SCIENCES & BIOENGINEERING SCIENCES

The Research Group
Artificial Intelligence Lab

has the honor to invite you to the public defense of the PhD thesis of

Timothy Verstraeten

to obtain the degree of Doctor of Sciences

Title of the PhD thesis:

A Multi-Agent Reinforcement Learning Approach to Wind Farm Control

Promotor:
Prof. dr. Ann Nowé
Co-promotor:
Prof. dr. Jan Helsen

The defense will take place on

Thursday, March 11, 2021 at 17h00

The defense can be followed through a live stream. Contact Timothy.Verstraeten@vub.be for more information

Members of the jury

Prof. dr. Elisa Gonzalez Boix (VUB, chair)
Prof. dr. Bernard Manderick (VUB, secretary)
Prof. dr. Nikolaos Deligiannis (VUB)
Prof. dr. Jens Kober (Delft University of Technology)
Prof. dr. Daniel Kudenko (Leibniz University Hannover)
Prof. dr. Amir R. Nejad (Norwegian University of Science and Technology)

Curriculum vitae

Timothy Verstraeten graduated as MSc in Computer Science with a specialisation in Artificial Intelligence at the Vrije Universiteit Brussel in 2015. Currently, he is a PhD student at the Artificial Intelligence Lab and the Acoustics & Vibration Research Group of the Vrije Universiteit Brussel. During his PhD, he focused on both fundamental AI research, such as multi-armed bandits, reinforcement learning, multi-agent systems and Bayesian models, as well as applicative AI research in the context of wind farm technology. He published 21 papers in top-tier conferences and journals, in the fields of AI, mechanical engineering and computational biology.

Abstract of the PhD research

Recently, we drastically shifted our energy production toward renewable energy sources, due to the pressing matter of climate change and the limited supply of fossil fuels. While offshore wind farms are an important driver toward renewable energy generation, their maintenance costs need to be significantly reduced to render them sustainable. Major causes of the elevated maintenance costs are failures due to unanticipated stress on the wind turbine components. Therefore, the health status of a wind turbine needs to be accurately quantified and incorporated in wind farm control schemes, such that unnecessary stress on high-risk turbines can be prevented. As this health status is determined by a complex multi-dimensional spectrum of stress factors, AI-driven control strategies are necessary. However, current wind farm controllers that use AI-driven optimization techniques are not scalable to the size of contemporary wind farms. In this dissertation, we focus on developing optimal and scalable AI-driven control methods. We adopt a multi-tiered methodology, in which we investigate several properties of wind farms independently, and then consolidate the acquired insights in a wind farm control solution. First, we develop a control algorithm for multi-device systems, in which the devices have similar technical specifications. The control method uses a similarity-based data exchange mechanism to increase the confidence of the environment model for a specific learning agent, based on relevant data of similar devices. We demonstrate that the use of such a mechanism increases learning accuracy by reducing uncertainty and bias due to negative transfer. Second, we propose a control method for generic multi-agent systems with a sparse dependency structure. Specifically, we exploit this sparse structure to factorize large multi-agent systems and learn optimal control decisions in the factored representation. We demonstrate, both theoretically and empirically, that our method significantly reduces the learning complexity when considering sparse dependency graphs, and thus can handle the combinatorial explosion with respect to the joint action space when dealing with large multi-agent systems. The developed control methods are applicable to a variety of multi-agent systems that contain similar agents or have a loosely-coupled structure. Finally, we combine the obtained insights on device similarity and sparse dependency structures and extend our approaches to an AI-driven wind farm controller that is scalable and optimal with respect to the complex cost-functions inherent to contemporary wind farms. We show that our method is capable of closing the gap between power demand and the produced farm-wide power, while still considering the penalties induced on high-risk turbines, by preventing stressful control decisions.