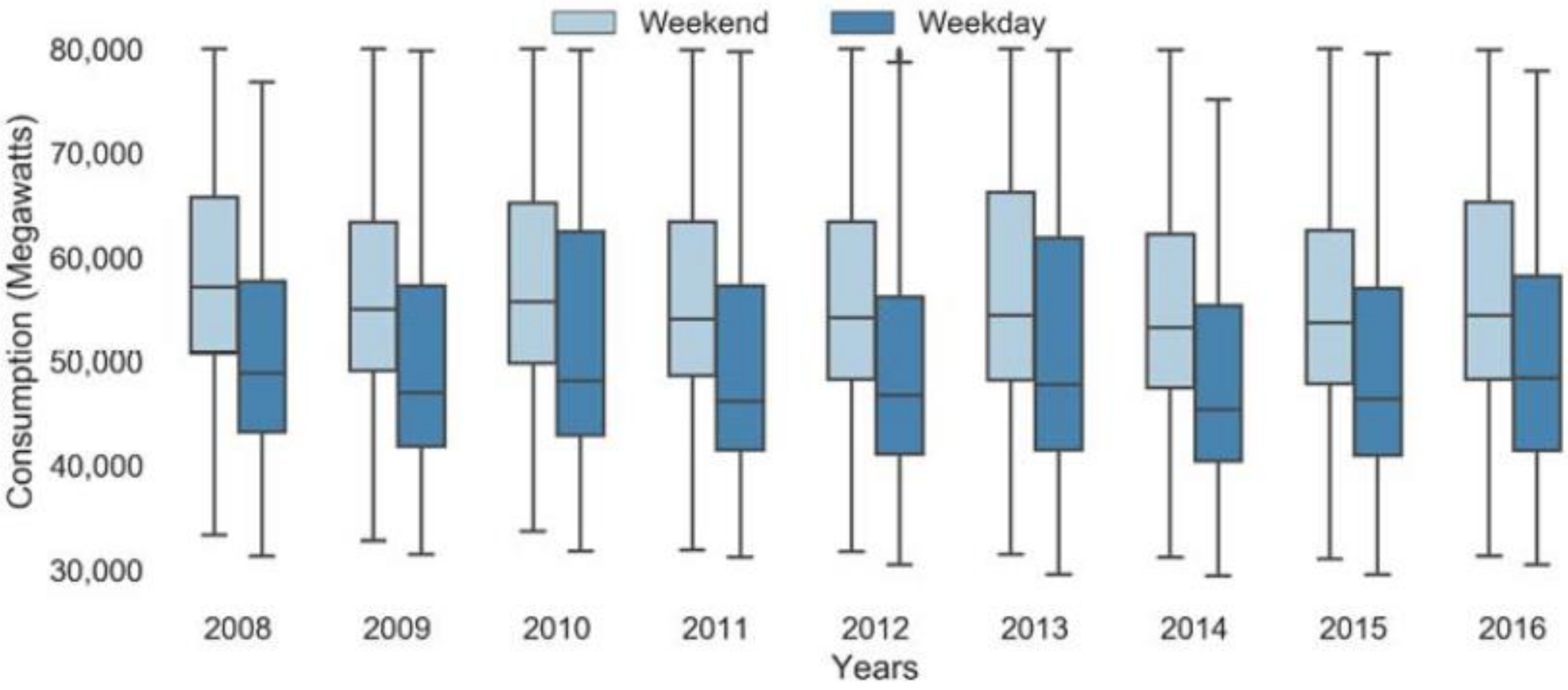

Figure 6. Box Plot of Electric Load Consumption Weekend vs. Weekday.

Source: Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches, Energies, 11 (7), 2018

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

Source: Vincent Becker, Wilhelm Kleiminger, Vlad C. Coroamă, Friedemann Mattern. Estimating the savings potential of occupancy-based heating strategies, Energy Informatics 1, 2018

Average floor space per occupant by period of construction, 2019

Period of construction	Floor space per occupant
Total	$46m^2$
before 1919	$47m^2$
1919 - 1945	$44m^2$
1946 - 1960	$41m^2$
1961 - 1970	$41m^2$
1971 - 1980	$46m^2$
1981 - 1990	$49m^2$
1991 - 2000	$49m^2$
2001 - 2005	$49m^2$
2006 - 2010	$48m^2$
2011 - 2015	$48m^2$
2016 - 2019	$47m^2$

Source: FSO - Buildings and dwellings statistics

https://www.bfs.admin.ch/bfs/en/home/statistics/construction-housing/dwellings/housing-conditions/floor-area-person.html