Post-doc position open at École Polytechnique & EDF/SystemX, Plateau de Saclay, Paris Region

A post-doc position is open on the topic of Machine Learning for a Multi-source Energy Management System. This is in the context of the Paris-Saclay Energies (PSE) project of Smart Energy Planning (SEP) platform, which involves various energy and environmental objectives. This position is a joint effort between industrial (EDF) and academic partner (École Polytechnique).

Topic: Machine Learning for a Multi-source Energy Management System (See below for full description)

Organization: École Polytechnique (the DaSciM team) and SystemX

Location: Plateau de Saclay, Palaiseau (greater Paris region).

Deadline and Starting date: The candidate should be available to start *at the latest* 1 October 2019, but preference to start earlier. The offer may close when a suitable candidate is found.

Duration: Funding is available for 18 months

Requirements: Candidates should have the following:

- A PhD in one of the areas: Computer Science, Electrical Engineering, Mathematics, Physics
- Publications in major conferences/journals
- Demonstrable skills and knowledge in Machine Learning and experience with relevant toolkits and in relevant projects
- Knowledge or at least strong interest in Reinforcement Learning
- Good programming skills in at least one language (preferably Python)

Contact: Jesse Read and Georges Hebrail. Candidates should send CV and cover letter by email to `jesse.read@polytechnique.edu`

SystemX PSE Project - Proposal for applying machine learning to multi-energy systems

Title: Machine Learning for a Multi-source Energy Management System

Context and objectives:

A multi-energy system involves multiple actors (residents, building managers, energy service providers, heat or electricity grid operators, etc). These actors have specific and potentially antagonistic requirements and behaviors. However, each actor has some flexibility, and may adapt its behavior to meet the global system constraints, while ensuring a sufficient level of satisfaction. “Satisfaction” can be technological (e.g., comfort level, quality of electricity) and/or economic (e.g., minimum operating cost).

The goal is to optimize the global operation, dealing with the constraints and inherent tradeoff with regard to individual actors’ interests. This proposal deals with introducing learning components into the local multi-energy system. These learning components can enrich a global centralized supervisor, or they can be placed in a decentralized way at the interfaces between a global supervisor and the different actors of the system. Such components should be able to control the system by allowing for certain flexibility (via peak load reduction, set point updates, energy storage, etc.), while guaranteeing a sufficient level of satisfaction for the system's actors.

The role of the learning entity/agent is to develop and enact a policy, i.e. to propose desired objectives, scenarios or control orders to the actors of the system. It should seek to improve its ability to obtain a compromise (a higher acceptance rate regarding the actors) and the overall efficiency of the system over time.

Since there is no existing real such system deployed in the energy sector today, this work proposes to study the problem via simulation, guided by energy sector experts and inspired by real site measurements. In line with the PSE project's incremental Proof-of-Concept approach, this work could start on a limited part of a system (e.g., with one or two actors).

In addition to simulation, it may be possible to evaluate the method on particular related virtual systems in deployment (e.g., computer networks, servers of computational resources) if proving suitable, which may suggest potential viability in the target domain.

Open Research Questions:

- Is it possible to generate instructions/control orders to under the constraints of sufficient level of satisfaction to actors, while optimizing global system performance?
- Can we determine or learn the priorities of actors? What is their level of flexibility? What can be the incentives for the actors?
- How to define objectives that are compatible with the actors’ levers of flexibility?
- Which machine learning/reinforcement learning approaches are most suitable?
- Which simulations (or alternative systems) are most effective for learning, in light of a successful transfer of a learning agent to a future real-world deployment of the target system.

Data used: simulation data + real site measurements + energy expert rules to define strategies to meet objectives

Techniques used/Keywords: sequential/adaptive learning, reinforcement learning, intelligent agents, transfer learning, lifelong learning, data streams, concept drift