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DOCTOR OF ENGINEERING SCIENCES

of **Glenn Ceusters**

The public defense will take place on **Tuesday 24th June 2025 at 5pm** in room **D.2.01** (Building D, VUB Main Campus)

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SAFE REINFORCEMENT LEARNING FOR OPTIMAL CONTROL IN MULTI-ENERGY SYSTEMS – AN ADAPTIVE SAFETY LAYER

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Abstract of the PhD research

Energy systems continue to become increasingly interconnected with each other as the energy technologies that allow for this sector coupling are more mature and are being more widely implemented. Multi-energy, carrier, -commodity or -utility systems then, in turn, allow for flexibility utilisation (i.e. storage, controllable loads) within and across all carriers based on measures such as their energy efficiency, purchasing, emissions, dependability or a combination thereof. Model-Predictive Control (MPC), has become a widely accepted and utilised optimal control technology in various industries – including the energy industry. However, MPC does require a detailed model in advance (i.e. plant models, input and output disturbance models, measurement noise models). Reinforcement learning (RL) has seen an increased uptake as it is model-free and inherently adaptive, yet has immature stability, feasibility, robustness, and constraint handling theory. The primary research objective of this thesis is to develop and validate a safe, model-free reinforcement learning methodology for multi-energy management that guarantees hard-constraint satisfaction, adapts dynamically (including constraints), preserves optimality, handles nonconvexity's, functions effectively in stochastic non-linear environments, and remains independent of specific RL algorithms. Specifically, this thesis makes several significant contributions to the field of reinforcement learning, control theory and multi-energy management. (1) Firsttime demonstration that reinforcement learning can outperform linear model-predictive control for multi-energy management. (2) Methodological contributions that showed that a (near-to) optimal multi-energy management policy can be learnt safely. (3) Developed a self-improving (adaptive) safety layer with general constraint handling. (4) Real-world validation of safe RL-based energy management system. Ultimately, this work paved the way for more robust and flexible data-driven energy management solutions, with broader implications for other domains where similar challenges exist, and thereby contribute to increments in energy efficiency that are necessary to achieve global climate protection goals.