Invited Session Proposal

Title: Safe and Fault-Resilient Control Learning and Design

Organizers:

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As almost all industrial and mission critical systems operate in closed loop, it has become imperative to develop control laws that render the systems resilient,intelligent and safe leading to guaranteed performance under normal and faulty conditions. Research domains such as Fault Detection and Isolation (FDI), Fault Tolerant Control (FTC) as well as Prognostics and Health Management (PHM) seek novel approaches that are safe and intelligent within control synthesis paradigm in order to mitigate the problems that arise due to abrupt faults or progressive degradations, even in the absence of system model or degradation models. Needless to say, closed-loop system operation is inevitable for ensuring stability, efficiency and autonomy in safety-critical systems such as power and water infrastructure and transport vehicles among others. Due to the criticality of these systems, it becomes imperative to comprehensively integrate prognostics-based information into control design/learning processes to handle functional degradation.
Over the past decade, there has been a significant surge in interest regarding the integration of state of health within the control design process. This increased attention is evident across various control domains, including model predictive control, linear matrix inequalities-based approaches, linear parametric varying model-based methods, set-based strategies, and learning-based approaches. These diverse methodologies incorporate predictions of the state of health, remaining useful life, or system reliability within the control framework, resulting in what is now referred to as health-aware control (HAC) design approaches. On the other hand, as most degradation mechanisms are nonlinear and unknown in nature, it is essential to consider data for prognostics as well as control reconfiguration calling for development of data-driven approaches. In this context, Reinforcement Learning (RL) based approaches are suitable for learning optimal control policies/laws in the presence of input-output data (without exact knowledge of system models). Considering safety within the RL framework is a fairly new problem. In particular, *Safe Reinforcement Learning* (Safe RL) prioritizes safety, stability, and optimality of systems, providing guarantees over an infinite time horizon. This invited session seeks to bring together researchers to stimulate discussions that focus on the latest advancements in topics including among others:

- safe control learning and design
- health aware control
- degradation aware control design and learning
- data-driven and machine learning fault detection
- resilient control learning
- data driven control learning for safety critical systems
- applications of safe RL in autonomous systems, robotics, and networked control systems
- computational methods and scalability challenges in safe reinforcement learning.