Machine Learning is Naturally Intertwined with Home Automation

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The Smart House

Strong Approach:

The house must learn to predict inhabitant's wills (are we sure?)

Weak approach:

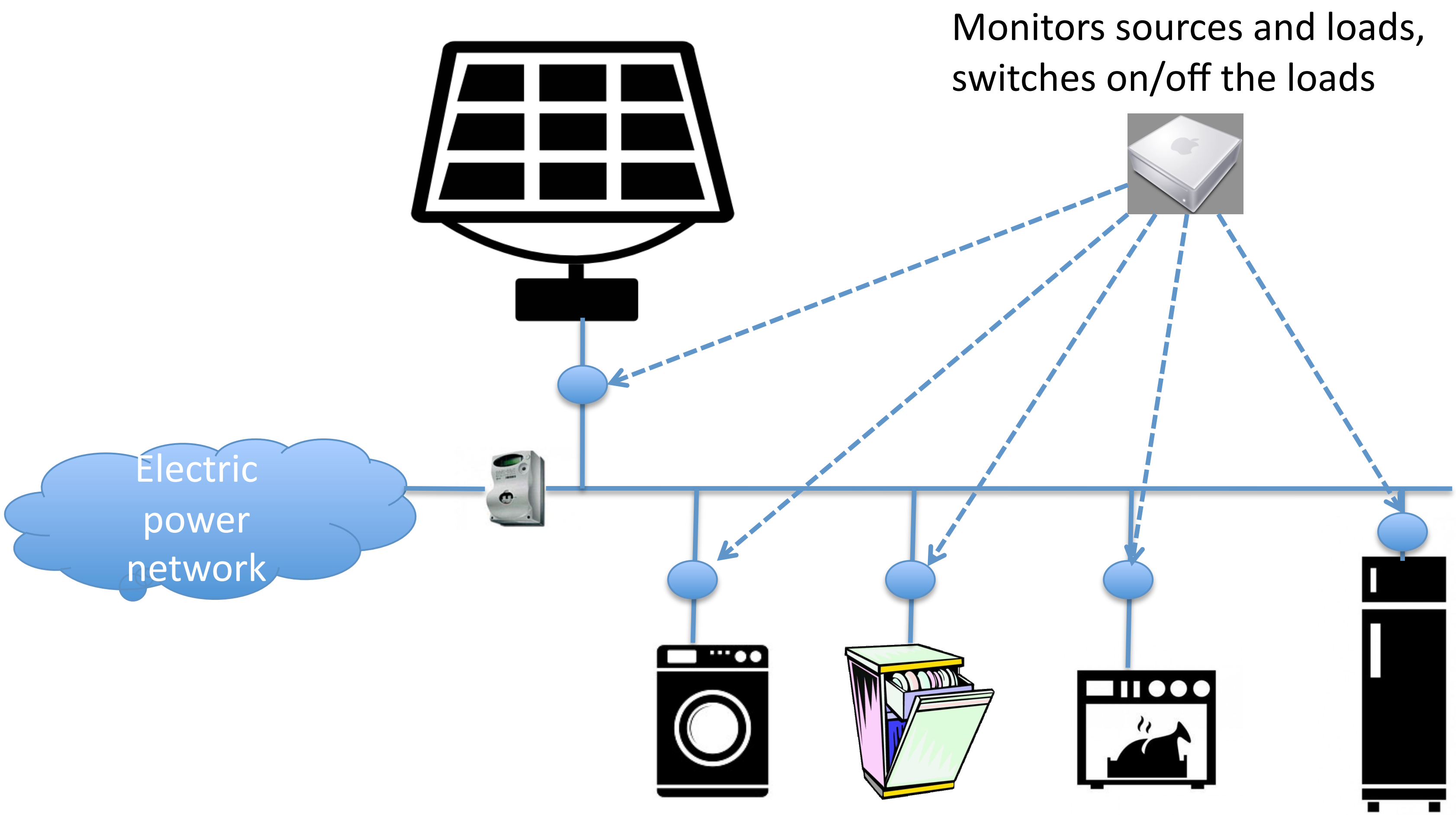
The house must provide a user friendly interface, with a high level of abstraction. Parameter tuning and behavior optimization are carried on by the environment. (we follow this approach)

In this line, two main topics deeply involve ML:

1. Security and safety enforcement.
2. Energy management (electric power and air conditioning)

Notice that, in both cases, the solution deeply depends upon the specific environment. The parameter tuning cannot be left to the user!

Electric Power Management



Goals

1. Never trespass the maximum load specified in the contract with the provider
2. Exploit as much as possible the alternative sources (sun, wind,…)
3. Possibly meet the dead-lines stated by the user

We assume an estimate of the energy produced by alternative sources is available.

It is required to learn the energy profile of the loads (appliances)

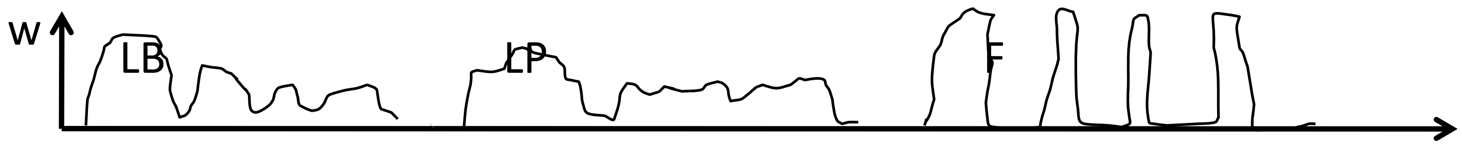
The Problem set as "Scheduling Optimization"

The user set the working program in the appliances and submits the list to the *energy manager*:

"Washing Machine(), Dish Washer(), Owen(20)"

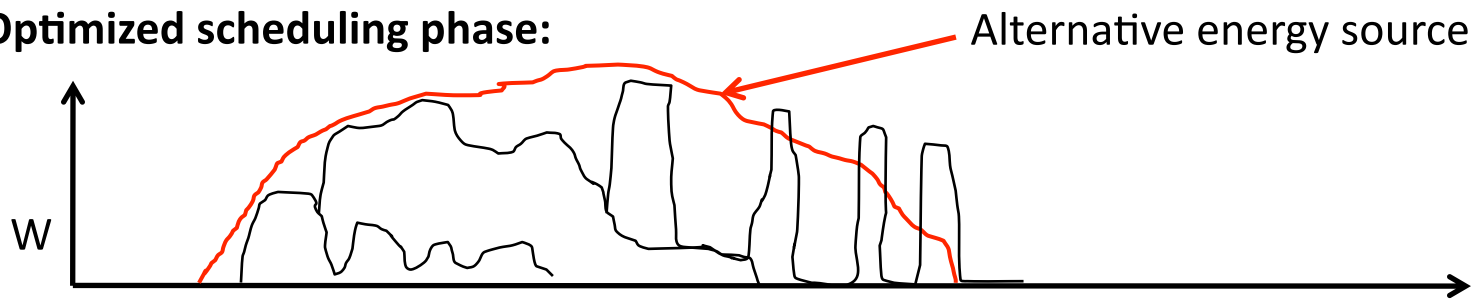
Learning Phase:

1. The manager executes the task sequentially monitoring the loads



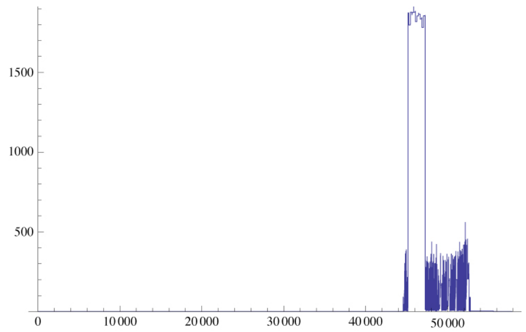
2. Constructs the specific energy profiles of the loads
3. Updates the general profiles of the appliences

Optimized scheduling phase:

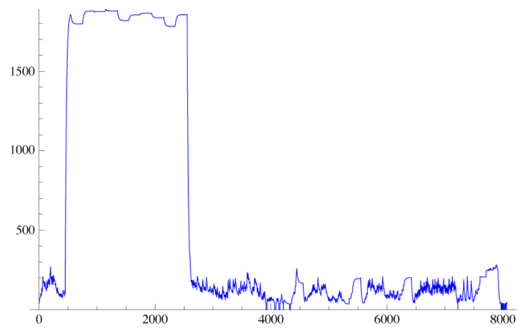


Example: Washing Machine

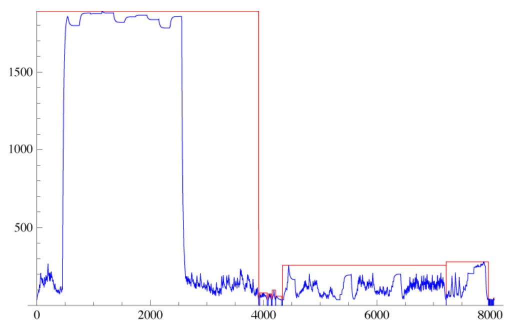
Cotton



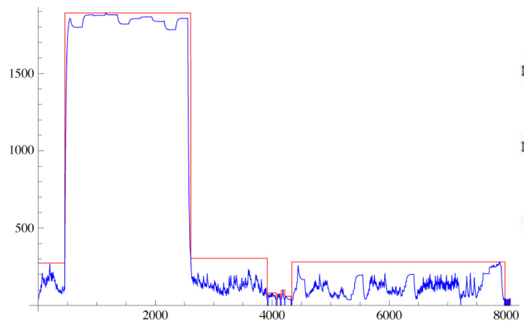
Recorded signal



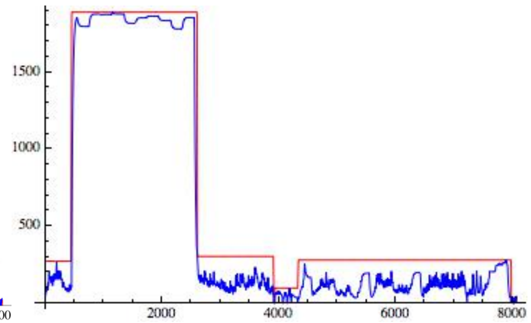
Learning episode



Rough profile



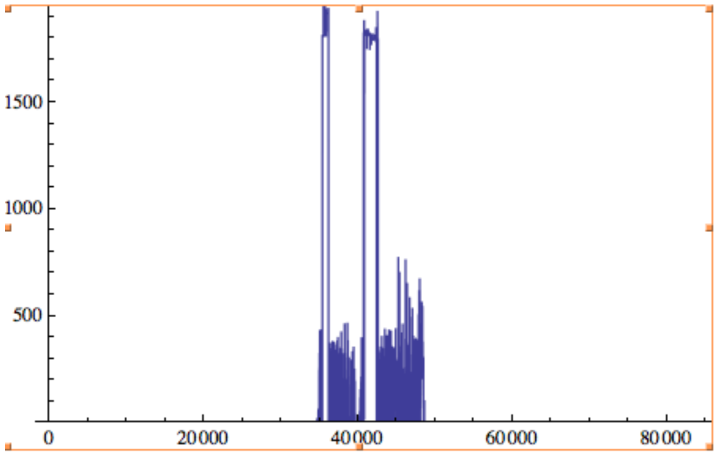
Refined profile: step 1

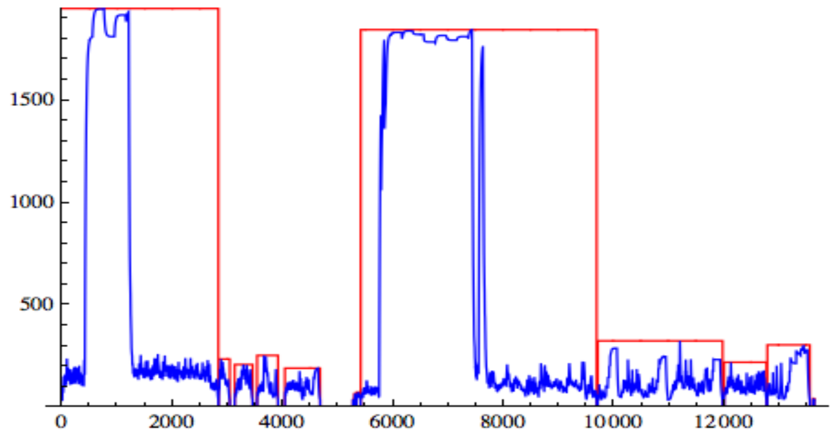


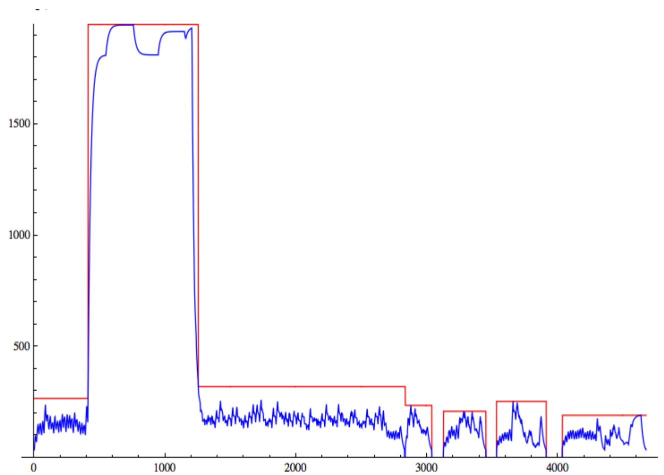
Refined profile: step 2

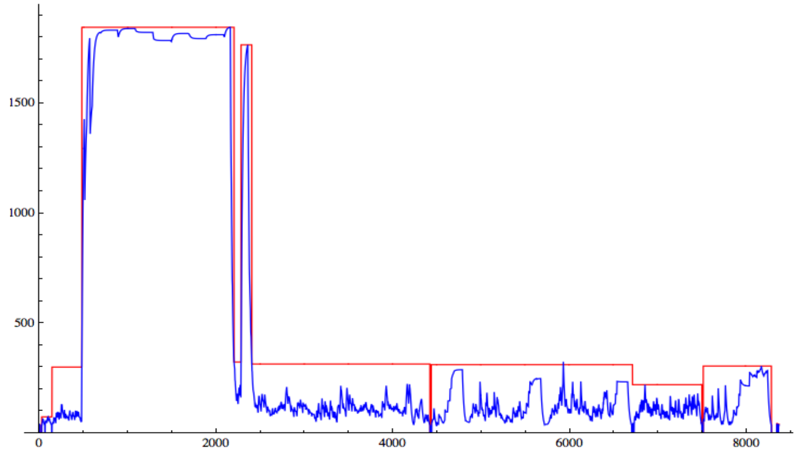
Washing Machine…

Synthetic / cotton



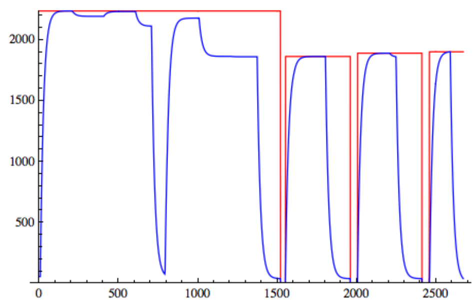


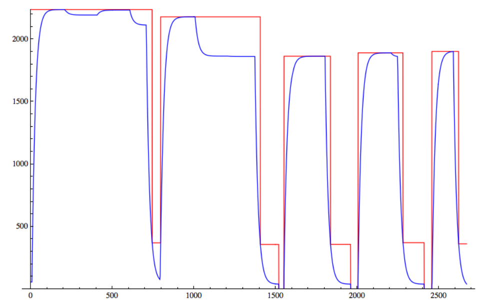




Washing Machine……

Wool





General Profile

Final representation

{“type”, start, end, height }

{"H", 454, 2605, 1890.81},
{"L", 2606, 3916, 304.805},
{"eps", 3917, 3933, 0},
{"L", 3934, 4334, 99.2},
{"L", 4335, 7979, 281.105},
{"L", 7980, 8006, 38.6991},
{"eps", 8007, 8020, 0},
{"L", 8021, 8025, 37.9294},
{"eps", 8026, 8039, 0},
{"L", 8040, 8072, 40.0964}}

The general profile is the set of the profiles for the different programs

Similar profiles are merged.
The block sequence is assumed to be identical and only the numerical attributes are generalized.

Merging occurs only if all blocks are “similar”

Using the Profile

In most cases the working program can be identified from the first blocks.

Then, from the energy available for starting another appliance can be computed considering the remaining blocks

Opportunjstic scheduling:

- If energy is available, another task is started choosing according to the energy profile and the dead-line set by the user.
- If the energy decreases below the expectation, the task having the least critical dead-line is preempted.

Current status of the Work

A first version of the profile extraction algorithm has been implemented.

The scheduling algorithm is under development.

Air Conditioning Management

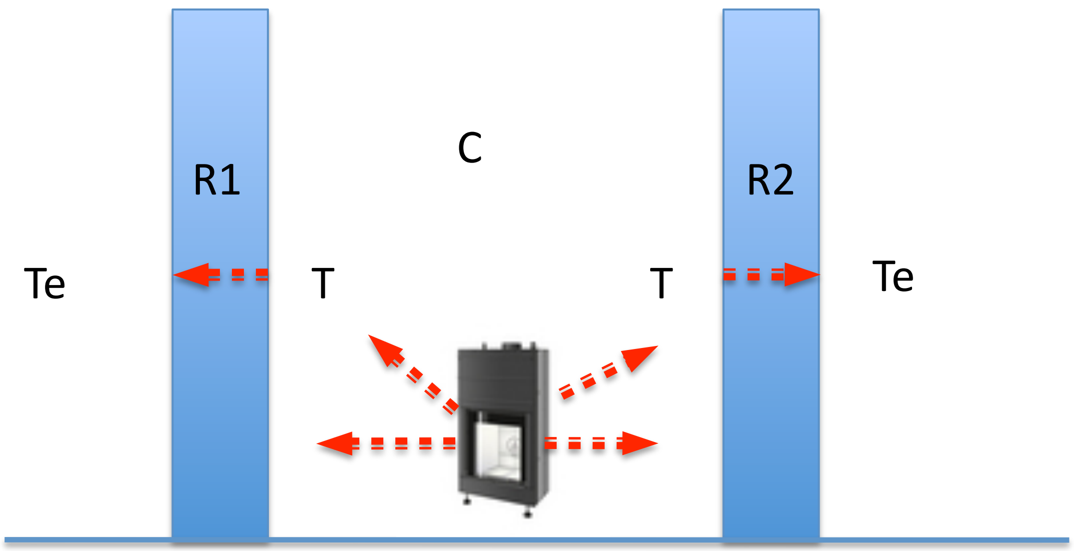
Tuning the air conditioning control “on-line” shows many drawbacks:

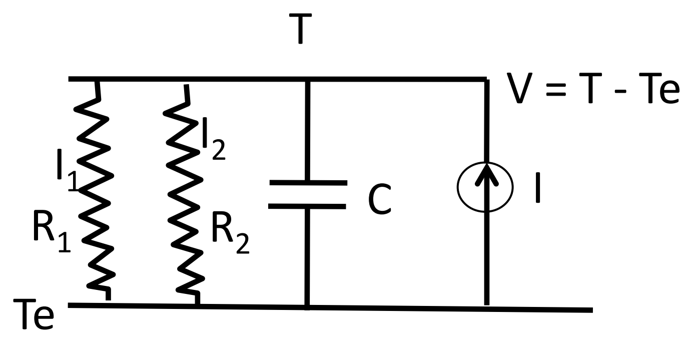
- It requires a lot of time and a lot of trials.
- It is uncomfortable for the inhabitants.

Propose Approach:

- To monitor the thermal flows in a building
- To build the thermodynamic model.
- To tune the air conditioning system using the model

A Simple Approach to Modeling Thermal Flows





Equivalent electric model

C = room thermal capacity

F1 = (T – Te)/R1 = Left wall flow

CT = Thermal energy stored in the room

Building the Model….

Given:

- The temperature evolution provied by a set of thermometers
- The thermal sources activity

Task:

- Automatically construct a model explaining the observed evolution
- The starting point can be the building map….