

Ph.D. in Information Technology
Thesis Defense

November 16th, 2026
At 14:00 p.m.
Sala Schiavoni - Building 20A

Laura Boca de Giuli – 38th Cycle

PHYSICAL AI FOR RELIABLE OPERATION OF COMPLEX SYSTEMS: LEARNING, CONTROL, AND MONITORING METHODS WITH APPLICATIONS IN ENERGY

Supervisor: Prof. Riccardo Scattolini

Co-Advisor: Dr. Alessio La Bella

Abstract:

Physical Artificial Intelligence (Physical AI) has the potential to enable the optimal and autonomous operation of complex systems, such as energy and process plants, reducing their environmental impact. However, current AI approaches still lack essential properties required for their widespread deployment, including interpretability, safety, computational efficiency, and the capability to monitor and adapt their behaviour over time — in a word, reliability. This doctoral thesis develops a comprehensive Physical AI framework equipped with these properties, pursuing the idea that AI should not blindly rely on data, but rather combine them with physical knowledge and human-inspired intelligent behaviours. The thesis is organised into three parts, covering the entire lifecycle of such intelligent systems. The first part addresses the learning of accurate, interpretable, and stable models for complex systems. A novel physics-informed recurrent neural network is proposed, embedding two fundamental characteristics of complex systems: their network topological relationships and stability properties. The resulting methodology achieves high predictive accuracy with low model complexity and enables the design of optimal model predictive controllers with guaranteed convergence, safety constraint satisfaction, and high economic performance. The second part addresses the long-term preservation of model performance under evolving environments, making it reliable and adaptive with enhanced computational efficiency. A novel lifelong learning methodology is proposed to monitor model performance and trigger tailored updates only when necessary, inspired by the human ability to refine knowledge using new informative data without forgetting previously acquired ones. The strategy uses statistical control charts to detect new system operating conditions and learns them through an ensemble of recurrent neural networks, while simultaneously compensating for persistent plant-model mismatch with online model structures such as Gaussian processes and Bayesian neural networks. An active learning algorithm is also integrated, in which the controller steers the system to collect informative data for more reliable model updates while ensuring safety constraint satisfaction and optimal performance. The third part addresses the long-term preservation of controller performance under evolving environments, providing it with autonomous maintenance capabilities and improved computational efficiency. A novel methodology is proposed to monitor multiple closed-loop performance indices via statistical control charts and trigger updates only when necessary. This methodology integrates reinforcement learning, employed to adapt control parameters, with the model adaptation framework developed in the second part of the thesis, enabling

the restoration of control performance when deterioration is detected. The proposed methodologies are validated through numerical simulations on two benchmark systems, namely a district heating network and a chemical plant, and through experimental tests on a real district heating system located in Milan, Italy. The results demonstrate that the proposed framework provides Physical AI with the aforementioned properties required for trustworthy deployment, paving the way for its large-scale adoption in complex systems and its contribution to a more sustainable and intelligent future.

PhD Committee

Prof. Gian Paolo Incremona, **Politecnico di Milano**

Prof. Sergio Lucia, **TU Dortmund University**

Prof. Mircea Lazar, **Eindhoven University of Technology**