UNIVERSITÀ DEGLI STUDI DI NAPOLI FEDERICO II

itee PhD information technology electrical engineering

DIETI. UNINA

PhD in Information Technology and Electrical Engineering
Università degli Studi di Napoli Federico II

PhD Student: Emanuele Musicò

Cycle: XXXIX

Training and Research Activities Report

Academic year: 2024-25 - PhD Year: Second

Tutor: prof. Francesco Lo Iudice

Co-Tutor: prof. Mario Di Bernardo

Date: October 31, 2025

1. Information:

- PhD student: Emanuele Musicò
- PhD Cycle: XXXIX
- DR number: DR997210
- Date of birth: 25/03/1999
- Master Science degree: Ingegneria dell'Automazione e Robotica
- University: Università degli studi di Napoli Federico II
- Scholarship type: PNRR-DM 118/2023 Mis.4.1: Dottorati Pubblica Amministrazione
- Tutor: prof. Francesco Lo Iudice
- Co-tutor: prof. Mario Di Bernardo
- Period abroad:
  Number of months to spend abroad: 6
  Number of months spent abroad: 6/6
  Institution: Institute of Industrial and Control Engineering, Universitat Politecnica de Catalunya, Barcelona, Spain
- Period with Public Administration:
  Number of months to spend in a public administration: 6
  Number of months spent in a public administration: 6/6
  Public Administration: CNR STEMS, Istituto di Scienze e Tecnologie per l'Energia e la Mobilità Sostenibile, Napoli, Italia

2. Study and training activities:

Activity	Type[1]	Hours	Credits	Dates	Organizer	Certificate[2]
SINCRO Research Seminar	Seminar	25	5	06-20/11/2024 04-11/12/2024 08-22-29/01/2025 05-19-26/02/2025 12-26/03/25 09-23/04/25	Prof. Mario Di Bernardo	N
I Pilastri della trasformazione digitale	Course	12	3	02-02-04-14-15-16/04/2025	prof. Nicola Mazzocca, DIETI - Unina	Y
Methodologies and Tools for conducting Systematic	Course	12	3	28-29/04/2025 05-06-09-12-14/05/2025	prof. Domenico Amalfitan	Y

Literature Reviews and Systematic Mapping Studies					**o - DIETI - UNINA**	
AI Code Generation: Foundations, Evaluation, and Security	**Course**	**12**	**3**	**7-10-14-15-17-31/10/2025**	**dr. Pietro Liguori, DIETI-Unina**	**Y**

1) Courses, Seminar, Doctoral School, Research, Tutorship
2) Choose: Y or N

2.1. Study and training activities - credits earned

	Courses	Seminars	Research	Tutorship	Total
Bimonth 1		1.6	8.4		10
Bimonth 2		2.6	7.4		10
Bimonth 3	3	0.8	6.2		10
Bimonth 4	3		7		10
Bimonth 5			10		10
Bimonth 6	3		7		10
Total II Year	9	5	46		60
Total I + II	26	10	84		120
Expected	30 - 70	10 - 30	80 - 140	0 – 4.8	

3. Research activity:

Title of the whole research activity: Application of Optimal Control and Reinforcement Learning tools to control complex/distributed systems

Description:
State-of-the-art applications of optimal control and reinforcement learning (RL) techniques for distributed and complex systems are at the forefront of modern control engineering, especially in sectors such as energy communities, microgrids, and fleets of autonomous vehicles including AGV control in warehouses.

Optimal Control and Reinforcement Learning

Optimal control relies on mathematical models of system dynamics to compute control policies that minimize a cost function, offering strong guarantees but often requiring a priori knowledge of the system and significant computational resources for high-dimensional or uncertain environments. Reinforcement learning, meanwhile, allows agents to learn control policies through trial and error, adapting to environmental changes and system uncertainties, making it particularly attractive for highly dynamic or partially observed systems.

Applications in Energy Storage, MicroGrids, and Renewable Communities

- **Optimal control** (e.g., Model Predictive Control, or MPC) is widely utilized in **microgrids** and **renewable energy communities** due to its ability to handle constraints and forecast-based decision-making, excelling when accurate models are available.
- **Reinforcement learning** has emerged as a powerful tool in this domain, enabling adaptive management strategies for complex assets like energy storage systems (ESS), where traditional modeling may not capture all variability. RL has recently demonstrated superior performance to rule-based methods, and in certain cases, RL can approach or surpass the performance of advanced MPC controllers, especially when fast adaptation to unforeseen scenarios or real-time computation is critical.
- There is evidence that RL is particularly promising for energy trading and dynamic storage control in microgrids, with methods validated on real-world data now outperforming classic approaches.

Applications in AGVs Fleet Control

- In **autonomous vehicle fleets** and **AGV scheduling/routing in warehouses**, RL has led to robust, adaptive strategies capable of handling real-time decisions and complex, stochastic environments where optimal control may not be tractable.
- RL excels in dynamically changing logistics contexts, optimizing AGV dispatch, navigation, and even energy efficiency and safety, surpassing rule-based or static optimal control methods as complexity grows.

Method Selection and Synergies

- **Optimal control** is generally preferred when the plant/system is well-modeled, constraints are clearly defined, and computational resources permit optimization online or offline.
- **Reinforcement learning** becomes preferable as the dimensionality, uncertainty, or variability of the system increases or when real-time adaptation is necessary.
- Recent advancements combine both approaches: RL can be used to learn or tune policy parameters within optimal control frameworks, or to operate within a model-based controller, leveraging the stability and constraint-handling of optimal control with the environment flexibility and adaptation of RL. These hybrid or unified approaches promise faster convergence, greater robustness, and the ability to generalize across problem instances, with some frameworks demonstrating superior performance to either method alone.

Applications should consider the system's degree of modelling certainty, scalability requirements, and need for adaptive decision-making, potentially leveraging the strengths of both **optimal control** and **reinforcement learning** for complex distributed systems.

Research Problems

During my first year I mainly focused on **Optimal Control** given my background as an Automation and Robotics Engineering. As a result, we carried out the Journal Paper [4] designing an optimal control algorithm for a renewable energy community endowed with a shared energy storage system (SBESS). In this framework we optimized the charging profile of the SBESS while obtaining significant reductions in the energy bill for all the prosumers. During my **second year** we worked to demonstrate that our non-convex formulation could be recasted as a convex optimal control problem and now we are trying to demonstrate that our formulation still holds even if we recast the problem as a distributed optimal control problem.
During the second year I also had the opportunity to collaborate with prof. Josep M. Olm at University Politecnica de Catalunya in Barcelona. Here I mainly focused on a Reinforcement Learning Application for AGVs in a warehouse. Starting from [7], a rule-based control algorithm which manages AGVs in a warehouse by avoiding deadlock and conflicts, we wanted to address the problem of optimally allocate tasks to the AGVs using a Multi-Agent RL Algorithm. Leveraging on the scalability and Adaptability of RL we want to overcome the issue given by a strongly stochastic environment, since task arrives at random moments in a warehouse, and by dealing with a complex system, since we have multiple AGVs moving in the same limited space trying to cooperate. The first goal is to train and test a Multi-Agent Proximal Policy Optimization Agent to allocate tasks to the AGVs to improve productivity while minimizing the total travel distance and the number of resolution maneuver of AGVs, hence by enhancing cooperation between the agents. As a future step we must account for energy constraint for the Battery Management of AGVs. During this second year I also have the opportunity to collaborate with CNR STEMS, Istituto di Scienze e Tecnologie per l'Energia e la Mobilità Sostenibile. Here we took a second order model of urban traffic and applied a continuification method. In this way we could study the behaviour of the model both in the microscopic and in macroscopic scale. We are studying the Optimal Velocity Follow The Leader Model which is widely used in the literature and applied a continuification method as in [10]. We consider the case where, in the microscopic scale, we have n identical agents in a ring road of length L. The reason behind this choice is well explained in [9]. From here we also know from [9] that, with some limitations, a single Autonomous Vehicle (AV) can stabilize the traffic flow. In [9] authors exploit a linearization method to study and analyse controllability and stability. We want to further investigate how multiple autonomous vehicles can cooperate to stabilize and steer the traffic flow while equipping AVs with an Optimal Controller/Reinforcement Learning controller. Once the control is applied we want to exploit the continuification, hence the pde formulation, to analyse and study stability criteria for the system.

[1] ZHU, Daokuan; XU, Tianqi; LU, Jie. A Deep Reinforcement Learning Approach to Efficient Distributed Optimization. *IEEE Transactions on Control of Network Systems*, 2025.

[2] SALAORNI, Davide, et al. A Reinforcement Learning Approach for Optimal Control in Microgrids. *arXiv preprint arXiv:2506.22995*, 2025.

[3] AITTAHAR, Samy, et al. Optimal control of renewable energy communities subject to network peak fees with model predictive control and reinforcement learning algorithms. *arXiv preprint arXiv:2401.16321*, 2024.

[4] MUSICÒ, Emanuele, et al. An Optimal Control Approach for Enhancing Efficiency in Renewable Energy Communities. *IEEE Control Systems Letters*, 2024.

[5] HU, Hao, et al. Deep reinforcement learning based AGVs real-time scheduling with mixed rule for flexible shop floor in industry 4.0. *Computers & Industrial Engineering*, 2020, 149: 106749.

[6] HO, G. T. S., et al. Integrated reinforcement learning of automated guided vehicles dynamic path planning for smart logistics and operations. *Transportation Research Part E: Logistics and Transportation Review*, 2025, 196: 104008.

[7] VERMA, Parikshit; OLM, Josep M.; SUAREZ, Raul. Traffic management of multi-AGV systems by improved dynamic resource reservation. *IEEE access*, 2024, 12: 19790-19805.

[8] LEWIS, Frank L.; VRABIE, Draguna; SYRMOS, Vassilis L. *Optimal control*. John Wiley & Sons, 2012.

[9] S. Cui, B. Seibold, R. Stern and D. B. Work, "Stabilizing traffic flow via a single autonomous vehicle: Possibilities and limitations," *2017 IEEE Intelligent Vehicles Symposium (IV)*, Los Angeles, CA, USA, 2017, pp. 1336-1341, doi: 10.1109/IVS.2017.7995897.

[10] C. C. d. W. S´ebastien Fueyo, "From microscopic driver models to macroscopic pdes in ring road traffic dynamics," hal-04806729, 2024.

4. Research products:

Published Journal Paper:

- **Musicò, E., Ancona, C., Iudice, F. L., & Glielmo, L. (2024). An Optimal Control Approach for Enhancing Efficiency in Renewable Energy Communities. *IEEE Control Systems Letters*.**

5. Conferences and seminars attended

- **2024 Conference on Decision and Control**
  Dates: 16-19/12/2024
  Location: Allianz MiCo, Milan Convention Centre, Italy

6. Periods abroad and/or in international research institutions

Period abroad: **Universitat Politecnica de Catalunya, Barcelona, Spain**
Period: 06/03/2025 – 06/09/2025

Here, supervised by prof. Josep M. Olm I tackled the problem of designing a reinforcement learning based algorithm to optimize Task Allocation for AGVs in a warehouse working under Improved Dynamic Resource Reservation Control Algorithm.

Period in Public Administration: CNR Instituto Motori, Napoli, Italia
Period: 01/09/2024 – 01/03/2025

Here, Starting from a microscopic second order urban traffic model where we apply a control strategy we want to apply the continuification to derive a PDE formulation for the macroscopic model and trying to carry out some stability/robustness results. Also trying to understand if the macroscopic model can help enhancing the microscopic control.

7. Tutorship

8. Plan for year three

- Research activities: Testing the MAPPO Algorithm and submitting the results to a Journal,
- Research activities: Distributing our Control Strategy for REC and SBESS presented in [4],
- Writing the thesis.