Ph.D. in Information Technology
Thesis Defenses

March 6th, 2025
At 1:30 p.m.
Room Carlo Erba – Building 7

Simone SMERALDO – XXXVII Cycle

A MULTI-AGENT OPTIMIZATION FRAMEWORK FOR DECENTRALIZED DATA-BASED DECISION-MAKING WITH APPLICATION TO REGRESSION ANALYSIS AND CLASSIFICATION.

Supervisor: Prof. Maria Prandini

Abstract:

As the proliferation of connected devices generates vast amounts of distributed data, traditional centralized approaches to data processing and analysis are becoming increasingly inadequate. The need for advanced methods that leverage local information while safeguarding data privacy has become crucial across various sectors, such as industrial automation, smart cities, and healthcare.

This thesis presents a multi-agent optimization framework designed to enhance decentralized data-driven decision-making, with a particular focus on regression analysis and classification tasks.

The primary objective of this research is to develop a comprehensive approach that addresses the challenges of decentralized data environments. It explores how collaborative learning techniques can harness large distributed datasets to enable multiple agents to optimize their decision-making capabilities while preserving local data characteristics and ensuring privacy. At the core of this work is a decentralized Multi-Task Learning (MTL) strategy, designed to allow multiple related tasks to be learned simultaneously while adapting to local conditions. This framework operates without requiring prior knowledge of agent similarities, making it highly suitable for complex

distributed environments. An optimization algorithm is introduced, which further extends MTL to decentralized classification tasks through the adoption of proximal support vector machines. The algorithm leverages a spectral regular- izer to encourage collaboration among agents while preserving their individual distinctions.

The proposed paradigm supports both batch and recursive modes of operation, while minimizing communication overhead and preserving data privacy. It enables agents to process data locally and collaborate with a central unit for more computationally demanding tasks, thus balancing the distributed capabilities of edge devices with the computational power of a central hub.

Synthetic experiments are performed to demonstrate the effectiveness of the framework, showcasing its robustness in handling nonlinear system identification problems and exploring its applicability to classification tasks involving both linearly and nonlinearly separable data. In regression, the proposed approach consistently outperforms alternative decentralized strategies by capturing local specificity while facilitating shared learning among agents. In classification,

it shows some potential in leveraging shared structural patterns and improve model consistency and generalization.

The practical impact of the proposed framework is demonstrated through a real-world case study in predictive maintenance. To this end, a novel feature extraction method for multivariate classification is developed in collaboration with Linde, a leading player in the process industry, and integrated within the proposed MTL framework for fault prediction and diagnosis. The resulting
algorithm is validated on the Tennessee Eastman Process simulation dataset, a widely used benchmark in predictive maintenance for the process industry. Additionally, a hybrid recommender system is developed, combining automated methods with human input to provide a flexible and robust solution for industrial diagnostic environments that are constrained by data limitations, variability, and the need for interpretability.
In summary, this thesis provides a relevant contribution to the field of decentralized data-driven decision-making by offering a comprehensive framework for collaborative learning in multi-agent systems. It highlights the transformative potential of decentralized approaches for optimizing decision-making across a wide range of applications, with a particular emphasis on industrial maintenance and diagnostics.

DANIEL EDUARDO ZAMUDIO ESPINOSA – XXXVII Cycle

BALANCING SERVICE PROVISION VIA AGGREGATION OF FLEXIBLE PROSUMERS

Supervisor: Prof. Maria Prandini

Abstract:

The worldwide carbon neutral goal for 2050 calls for a substantial increase in the share of electrical energy generation from renewables. In turn, the high penetration of non-dispatchable and uncertain renewable energy sources like solar and wind power poses challenges to the grid operator in maintaining the balance between power generation and consumption. This thesis addresses such an issue by introducing a framework for balancing services provision to the electrical grid by a pool of prosumers equipped with flexible energy resources, i.e., units whose power exchange profile can be modified to a certain extent upon request by the grid. The proposed approach optimizes the balancing capacity while pre-computing the disaggregation policy that distributes the balancing power request by the grid to the flexible energy resources, also accounting for network congestion constraints and limits on their availability. The disaggregation policy can be greedy, reactive, or proactive. In the greedy case, the power provided by each unit in each time slot is a function of the balancing power demand in that same time slot only, while in the reactive and proactive cases, it is a function also of the request in the past (reactive) and even in the future (proactive) time slots, which however requires that the whole power request is communicated to the aggregator before the service window starts. Notably, the availability of a pre-computed disaggregation policy makes the balancing service more efficient and better aligned with the markets' trend towards real-time operations. Additionally, the proposed framework gives the possibility to optimize the baseline profile of the distributed energy resources and is amenable for a decentralized implementation, which enhances scalability while allowing preservation of the privacy of local information. The effectiveness of the proposed approach is demonstrated on some numerical case studies via extensive simulations and a comparative analysis.

PhD Committee

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