## PROPOSITION DE SUJET DE THESE

**Intitulé : Approximating cost structures in decentralized auctions and optimization for multi-agent task allocation**

Référence : **TIS-DTIS-2024-14**
*(à rappeler dans toute correspondance)*

| **Début de la thèse : 09/2024** | **Date limite de candidature : 06/2024** |
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**Mots clés**

Multi-agent systems, auctions, coordination, approximate bidding, reinforcement learning

**Profil et compétences recherchées**

Master student with strong skills amongst AI, optimization, multi-agent, RL

**Présentation du projet doctoral, contexte et objectif**

In the context of multi-robot or multi-vehicle applications, such as search-and-rescue, urban UAV trafic management, coordination is a key element which provides multi-perspective and multi-skill approach to problems hardly covered by single robots. Yet, from the performance viewpoint, optimizing resource usage, mission duration and quality, coordination is a hard problem. In fact, when (semi-)autonomous agents have to decide which tasks to fulfill, which path to follow or which multi-agent action to perform, one have to solve hard combinatorial problems such as task allocation [1], resource allocation [2], multi-agent pathfinding [3] or multi-agent trajectory repair [4]. Such problems can be solved using classical centralized approach, such as, combinatorial auctions or mathematical programming [5]. However, in the context of missions where the decisions might be decentralized to (i) improve robustness to disconnections or (ii) improve reactiveness (without waiting for a central authority to make the decision), decentralizing such decision making is crucial. Moreover, these algorithms strongly rely on the capability for agents to bid over items (tasks/actions/resources/etc.) or bundle of items. In classical auctions or mathematical programming approaches, this bidding requires to be able to valuate each combinations (or some of them) of items, or to use more compact representations of set of interdependent items [6]. This information may take the form of large tables or graphs, may be too large to be computed at fast pace or to be exchanged within unreliable communication infrastructure. Moreover, in the case of multi-agent tasks (requiring several agents to be performed), as in CBGA algorithm [7], or in the case of multi-mode tasks (tasks that can be fulfilled in different manners) as in MM-CBGA algorithm [8], data structures are becoming even larger (to process and to communicate).

Beside auctions, such table-based decision representation is also at the core of some distributed optimization algorithms (DCOP) [9], especially inference-based ones, such as DPOP of Max-Sum, and we aim at providing generic theoretical tools to use both in auctions and DCOPs domains.

In the domain of reinforcement learning, such approximation and compacting problem has been handled using deep neural networks or other approximation functions to represent and functionally approximate Q-tables for instance [10]. We aim at exploring the use of such techniques in the context of auctions and DCOPs.

The idea of this thesis is thus to bring approximation to bidding data structure as to implement decentralized auctions and distributed inference with good reactiveness and low communication load. The idea is to first devise approximation schemes for mono-agent mono-mode tasks decentralized allocation, in the consensus-based bundle allocation framework (CBBA) [11], and then to extend the models for multi-agent tasks (CBGA) and multi-mode tasks (MM-CBGA). In a second time, we will investigate how to implement this approximation schemes to the inference-based DCOP framework, in complete (DPOP) and incomplete (Max-Sum) solution methods.

We previously applied auctions and DCOP domains such as Earth observation [8][12], UTM [4], and multi-robot missions [13]. We thus envision to implement and evaluate the theoretical and algorithmic contributions of this thesis to one or more of these application domains.

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**Collaborations envisagées**

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