PROPOSITION DE SUJET DE THESE

Intitulé : Robust and fast distributed model predictive control for dynamic operations of multi-agent systems with application to multi-robots swarming

Référence : **TIS-DTIS-2026-10** *(à rappeler dans toute correspondance)*	
Début de la thèse : Octobre/Novembre 2026	**Date limite de candidature :**

Mots clés

Model Predictive Control, robust distributed control, robot swarming

Profil et compétences recherchées

The PhD candidate is expected to hold a Master's or engineering degree in automatic control, mathematics or closely related field.

Good communication skills English, both written and spoken, are mandatory. Ability to work autonomously is also required.

Prior experience with predictive control, learning algorithms and optimization are considered assets.

Présentation du projet doctoral, contexte et objectif

Model Predictive Control (MPC) is a well-known, advanced control technique devoted to general, multivariate, dynamical systems subject to constraints [1]. These constraints - which often represent hard physical limitations or security concerns - can be imposed, for instance, on the states, control input and its rate of variation, and outputs, among others. These features have made MPC a highly attractive topic over the last decades, resulting in several extensions spanning many different applicative fields [2]. For multi-agent systems, distributed approaches of MPC (DMPC) have been developed [3,4].

An interesting question, as recently formalized by [5], that arises in modern control applications (such as robotics, power grids, among others) is the use of MPC in scenarios where the operation might change dynamically, i.e. when the context changes *on-the-fly*, or *online*. This is the case, for instance, if agents explore previously uncharted environments, if a fault occurs, if the control objective changes, or if new information, acquired online, is to be considered. To comply with this scenario, the MPC's structure (e.g., its prediction horizon, constraints, costs, decision variables, etc.) must be adapted accordingly.

Adaptation to changes in control reference can for example be handled by set-point tracking MPC approaches where an artificial reference is added to the decision variables of the MPC problem, in addition to the control sequence to be determined [6,5]. An extension of set point-tracking MPC to distributed control of multi-agent systems has recently been proposed in [7], as well as an application to multi-robots guidance with partitioning constraints [8]. However, if there are mismatches between the model available for prediction and the real system (e.g. due to model errors, perturbations, noises, etc.), robust approaches must be developed.

The first objective of this PhD work is to develop robust distributed MPC approaches for dynamic operations. As a starting basis, the first work will focus on developing robust extensions of distributed set-point tracking MPC methods. Different frameworks previously developed for robust MPC [9] will be investigated, such as tube-based or chance-constrained approaches [10,11].

Multi-robot swarming will be considered as an application context. More precisely, an extension to the distributed guidance algorithm with Voronoi partitioning constraints, previously developed in [8, 12, 13], will be considered. The proposed algorithms will be validated in simulation and in experiments involving ground mobile robots or drones available at ONERA facilities.

Concerning this envisaged application, another objective of this PhD work is to develop fast DMPC approaches with low computation costs. A possible solution already investigated in the literature is the use of machine learning techniques to train a neural network that would approximate the solution to the optimization problem to be solved in MPC [14]. Although computationally demanding for offline training, online optimization is avoided resulting in fast evaluation of the control input. The PhD work will investigate how new structures, such as Transformers neural networks that have recently proved to be efficient for MPC [15], could be used for the considered distributed and set-point tracking MPC problems.

References :

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Collaborations envisagées

Sorin Olaru, CentraleSupélec, L2S

Laboratoire d'accueil à l'ONERA	**Directeur de thèse**
Département : Traitement de l'information et Systèmes	Nom : Sorin OLARU
Lieu (centre ONERA) :	Laboratoire : CentraleSupélec-L2S
Contacts : Alex REIS et Sylvain BERTRAND	
Email : alex.dos_reis_de_souza@onera.fr sylvain.bertrand@onera.fr	Email : sorin.olaru@l2s.centralesupelec.fr

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