IFAC World Congress 2017 open invited track on: "Multi-agent distributed learning and optimization of dynamical systems"

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Abstract: The proliferation of relatively inexpensive devices capable of communicating, computing, sensing, interacting with the environment and storing information is promising an unprecedented number of novel applications through the cooperation of these devices toward a common goal. These applications include swarm robotics, wireless sensor networks, smart energy grids, smart traffic networks, smart camera networks. These applications also pose new challenges, of which *distributed learning and optimization* is one of the major ones. The objective of this open track is to collect contributions that will provide the most up-to-date state-of-the-art in the growing body of literature in distributed optimization from a *dynamical systems perspective*. In fact, although a large literature is available in the realms of distributed learning and optimization for large scale static systems, fewer results are available for dynamical systems, i.e. systems that change over time, thus requiring the development of novel tools that are theoretically rigorous while being still practical.

Keywords: Distributed Optimization Algorithms, On-line distributed plug-and-play learning, Large-scale systems

1. IFAC TECHNICAL COMMITTEE FOR EVALUATION

The open invited track will be supported by the IFAC Technical Committee 1.5 Networked Systems.

2. DETAILED DESCRIPTION

The emergence of large-scale systems composed of multiple agents capable of autonomous sensing, decision-making, communication and actuation is changing the traditional control paradigm based on centralized control. The design of centralized control systems with infinite CPU resources and reliable communication can be considered a solved problem. However, in large-scale multi-agent systems interacting with a dynamical environment, the centralized controller assumption is not a scalable solution and *distributed architectures* must be sought. Another major difference in this context is that these smart agents might be added or removed, thus requiring *plug-and-play architectures*. Finally, *communication is* often performed over *unreliable* shared media such as wireless or Internet which give rise to packet losses and random delays. These three elements represent three fundamental constraints on the design of any practical cooperative smart system.

In particular, one of the major task that such a smart multi-agent system has to be able to perform is to obtain a model of the underlying system in order to be able to design high-performance controllers. The availability of the model a-priori possibly via first principles is unlikely for large-scale systems which are often very complex. As such, an *on-line distributed plug-and-play learning* process is ought. This aspect is the target of this proposed Invited Open Track. Although there is a large and successful literature concerned with learning of static unknown models based on machine learning and non-parametric estimation tools (Cucker and Smale (2001); Hastie et al. (2001)), little is still known when the underlying model is dynamic, i.e., is varying over time. Think, for example, to the task of measuring the pollution over a city via a number of UAVs, or the arrival process of people to be served in a smart transportation systems such as shared taxis, or the power generated by a large number of renewables in a electric distribution networks. The traditional approach is to cast the learning process as an *optimization problem* for which powerful tools are available to solve them in distributed

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framework via iterative algorithms (Bertsekas and Tsitsiklis (1989); Boyd et al. (2011)). These algorithms compute a solution asymptotically, or at best after a certain number of iterations. If the underlying model to be learned changes at a pace that is comparable with the time required to compute a solution, the obtained model might be obsolete by the time a solution is computed.

Based on these premises, there is a need for novel algorithms that can cope with these challenges and can provide an on-line estimate of the model to be learned possibly with some certificate guarantees of such estimate. Although some preliminary results are appearing (Sarkka et al. (2013); Atanasov et al. (2015); Xu et al. (2016); Todescato et al. (2016); Simonetto et al. (2016)), many questions remain elusive. As so, the goal of this Invited Open Track is to collect contributions from researchers who work at the intersection of three areas: *statistical learning*, *distributed optimization* and *dynamical systems*. In particular, we solicit contributions that specifically address at least one of the following aspects:

- parametric vs non-parametric learning and optimization
- multi-agent architectures: distributed vs cloud-based vs cluster-based
- impact of unreliable communication
- Bayesian vs Fisherian learning
- robust cooperative learning and optimization
- static vs dynamic learning and optimization
- adaptive learning and optimization
- computational vs communication complexity
- cyber-attacks and outliers in the context of distributed learning and optimization

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