

Call:



PEPER

Prosumption Prediction with Machine Learning

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DATAIA-JST International Symposium





Definitions

Energy consumption monitoring

Weather forecast for renewable energy

Human behavior/presence

Multimodal machine learning for energy management

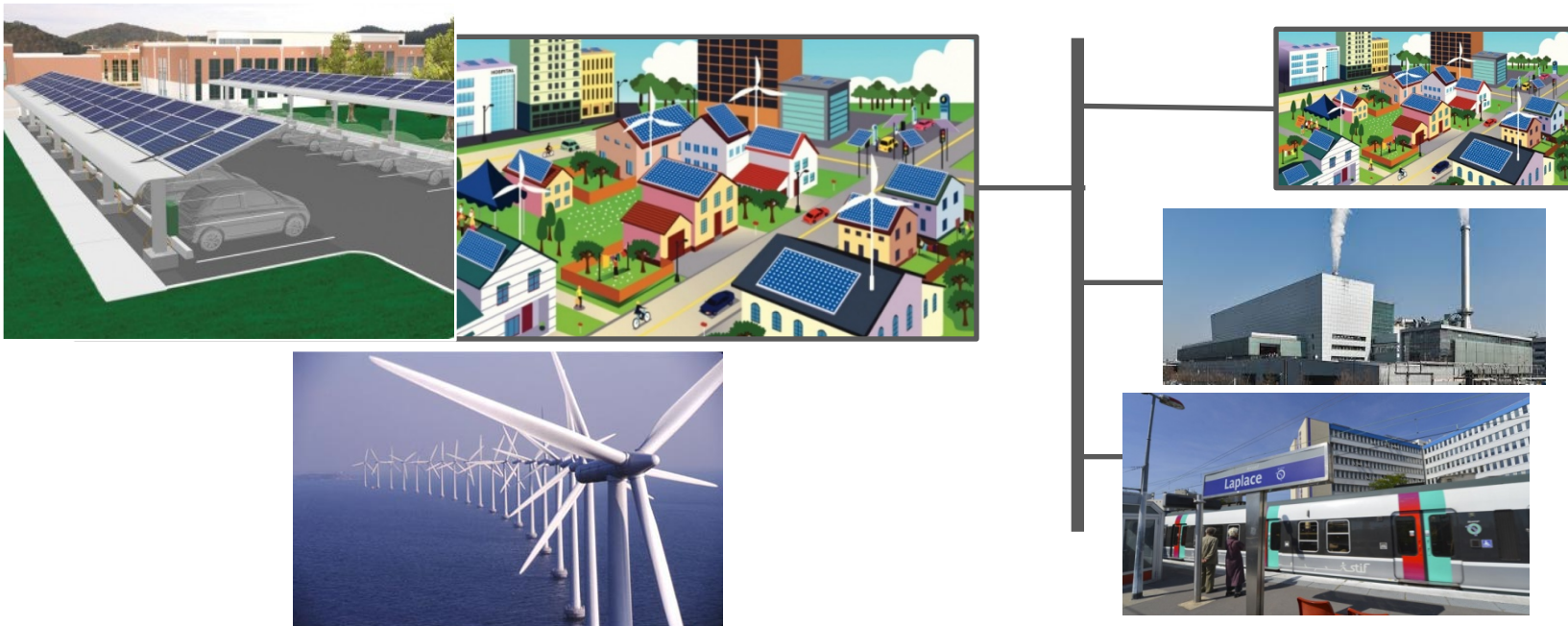
Deep reinforcement Q-learning

Project deployment

Conclusion



Production / consumption / storage in a microgrid



We need a 'smart' mechanism to coordinate those actors :

- ▶ At the local scale intra microgrid
- ▶ Between microgrids = smart grid



- **Consumption, Renewable energy and weather forecast**
- **Smart management of a single building**
- **Recommendations on best coupling between different microgrids**

Approach :

- ▶ Use multi modal data
- ▶ Construct machine learning models (state, action, reward)
- ▶ multi-objective reward and multi agent coupling

Scientific challenges :

- ▶ Best choice of data and granularity
- ▶ Adaptation and evolution of machine learning algorithms
- ▶ Go from theory to practice



PEPER PARTNERS



PARIS SACLAY

Communauté d'agglomération

SAMOVAR

Telecom SudParis
Computer science
Telecommunications

LMD

Polytechnique X
LMD - Dynamic Meteorology
Laboratory
The laboratory studies
climate, air quality, and
changes in planetary
environment

Laboratoire GeePs

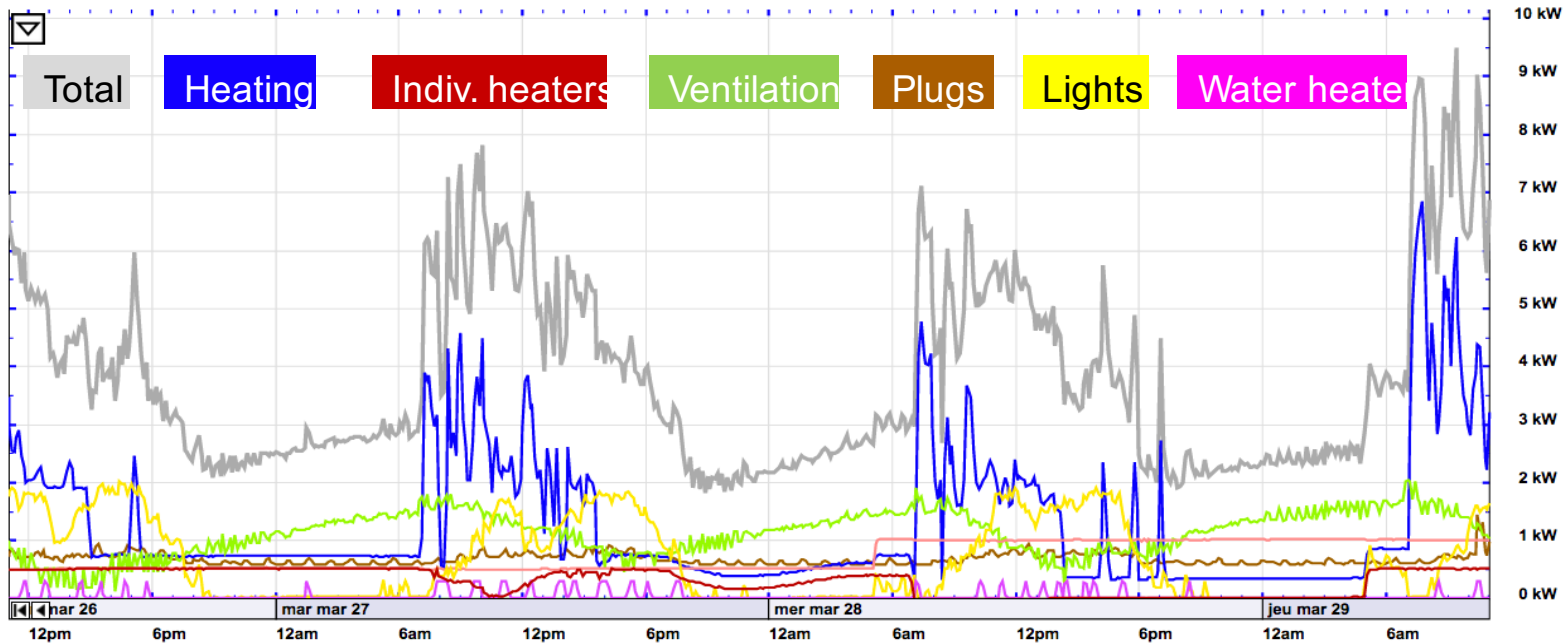
Centrale Supelec
Energy expertise



Open to any
collaboration?



- Electric/energy consumption, ...
- Realtime onsite Measurement (homes, buildings, campus)



Example: energy consumption monitoring in the :
Drahi-X Novation Center, Ecole Polytechnique

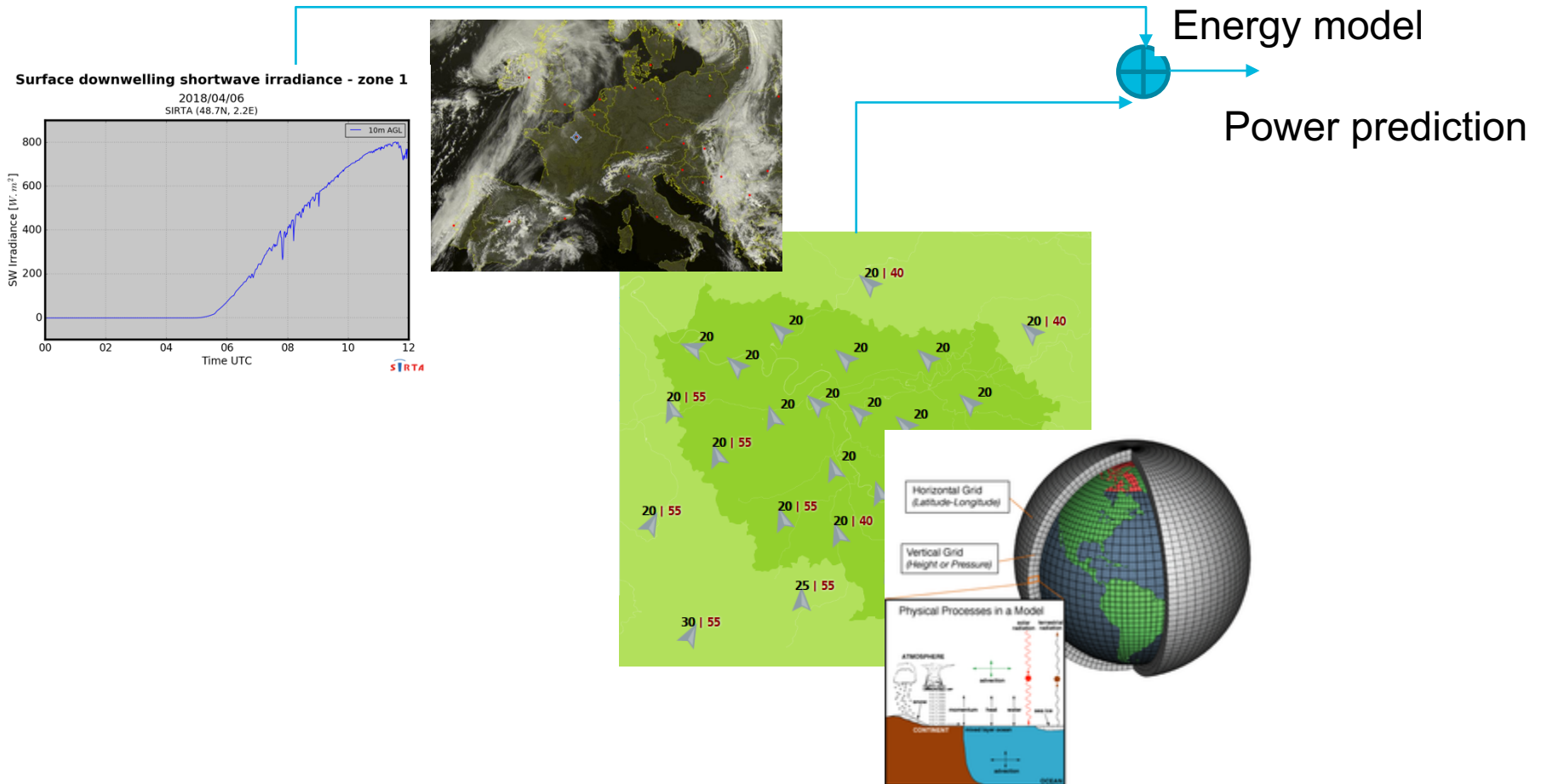


METEOROLOGICAL DATA



Meteorological data :

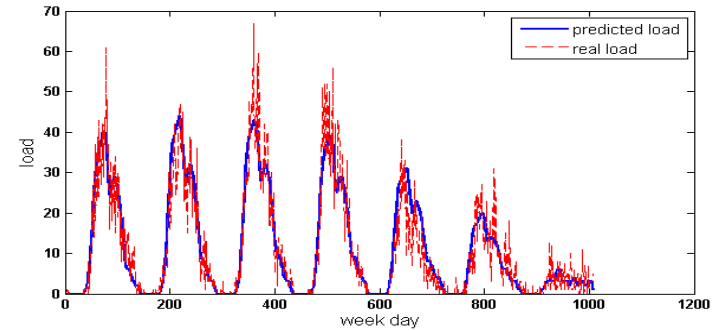
- Temperatures, wind, sun radiation, rain fall, humidity...
- Local measurement, satellite observation, prediction in regions



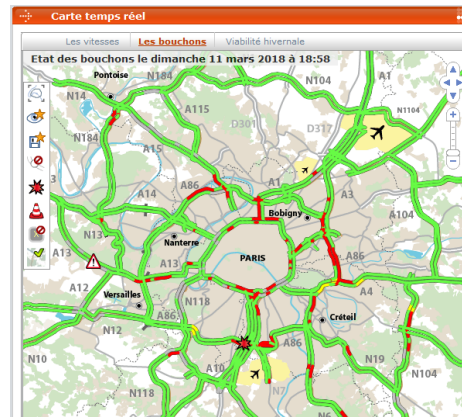


Human presence based on cellular data :

- ▶ Fine grain presence based on Cellular data : source Orange, optical Bouygues) :



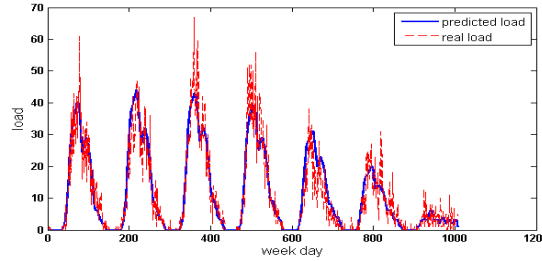
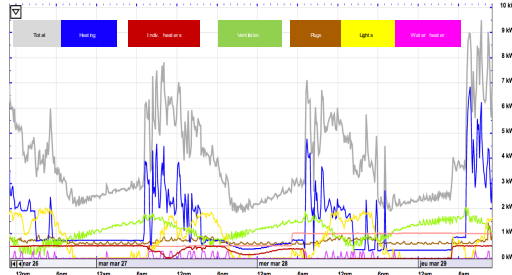
- ▶ Road and urban data sources UberMotion, sytadin, waze...



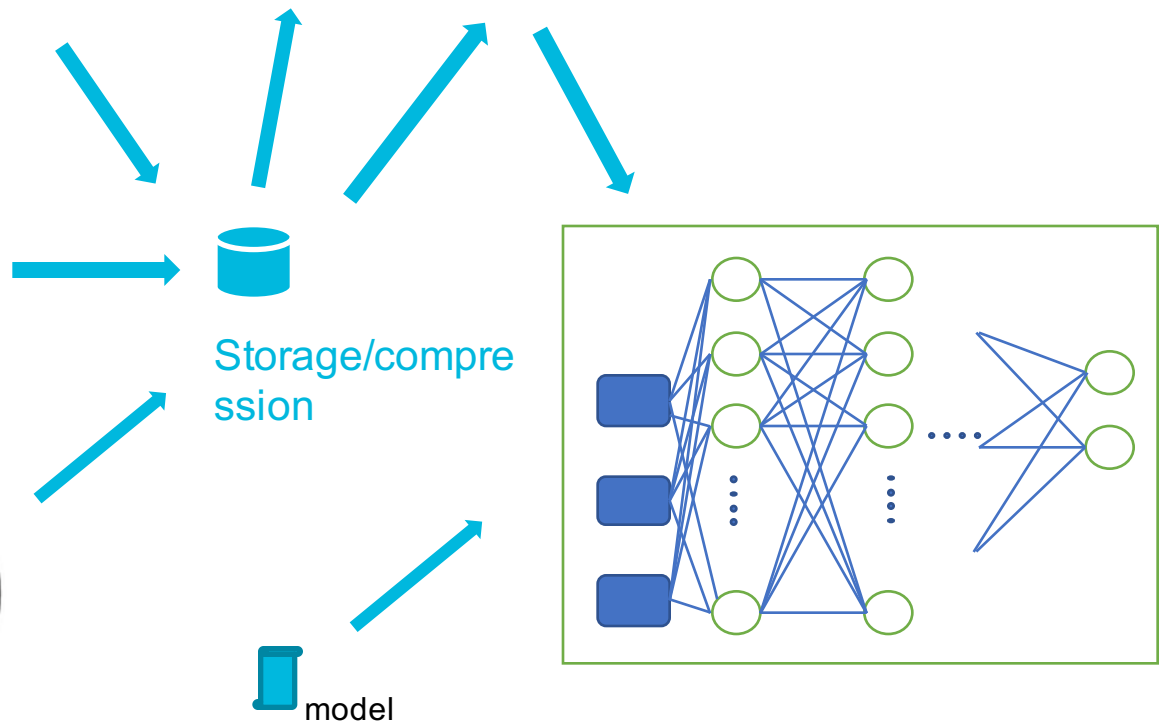


Classified and predicted human presence data

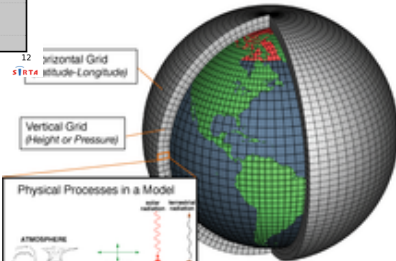
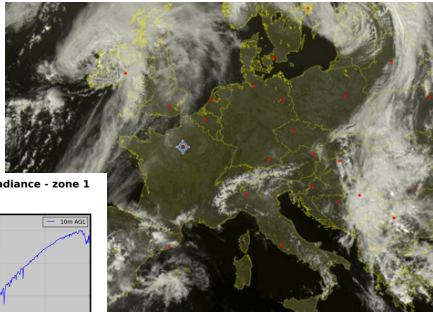
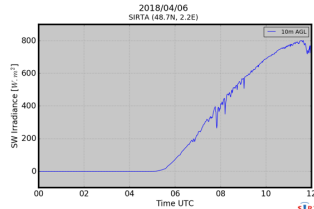
Realtime data



Classification prediction



Surface downwelling shortwave irradiance - zone 1



Example : application of DDQN to utility building

Data (states) :

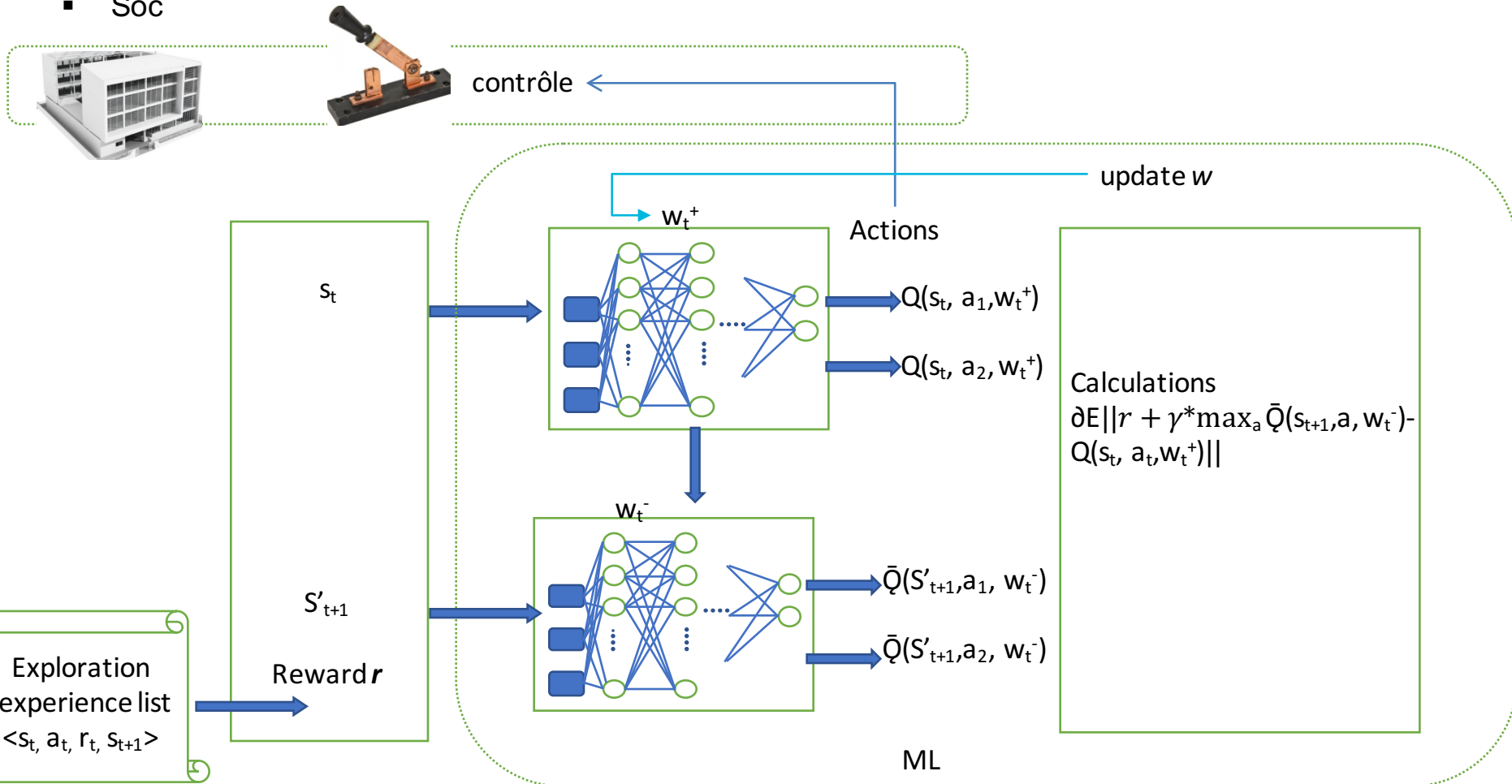
- Human Presence
- weather (int/ext)
- Soc

actions (decisions) :

- Start / Stop
- Store/displace

Reward (multi-criteria) :

- cost
- Comfort (MVP)



TAKE A SIMPLE EXAMPLE: THE FROZEN LAKE GAME



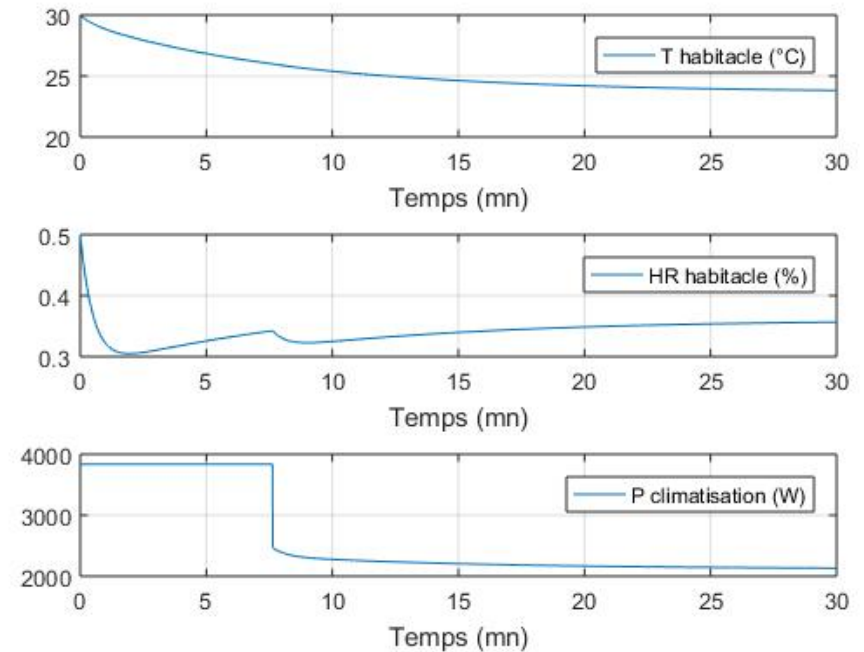
			
			
			
			

source: Thomas Simonini

A SIMPLE EXAMPLE: ELECTRIC VEHICLE TRADEOFF AIR <-> MOTOR....

We have a dilemma:

1. Arrive to destination or put yourself comfortable?



17° 18° 19° 20° 21° 22° 23° 24° 25° 26°

Source: Florence Ossart, et al. Comparative Study of Real-Time HEV Energy Management Strategies. *IEEE Transactions on Vehicular Technologies* 2017



Our starting point: « Deep Reinforcement Learning »

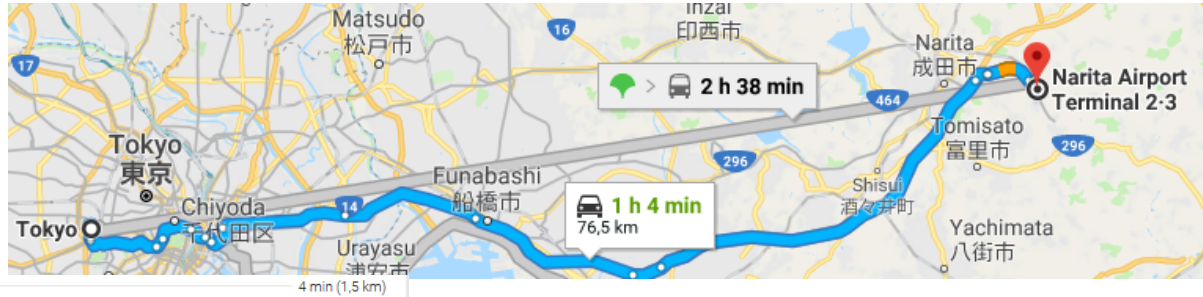
```
if d == True:
    #Reduce chance of random action as we train the model.
    e = 1./((i/50) + 10)
    print("finally!!!!!!!!!!!!!!")
    break
jList.append(j)
rList.append(rAll)
"""
```

```
s 0
trouve.....j. 16 .....
s 43
trouve.....j. 37 .....
Saved Model ./dqn/mod49.cptk
s 37
(Down)
789ABCDEFGHJKLMNOPQRSTUVWXYZ123456s*_~+$/%~#
(Down)
789ABCDEFGHJKLMNOPQRSTUVWXYZ123456s*_~+$/%~#
(Down)
789ABCDEFGHJKLMNOPQRSTUVWXYZ123456s*_~+$/%~#
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```

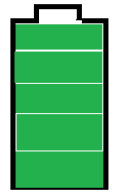
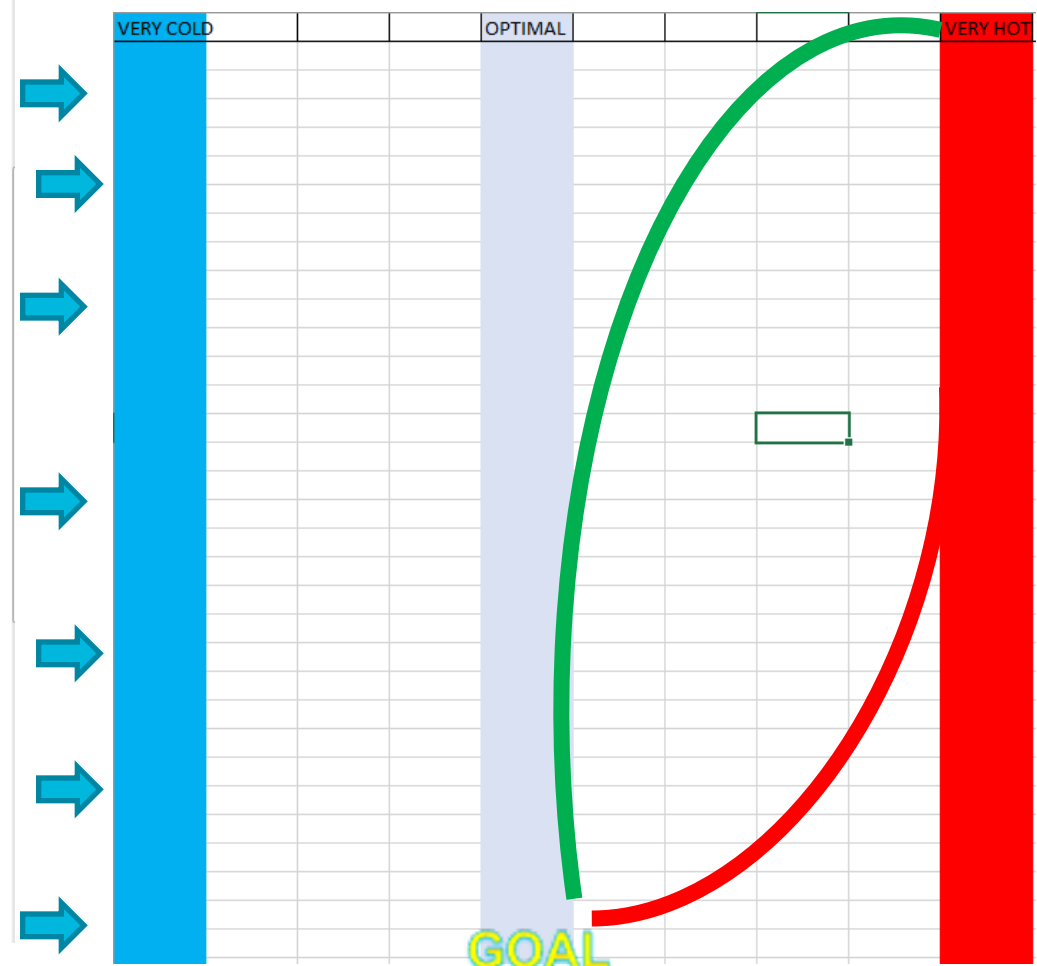
```
In [1]: import tensorflow as tf
import numpy as np
import gym
import gym_banana
#W = tf.Variable(tf.random_uniform([NhStat, 2], 0, 0.01))
```

The project will combine supervised, unsupervised and reinforcement methods

SECOND STEP ADD DISTANCE DIMENSION



- ↑ 1. Prendre la direction nord
4 min (1,5 km)
- ↙ 2. À 都庁北 (交差点) , prendre à gauche
290 m
- ↙ 3. À 新宿中央公園北 (交差点) , prendre à gauche
120 m
- ⤴ 4. Prendre la bretelle à droite vers 首都高速4号新宿線
550 m
▲ Route à péage
5. Suivre 新宿料金所 pour rejoindre 首都高速4号新宿線
350 m
▲ Route à péage
6. Rejoindre 首都高速4号新宿線
160 m
▲ Route à péage
7. Rejoindre 首都高速4号新宿線
59 min (74,4 km)
- ↘ 6. Rejoindre 首都高速4号新宿線
▲ Route à péage
- ↘ 7. Prendre la sortie 三宅坂 J C T vers 神田橋・箱崎
4,9 km
▲ Route à péage
- ↘ 8. Rejoindre 首都高速都心環状線
750 m
▲ Route à péage
- ↘ 9. Rester à gauche à l'embranchement pour continuer sur 首都高速都心環状線, suivre 箱崎・銀座
2,5 km
▲ Route à péage
- ↘ 10. Utiliser les 2 voies de gauche pour prendre la sortie 江戸橋 J C T en direction de 向島・湾岸線・箱崎
1,1 km
▲ Route à péage
- ↑ 11. Continuer sur 首都高速6号向島線
700 m

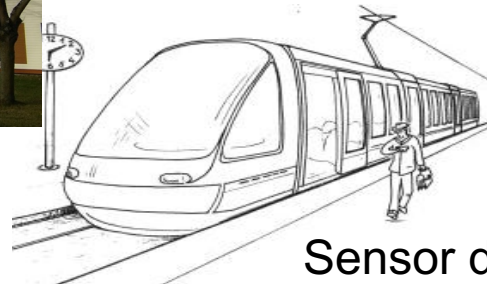


GOAL



We plan for a distributed platform around Paris suburb (Saclay-Evry)

- ▶ monitoring of several categories of buildings (residential, dorms, official, utility)
- ▶ Share of data and distribution of ML agents



Sensor deployment, big data deployment, quality control



- . **An energy machine learning project (multi modal data)**
- . **Many prediction algorithms are needed**
- . **A choice of the Deep Reinforcement learning**
- . **Translating problems to SAR will be a challenge**
- . **Prototyping will be a priority**
- . **Open to collaborations**