Deep learning methods for on-line flexibility prediction and optimal resource allocation in smart buildings

Technische Universiteit Eindhoven University of Technology

Where innovation starts

Machine learning methods for on-line flexibility prediction and optimal resource allocation in smart buildings

Elena Mocanu, Phuong H. Nguyen, Madeline Gibescu, J.G. Slootweg

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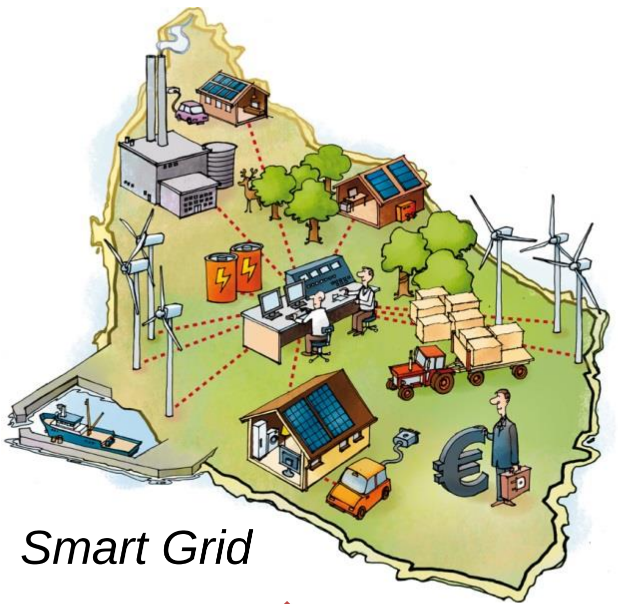
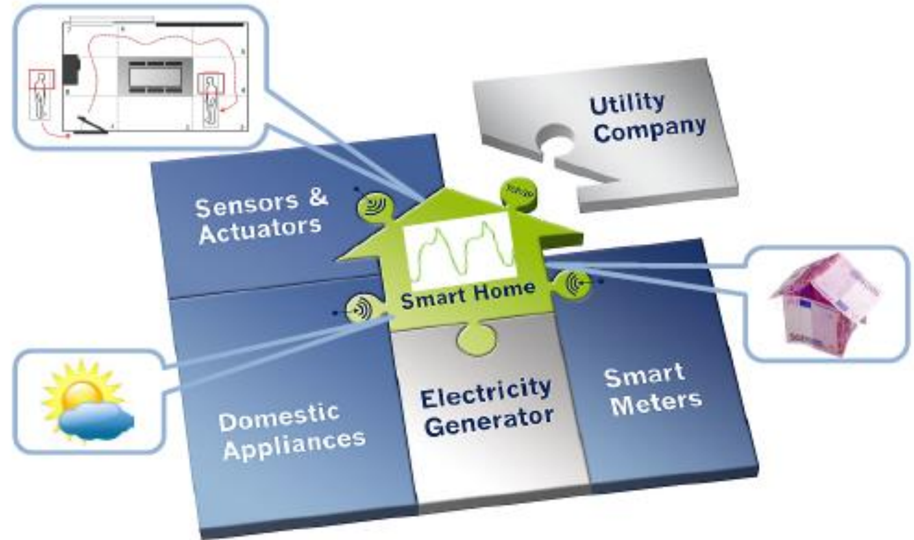
Outline

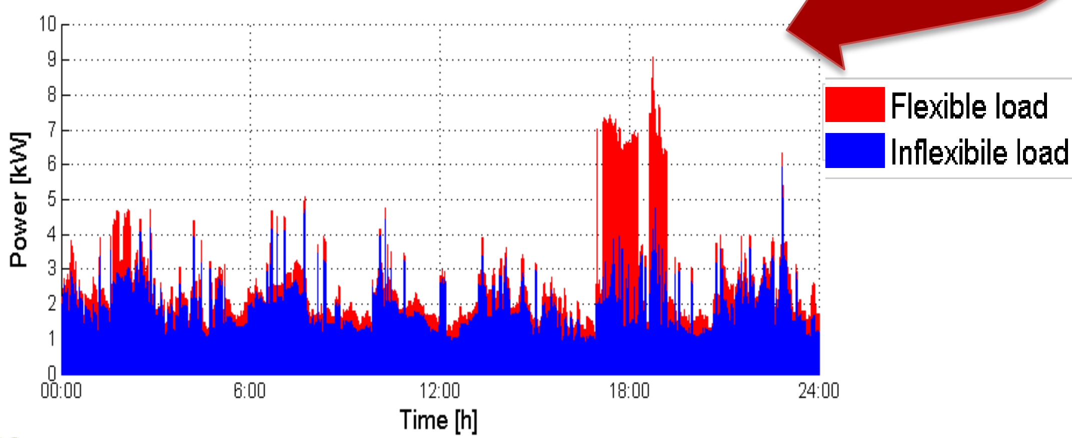
- Introduction
- Machine learning → Deep learning

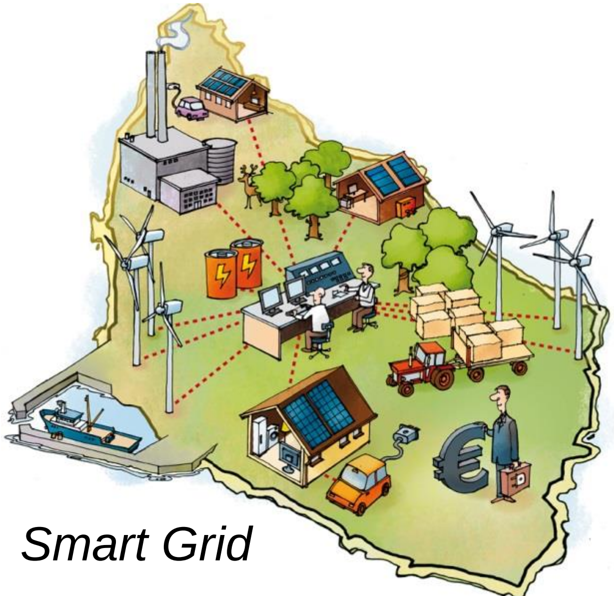
1) On-line flexibility prediction
   - Flexibility identification
   - Flexibility prediction
2) Optimal resource allocation
   - Deep reinforcement learning

- Conclusion and future work

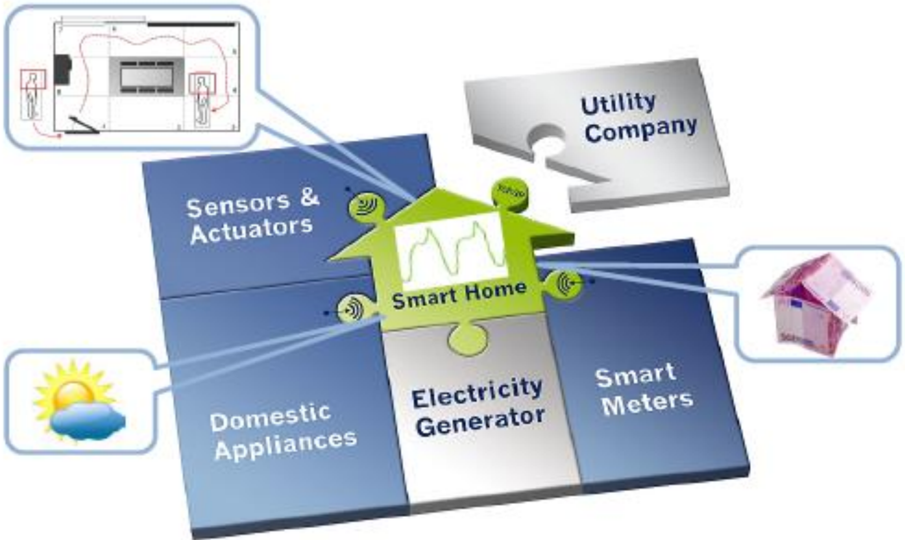

Smart Grid

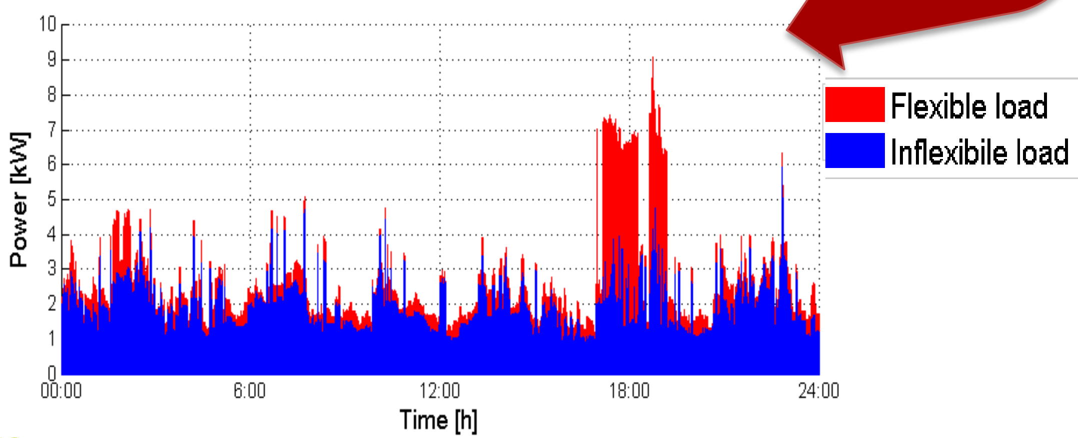

Sensors & Actuators
Utility Company
Smart Home
Domestic Appliances
Electricity Generator
Smart Meters


Power [kW]
Time [h]
00:00
6:00
12:00
18:00
24:00
Flexible load
Inflexibile load



Smart Grid





Building energy flexibility

Identification
+
prediction
+
control

Problem formulation

1) Energy dissagregation: **Given** a set of observation $\mathbf{D}^{(t)} \in \mathbb{R}^{d \times n}$ learn a model for every electrical device, $\hat{d}$.

Traditional versus *Big data era*

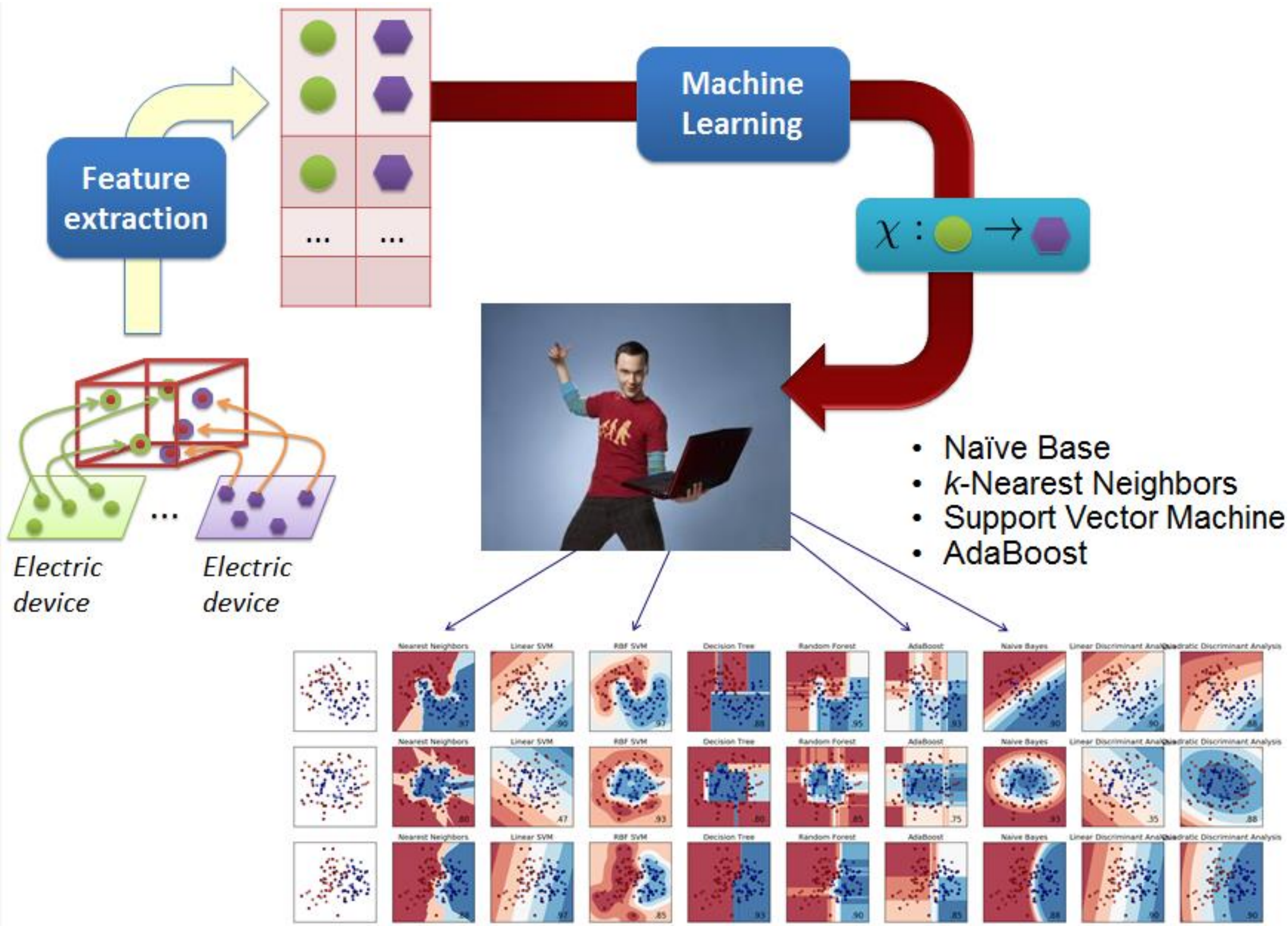
2) Flexibility identification: **Given** the set of building demand energy profiles $\mathbf{B}^{(t)}$ and their corresponding sum of disaggregated electrical parts $\sum_{i=1}^{d} \hat{d}$ classified at every moment in time find how many devices are operating in the building.

3) Flexibility prediction: **Given** the set of building demand energy profiles, $\mathbf{B}^{(t)}$ learn the *time-of-use* (ToU) predictive function (or the power consumption) for every device such that the empirical loss is minimized,

$$min\|ToU_{\hat{d}}(d|\hat{d}, \mathbf{B}) \wedge ToU_{empirical}(d|\mathbf{D})\|$$

IEEE PES Power & Energy Society® IEEE

Building flexibility identification



- Naïve Base
- *k*-Nearest Neighbors
- Support Vector Machine
- AdaBoost

Visualization of different classifiers using an open library (http://scikit-learn.org/stable/)

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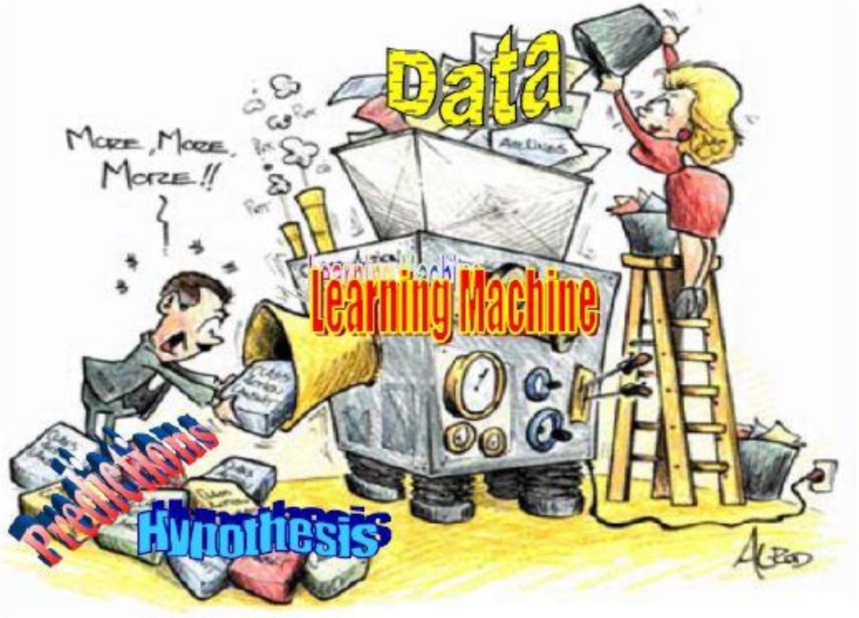
Machine learning

- Given observations $\mathcal{D}_{Energy} = \{\mathbf{U}^{(i)}, \mathbf{v}^{(i)}\}_{i=1}^{l}$
- Learn a predictive function
- Goal: Minimize the empirical loss



Why Deep Learning?

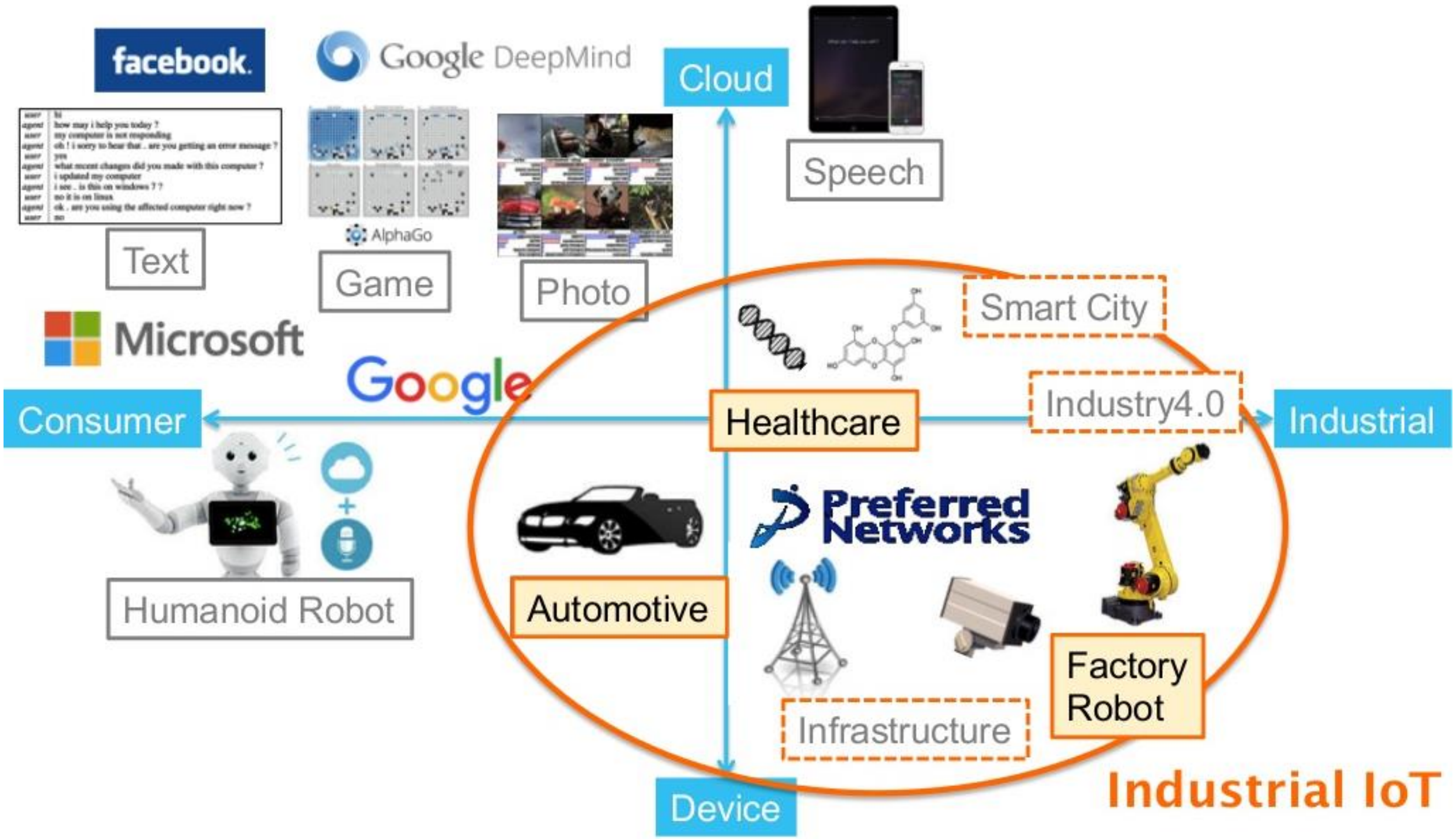


Image Source: Yahoo Japan, 20 March 2016

What is Deep Learning ?

Origins (1980-1990) :

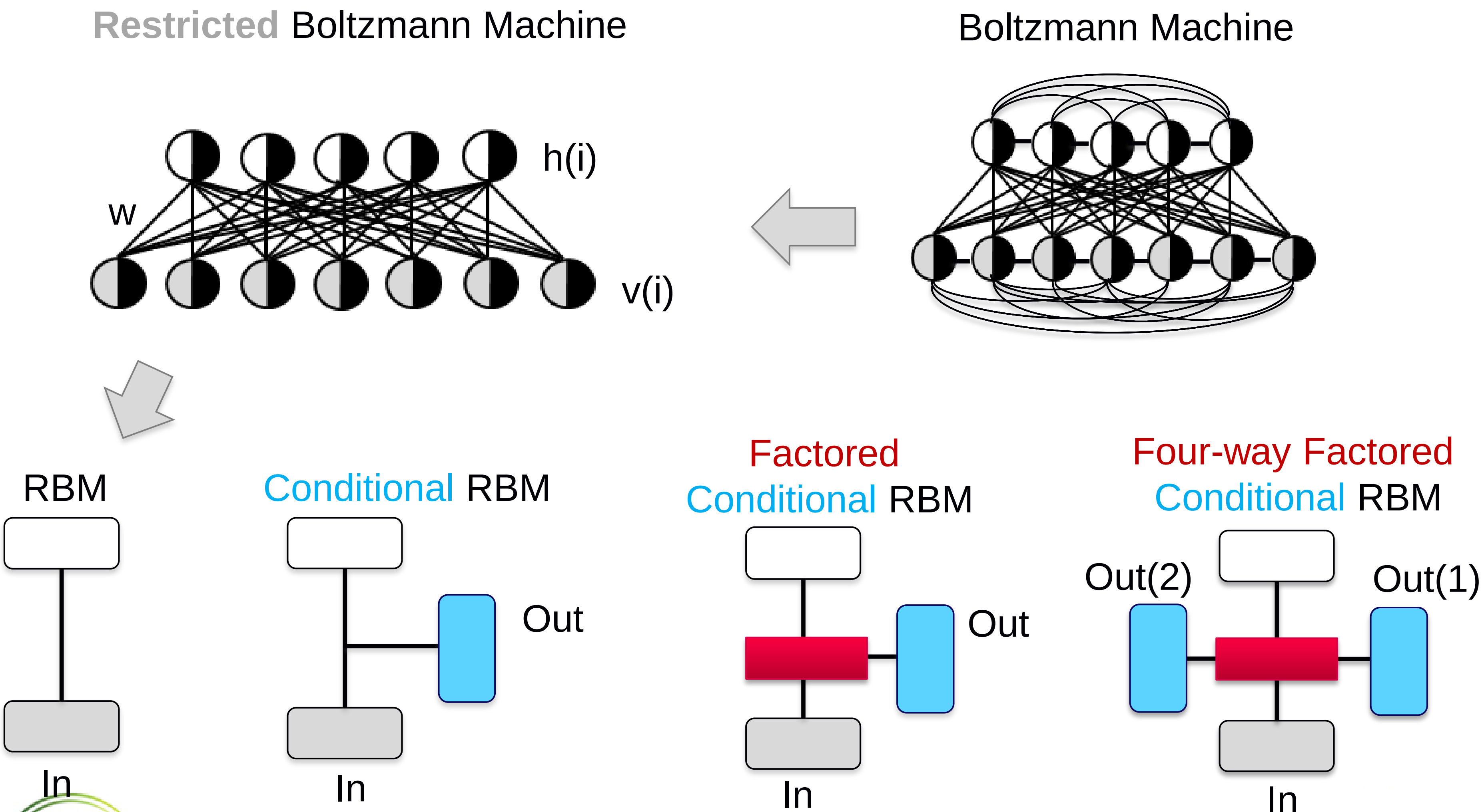
- Boltzmann Machines, Restricted Boltzmann Machines. (Smolensky ,1986, called them "harmoniums")

- Successful on simple test cases.
- People: Geoffrey Hinton, Terry Sejnowski, Emile Aarts, Jan Korst.

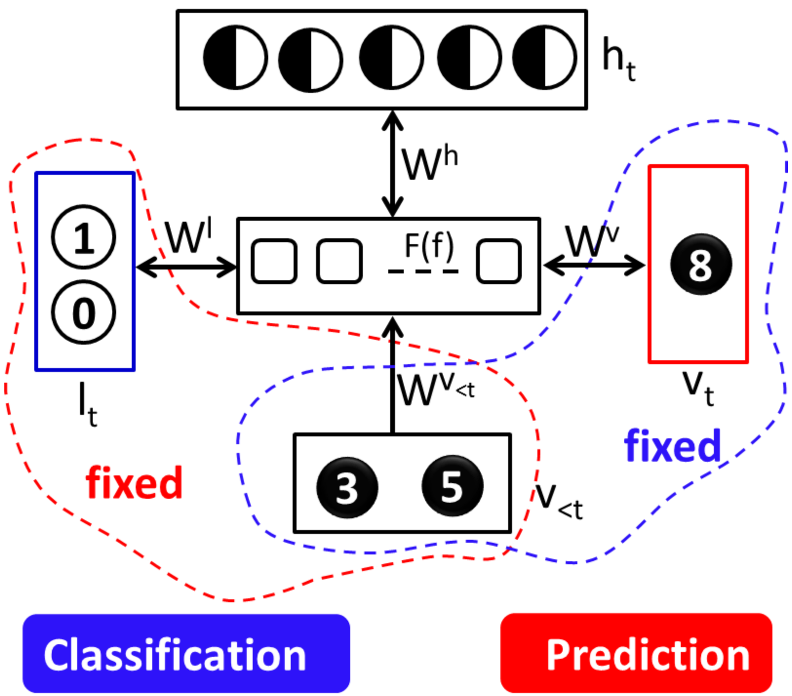
Breakthrough in 2006:

- Ability to train deep architectures by using layer-wise unsupervised learning, whereas previous purely supervised attempts had failed.

The intuition behind our proposed method

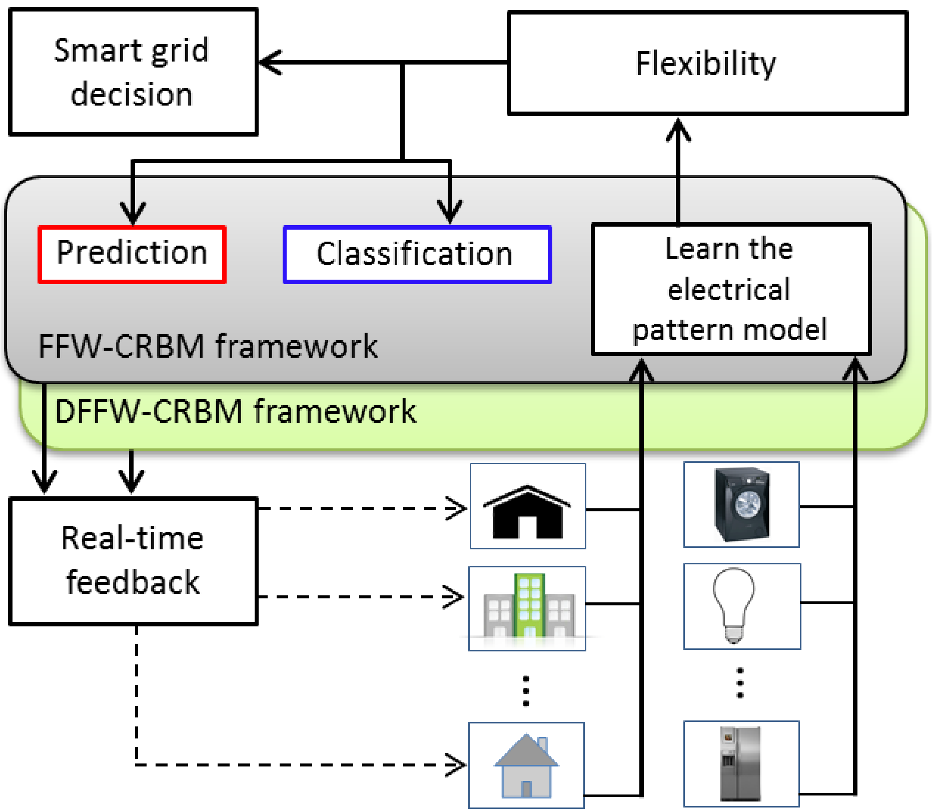


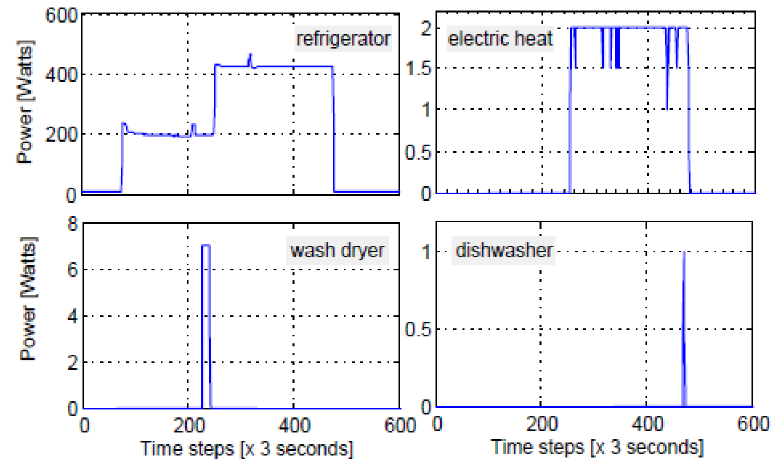
Factored four way conditional restricted Boltzmann machine (FFW-CRBM)



Classification and prediction schemes for FFW-CRBM

IoT architecture used for the real-time identification and prediction procedure of the buildings energy flexibility



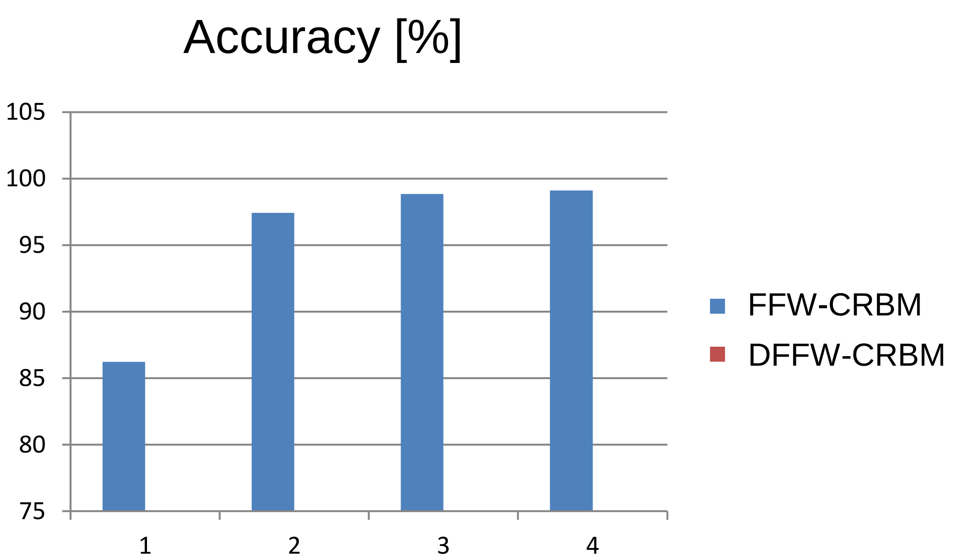


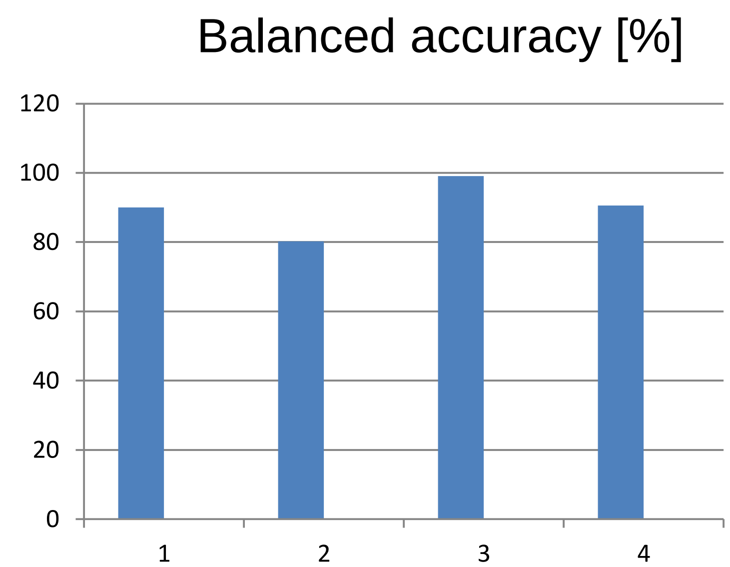
REDD: A Public Data Set for Energy Disaggregation Research

[Kolter and Johnson]

Results – flexibility identification

Appliance	Method	Accuracy [%]	Balanced accuracy [%]
refrigerator	FFW-CRBM	86.23	90.05
	DFFW-CRBM	83.10	91.27
dishwasher	FFW-CRBM	97.42	80.21
	DFFW-CRBM	97.26	87.06
washer dryer	FFW-CRBM	98.83	99.03
	DFFW-CRBM	99.06	92.16
electric heater	FFW-CRBM	99.10	90.58
	DFFW-CRBM	99.03	92.05





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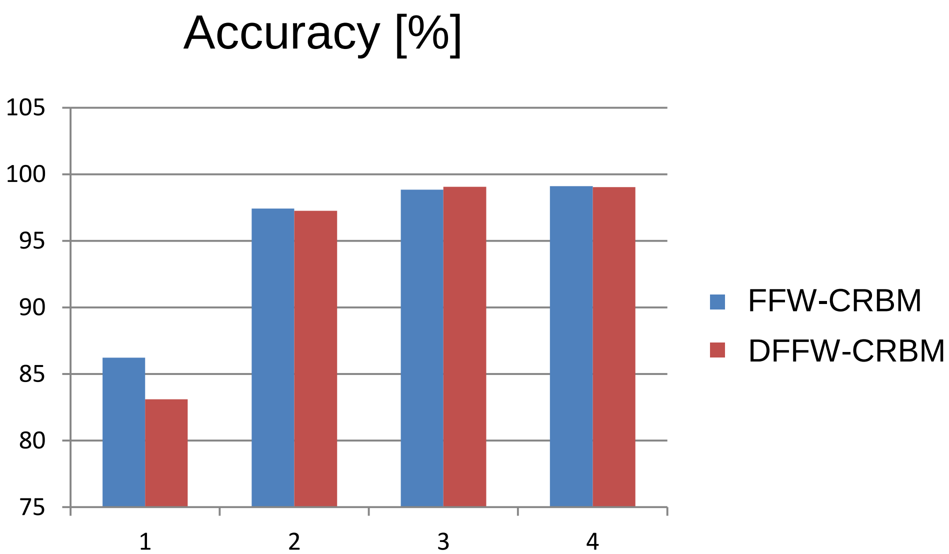
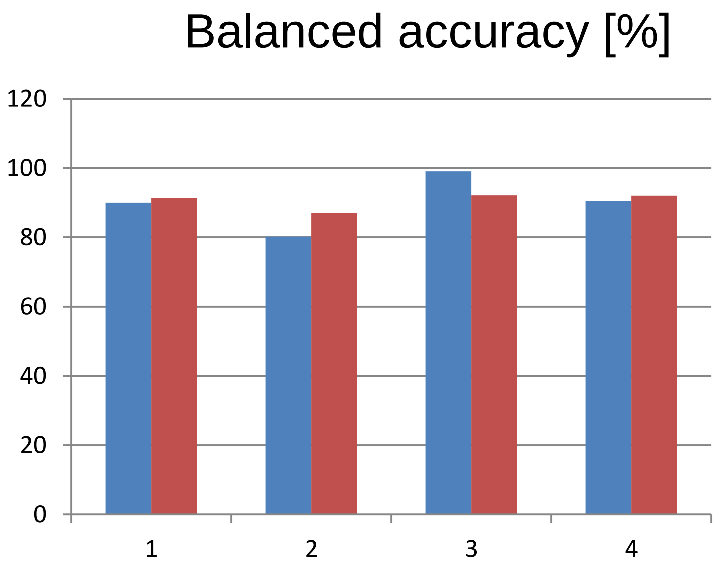
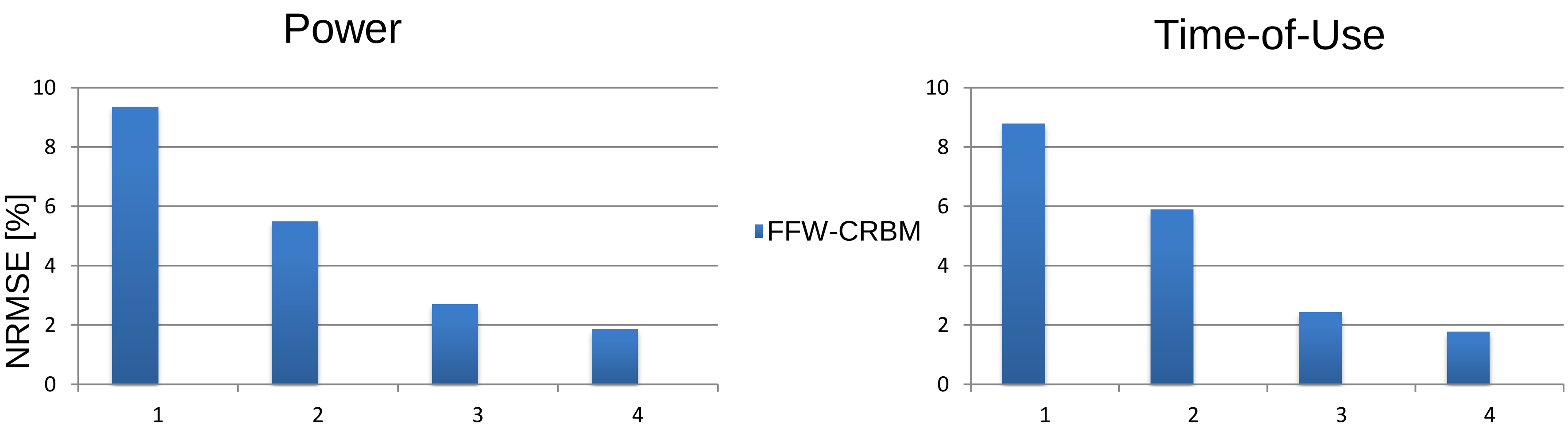


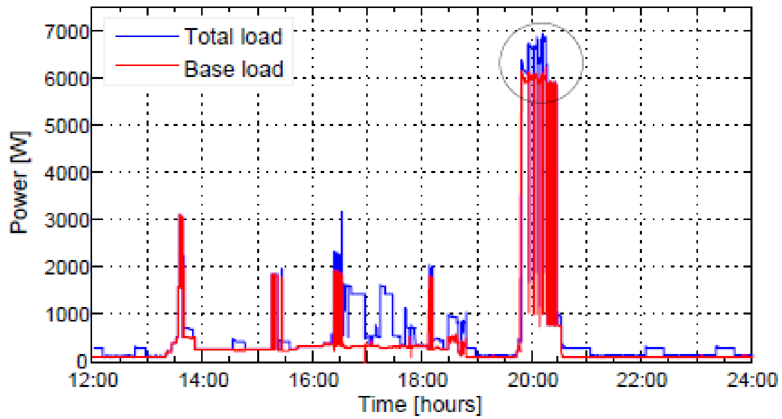


Results – flexibility prediction

Appliance	Method	Power NRMSE [%]	Time-of-use NRMSE [%]
refrigerator	FFW-CRBM	9.36	8.79
	DFFW-CRBM	9.27	8.71
dishwasher	FFW-CRBM	5.49	5.89
	DFFW-CRBM	5.41	5.87
washer dryer	FFW-CRBM	2.70	2.43
	DFFW-CRBM	2.59	2.44
electric heater	FFW-CRBM	1.86	1.78
	DFFW-CRBM	1.85	1.77



Results – flexibility prediction



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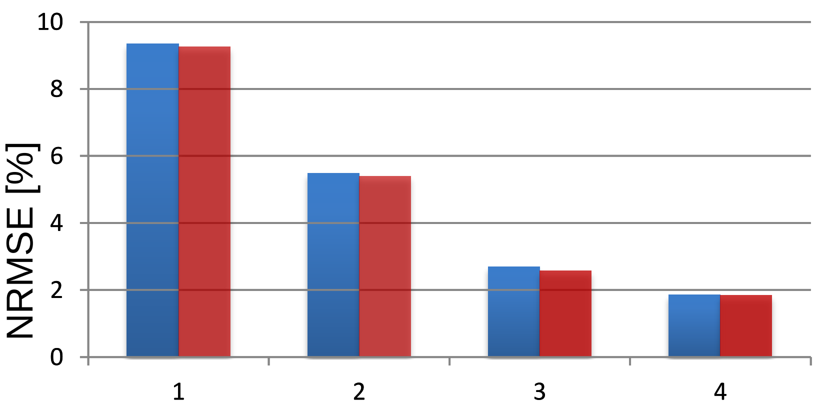
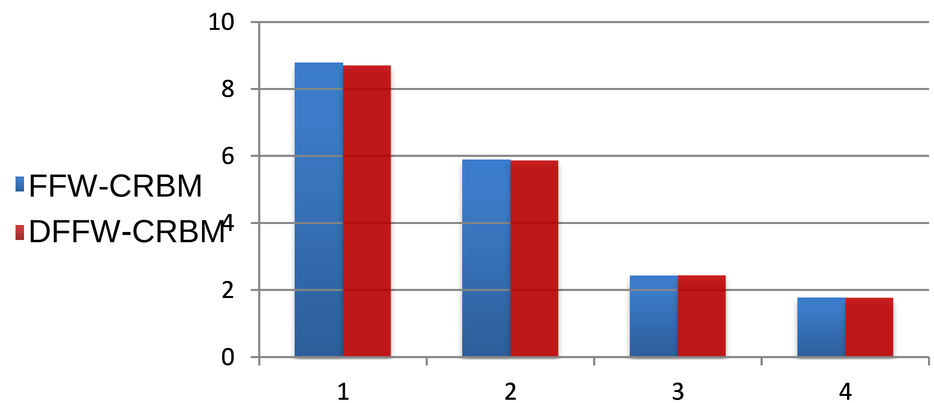
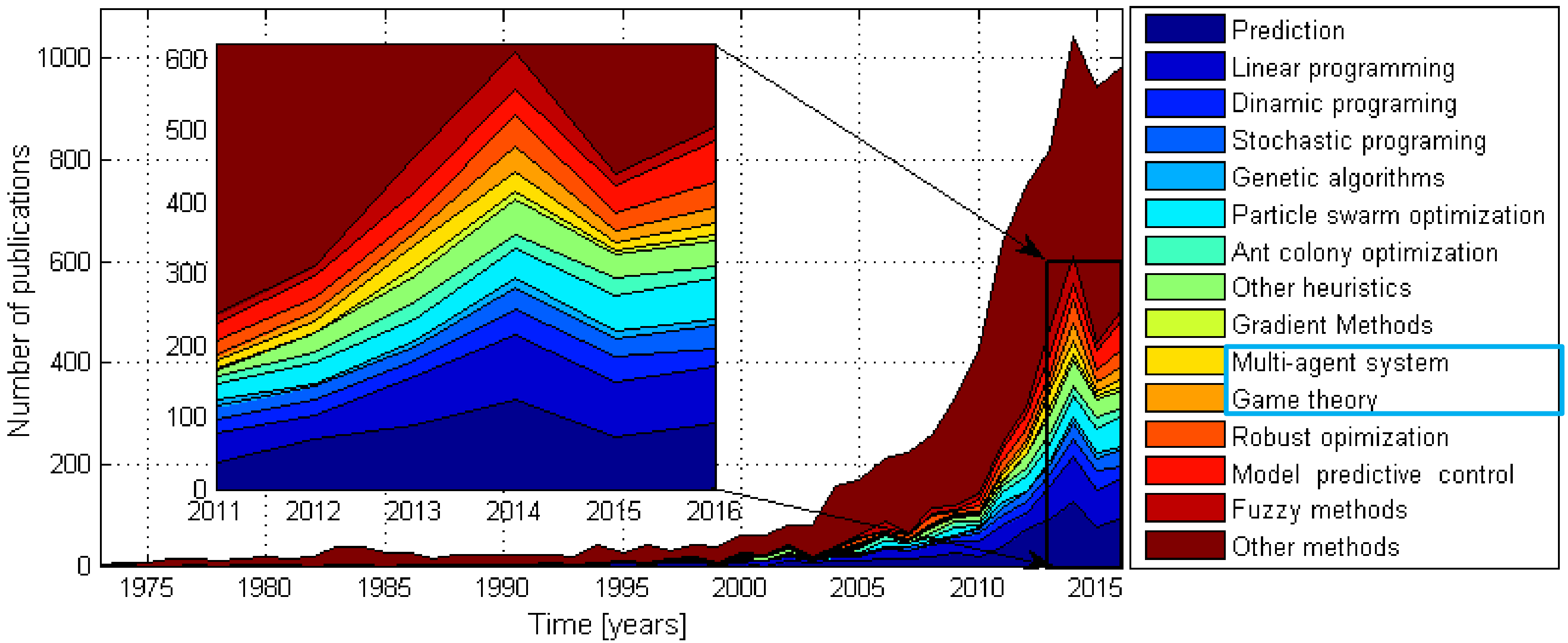




On-line resource allocation



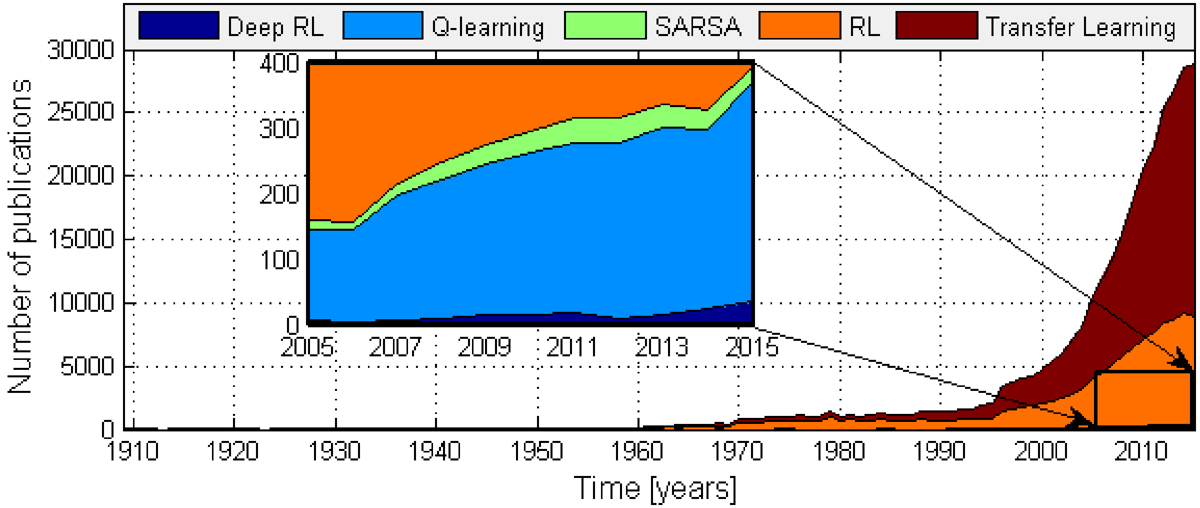
On-line resource allocation

[2015] Human-level control through deep reinforcement learning, *Minh et all*, Nature

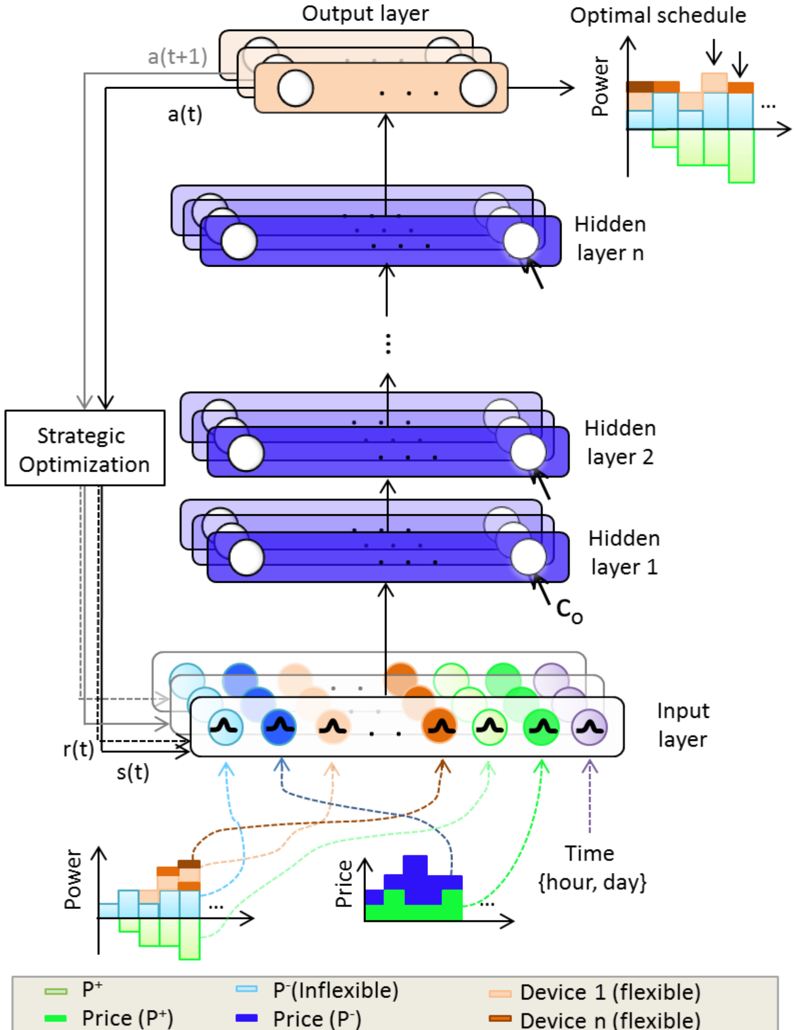
“This work bridges the divide between high-dimensional sensory inputs and actions, resulting in the first artificial agent that is capable of learning to excel at a diverse array of challenging tasks.”

[2016] AlphaGO versus Lee Sedol - professional Go player

~10^{170} compared to ~10^{50} for chess (Kasparov, 1997)



Optimal resource allocation



Reinforcement learning

$$\{s,a\} \rightarrow Q(s,a)$$

Deep learning

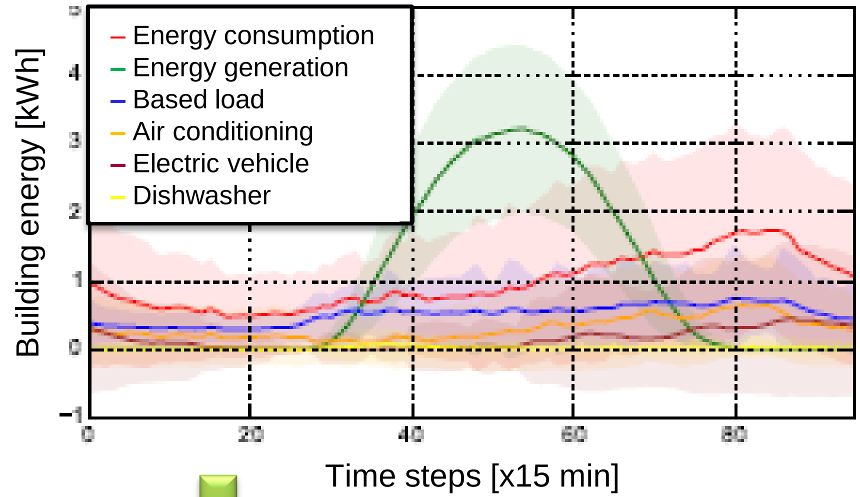
$$\xrightarrow[data]{Input} DNN_{(k)} \xrightarrow[Data\ estimation]{Output}$$

Deep reinforcement learning

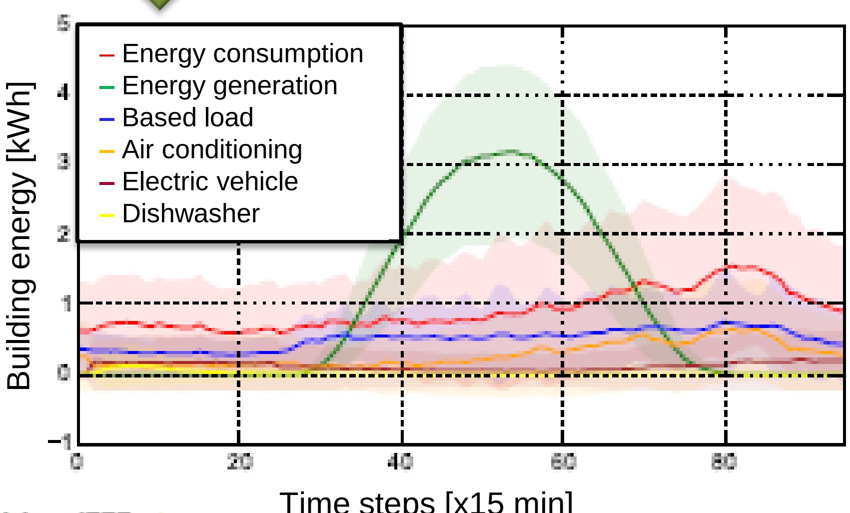
$$\begin{cases} \xrightarrow[states]{Input} DNN_{(k)} \xrightarrow[Q(s,a)]{Output} & \text{Deep Q-learning} \\ \xrightarrow[states]{Input} DNN_{(k)} \xrightarrow[p(a|s)]{Output} & \text{Deep Policy Gradient} \end{cases}$$

Optimal resource allocation

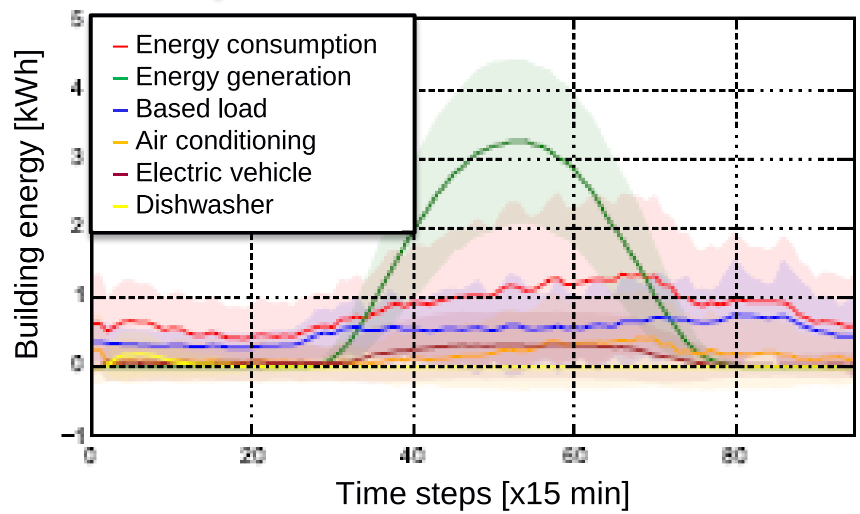
Deep reinforcement learning



Cost minimization

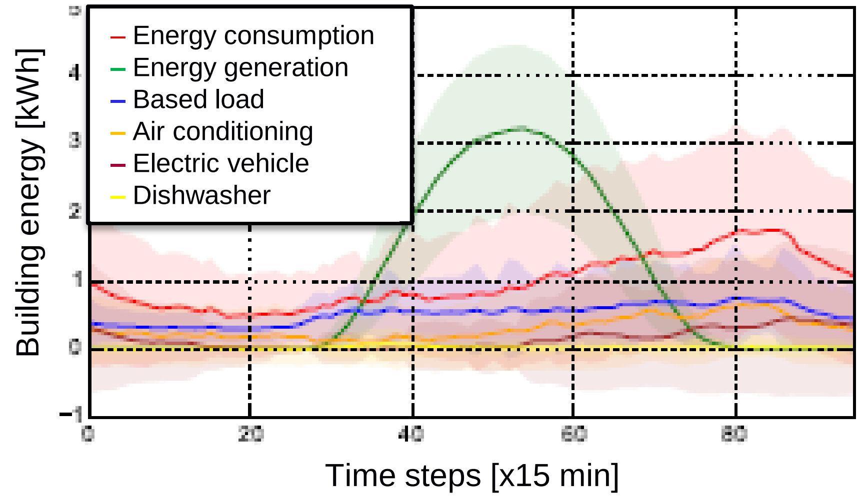


Peak reduction

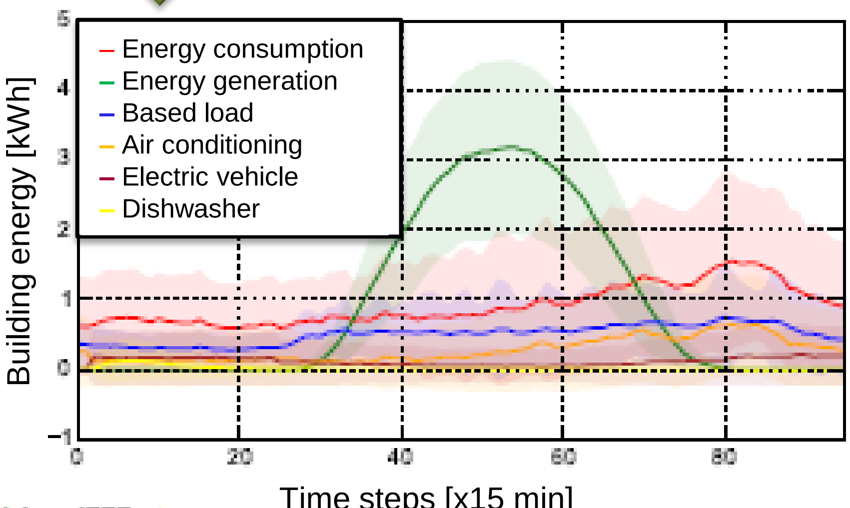


Optimal resource allocation

Deep reinforcement learning



Cost minimization



Results: 27% cost reduction

Pecan Street dataset

- Building level
- Aggregated level

Conclusions

Part I

- We proposed a novel IoT framework using FFW-CRBMs and DFFW-CRBMs to perform simultaneously and in real-time flexibility identification and prediction
- The evaluation on the REDD dataset shows that:
  - Both models perform very well, reaching a similar performance with state-of-the-art models on flexibility identification
  - Both models are capable of performing also flexibility prediction (i.e. real-time estimation of the power consumption and time-of-use of the flexible appliances)

Part II

- We introduce Deep Reinforcement Learning for on-line resource allocation at both building and aggregated level
- The evaluation on the Pecan Street dataset shows that
  - We are able to minimize the peak consumption, as well as to reduce the building energy cost with approximately 27%.

- References

Part I

[1] Mocanu E., Nguyen P.H. and Gibescu M. *Energy disaggregation for real-time building flexibility detection.* IEEE Power and Energy Society General Meeting, 2016, Boston, USA.

[2] Mocanu D.C., Mocanu E., Nguyen H.P., Gibescu M. and Liotta A. *Big IoT data mining for real-time energy disaggregation in buildings.* Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (IEEE SMC), 2016, Hungary.

Part II

[3] Mocanu E., Mocanu D.C., Nguyen H.P., Liotta A. , Webber M.E., Gibescu M. and Slootweg J.G.

On-line Building Energy Optimization using Deep Reinforcement Learning, CoRR, 2017, (submitted for journal publication)

Thank you for your attention! Questions?