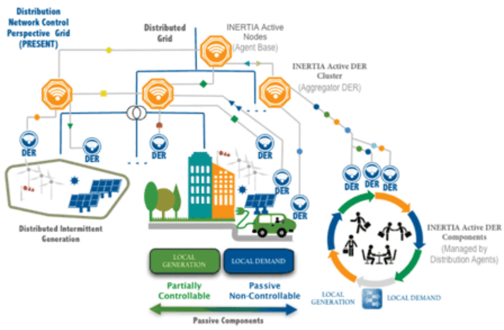
Master's Project

Project Title: Control-Aware resource allocation with constraints

Brief Introduction

Reinforcement learning (RL) and Artificial intelligence (AI) has seen a major resurgence in recent years, partly owing to recent advances in computational capacities and owing to advances in deep neural networks for function approximation and feature extraction. They offer an attractive set of tools that have proven to be useful in solving optimal control, resource allocation and multi-agent learning problems arising in cyber-physical systems (CPS), Internet of Things (IoT) and large-scale industrial systems. Further, the model-free nature of RL solutions, allows for a simple effective way to solve diverse problems.

The above mentioned systems are all characterized by large sizes. However, typical resources such as communication channels, computational resources, network bandwidth, etc., do not scale with system size. In other words, "control-aware" (maximizing some control performance) resource allocation is an important problem. As noted earlier, this is a hard problem since the number of communication channels available is much smaller than what is ideally required for information dispersion. Some preliminary studies were conducted in [2], and a scalable solution was developed in [1].



source: ercim-news.ercim.eu

Problem Statement

The first task, is to extend [1] to scheduling scenarios wherein there is a cost associated with transmissions. Once such an extension is developed, the student is required to investigate the performance of this extension for scheduling over a real-world public network. Depending on progress made, the student may solve the scheduling problem in the presence of "power" constraints. This scenario typically arises in applications wherein all the communicating channels may not transmit at maximum power. Solving this last problem involves understanding and applying reinforcement learning algorithms for constrained Markov Decision Processes.

Prerequisites

The student must have a thorough understanding of Dynamic Programming Principles, Control Theory and Basic Machine Learning. Knowledge of Python and Tensorflow/Keras is a plus.

References

[1] A. Redder, A. Ramaswamy and D. E. Quevedo : Deep reinforcement learning for scheduling in large-scale networked control systems arXiv preprint arXiv:1905.05992v1, 2019.

[2] B. Demirel, A. Ramaswamy, D. E. Quevedo and H. Karl : DeepCAS: A Deep Reinforcement Learning Algorithm for Control-Aware Scheduling. IEEE Control Systems Letters (2018, 10.1109/LCSYS.2018.2847721) and CDC, 2018.

Contact: Prof. Daniel Quevedo, Dr. Arun Ramaswamy `dquevedo@ieee.org, arunr@mail.upb.de`