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Multi-Agent Mission Planning

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Note:
Every time you were convinced
you couldn't go on, you did!

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Sammanfattning

Multi-agent-system (MAS) har använts i olika omgivningar och ramverk och har på så sätt framgångsrikt tillämpats i en mängd applikationer för att uppnå olika mål. Det har visat sig att MAS är mer kostnadseffektiva jämfört med att bygga en enda agent med alla de funktioner som ett uppdrag kan kräva. Dessutom är kostnaden inte den enda drivande faktorn för att använda MAS, t.ex. är säkerhet en annan viktig aspekt: Genom att använda en grupp agenter i en tuff eller extrem miljö istället för ett mänskligt team så minskar säkerhetsriskerna. Dessutom erbjuder MAS en högre grad flexibilitet och robusthet jämfört med en lösning med en enda agent. Flexibiliteten uppnås genom att dela upp resurser i separata grupper, medan robusthet erhålls då ett kritiskt fel hos en agent inte nödvändigtvis äventyrar ett uppdrags framgång. Det är värt att notera att ett uppdrag kan ha många olika begränsningar och aspekter, men det mest triviala fallet har en enda agent och en enda uppgift.

Denna typ av uppdrag kan planeras av en mänsklig operatör som övervakar uppdraget utan behov av en automatiserad planerare. å andra sidan är mer komplexa uppdrag, som använder ett stort antal heterogena agenter och uppgifter och som dessutom kan ha olika begränsningar (prioritet, synkronisering etc.), inte så triviala att planera för en mänsklig operatör. Dessa komplexa problem utgör en stor utmaning för att få till en genomförbar plan, för att inte tala om den bästa möjliga planen. Dessutom har den ökade datorkraften hos tillgängliga plattformar i robotsystem gjort det möjligt att använda parallella uppgiftsutföranden. Mer specifikt innebär det möjlighet för parallellitet i avkänning-, beräkning-, rörelse-, och manipulationsuppgifter. Detta har i sin tur fördelen att det kan skapas mer komplexa robotuppdrag. Det har dock kommit till priset av ökad komplexitet för optimering av uppgiftsallokeringsproblemet.

För att kringgå dessa problem är en automatiserad planerare nödvändig. Dessa typer av problem är notoriskt svåra att lösa, särskilt om kravet är att hitta

den bästa möjliga lösningen. Därför är det viktigt att hitta en balans mellan optimalitet och den beräkningstid som behövs för att ta fram en plan.

Denna avhandling behandlar den formella definitionen av två särskilda MRTA-problemkonfigurationer (Multi-Robot Task Allocation) som används för att representera problem med uppdragsplanering med flera agenter. Mer specifikt kan bidraget från denna avhandling delas upp i tre kategorier.

För det första föreslås i detta arbete en modell för att representera olika problemkonfigurationer, även kallade uppdrag, på ett strukturerat sätt. Denna modell kallas TAMER, och det möjliggör också tillägg av nya dimensioner på ett mer systematiskt sätt, vilket utökar antalet problem som kan beskrivas jämfört med tidigare föreslagna MRTA-taxonomier.

För det andra definierar och tillhandahåller denna avhandling två olika problemformuleringar, i form av formuleringen Mix-Integer Linear Problem, av det utökade och färgade resande försäljningsproblemet (ECTSP). Dessa modeller implementeras och verifieras i CPLEX-optimeringsverktyget för de valda probleminstanserna. Dessutom utformas ett suboptimalt tillvägagångssätt för att lösa dessa komplexa problem. Föreslagna lösningar baseras på metoden Genetisk Algoritmer (GA), och de jämförs med de lösningar som erhålls av toppmoderna problemlösare. Fördelen med att använda GA för planering jämfört med klassiska metoder är att det har bättre skalbarhet vilket gör det möjligt att hitta lösningar på storskaliga problem. även om dessa lösningar i de flesta fall är suboptimala erhålls de mycket snabbare än med andra exakta metoder. En annan fördel representeras i en form av ”när som helst stopp”-alternativ; i tidskritiska operationer är det viktigt att ha möjlighet att stoppa planeringsprocessen och använda den suboptimala lösningen när det behövs.

Slutligen tar detta arbete upp den enda dimensionen av MRTA-problemet som inte har fått mycket uppmärksamhet i tidigare forskning. I synnerhet har problemkonfigurationer inklusive MT-robotar (Multi-Task) försummats och för att komma till rätta med det har det, för det första, definierats de fall där uppgiftsparallellitet kan uppnås. Dessutom har införts åtskillnad mellan fysiska och virtuella uppgifter och deras ömsesidiga relation när det gäller parallellutförande av uppgifter. Två modeller har föreslagits och jämförts, den första uttrycks som ILP och implementeras i CPLEX-optimeringsverktyget och den andra definieras som en CP-modell (Constraint Programming) och implementeras i CP-optimeringsverktyg. Båda dessa problemlösare har utvärderats på en rad probleminstanser.

Abstract

Multi-Agent Systems (MASs) have been utilized in various settings and frameworks, and have thus been successfully applied in many applications to achieve different goals. It has been shown that MASs are more cost-effective as compared to building a single agent with all the capabilities a mission may require. Moreover, the cost is not the only driving factor for the adoption of MASs, e.g., safety is another important aspect: Deploying a group of agents, in a harsh or extreme environment, instead of a human team decreases the safety risks. Furthermore, MASs offer more flexibility and robustness when compared to a single-agent solution. The flexibility comes from dividing resources into separate groups, while robustness comes from the fact that a critical error in one agent does not necessarily endanger the success of a mission. Note that a mission may have many different constraints and aspects, however, the most trivial case has a single agent and a single task.

These kinds of missions can be planned by a human operator, overseeing a mission, without the need for an automated planner. On the other hand, more complex missions, that are utilizing a large number of heterogeneous agents and tasks, as well as constraints (precedence, synchronization, etc.) are not that trivial to plan for a human operator. These complex problems pose a great challenge to making a feasible plan, let alone the best possible one. Moreover, the increase in the power of available computing platforms in robotic systems has allowed the utilization of parallel task execution. More specifically, it allowed for possible parallelism in sensing, computation, motion, and manipulation tasks. This in turn had the benefit of allowing the creation of more complex robotic missions. However, it came at the cost of increased complexity for the optimization of the task allocation problem. To circumvent these issues, an automated planner is necessary. These types of problems are notoriously difficult to solve, and it may take too long for an optimal plan to be found. Therefore, a balance between optimality and computation time taken to produce a plan

become very important.

This thesis deals with the formal definition of two particular Multi-Robot Task Allocation (MRTA) problem configurations used to represent multi-agent mission planning problems. More specifically, the contribution of this thesis can be grouped into three categories.

Firstly, this work proposes a model to represent different problem configurations, also referred to as missions, in a structured way. This model is called TAMER, and it also allows the addition of new dimensions in a more systematic way, expanding the number of problems that can be described compared to previously proposed MRTA taxonomies.

Secondly, this thesis defines and provides two different problem formulations, in a form of Mixed-Integer Linear Problem formulation, of the Extended Colored Travelling Salesman Problem (ECTSP). These models are implemented and verified in the CPLEX optimization tool on the selected problem instances. In addition, a sub-optimal approach to solving these complex problems is devised. Proposed solutions are based on the Genetic Algorithm (GA) approach, and they are compared to the solutions obtained by state-of-the-art (and state-of-practice) solvers, i.e., CPLEX. The advantage of using GA for planning over classical approaches is that it has better scalability that enables it to find solutions for large-scale problems. Although those solutions are, in the majority of cases, sub-optimal they are obtained much faster than with other exact methods. Another advantage is represented in a form of "anytime stop" option. In time-critical operations, it is important to have the option to stop the planning process and use the sub-optimal solution when it is required.

Lastly, this work addresses the one dimension of the MRTA problem that has not caught much of the research attention in the past. In particular, problem configurations including Multi-Task (MT) robots have been neglected. To overcome the aforementioned problem, first, the cases in which task parallelism may be achieved have been defined. In addition, the distinction between physical and virtual tasks and their mutual relationship in terms of parallel task execution has been introduced. Two models have been proposed and compared. The first one is expressed as ILP and implemented in the CPLEX optimization tool. The other one is defined as a Constraint Programming (CP) model and implemented in CP optimization tools. Both solvers have been evaluated on a series of problem instances.

List of Publications

Papers Included in the PhD Thesis[1]

Paper A *TAMER: Task Allocation in Multi-robot Systems Through an Entity-Relationship Model*. **Branko Miloradović**, Mirgita Frasheri, Baran Çürüklü, Mikael Ekström, and Alessandro V. Papadopoulos. 22nd International Conference on Principles and Practice of Multi-Agent Systems (PRIMA'19).

Paper B *A Genetic Algorithm Approach to Multi-Agent Mission Planning Problems*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. In: Parlier G., Liberatore F., Demange M. (eds) Operations Research and Enterprise Systems. ICORES 2019. Communications in Computer and Information Science, vol 1162. Springer, Cham.

Paper C *GMP: A Genetic Mission Planner for Heterogeneous Multi-Robot System Applications*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. In IEEE Transactions on Cybernetics, 2021 (in press). DOI: https://doi.org/10.1109/TCYB.2021.3070913

Paper D *Optimizing Parallel Task Execution for Multi-Agent Mission Planning*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. Submitted to Journal of Intelligent & Robotic Systems in September 2021. Revised version submitted in December 2021.

[1]The papers have been reformatted to comply with the doctoral thesis template.

Additional Peer-Reviewed Publications, not Included in the PhD Thesis

1. *Exploiting Parallelism in Multi-Task Robot Allocation Problems*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC 2021).

2. *Planning and supervising autonomous underwater vehicles through the mission management tool*. Afshin Ameri, Baran Çürüklü, **Branko Miloradović**, Mikael Ekström. IEEE Global Oceans 2020: Singapore – U.S. Gulf Coast (2020).

3. *Indoor Positioning System for Occupation Density Control*. Djordje Stojanović, Milica Vujović, **Branko Miloradović**. Proceedings of The 40th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA 2020).

4. *Extended Colored Traveling Salesperson for Modeling Multi-Agent Mission Planning Problems*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. In Proceedings of the 8th International Conference on Operations Research and Enterprise Systems (Vol. 1, pp. 237-244), 2019.

5. *A Genetic Mission Planner for Solving Temporal Multi-Agent Problems with Concurrent Tasks*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström. 8^{th} International Conference on Swarm Intelligence (ICSI), 2017.

6. *A Genetic Planner for Mission Planning of Cooperative Agents in an Underwater Environment*. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström. 9^{th} IEEE Symposium Series on Computational Intelligence (SSCI), 2016.

7. *On Developing Lightweight Robot-Arm of Anthropomorphic Characteristics*. Aleksandar Rodić, **Branko Miloradović**, Svemir Popić, Djordje Urukalo. New Trends in Medical and Service Robots (2016).

8. *Low–cost Anthropomorphic Robot Hand with Elastic Joints – Early Results*. **Branko Miloradović**, Baran Çürüklü, Milica Vujović, Svemir Popić, and Aleksandar Rodić. 2^{nd} International Conference on Electrical, Electronic and Computing Engineering (IcETRAN), 2015.

9. *Light Weight Robot Arms - An Overview*. Svemir Popić, **Branko Milo-radović**. INFOTEH, Jahorina, 2015.

List of Abbreviations

AI	Artificial Intelligence
ATSP	Asymmetric Traveling Salesmen Problem
AUV	Autonomous Underwater Vehicle
CD	Complex Dependencies
CP	Constraint Programming
CTSP	Colored Traveling Salesmen Problem
EA	Evolutionary Algorithm
ECTSP	Extended Colored Traveling Salesperson Problem
ER	Entity Relationship
ERX	Edge Recombination Crossover
GA	Genetic Algorithm
GMP	Genetic Mission Planner
GS	Greedy Search
IA	Instantaneous Assignment
ID	Intra-schedule Dependencies
ILP	Integer Linear Programming
MASs	Multi-Agent Systems

MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MMT	Mission Management Tool
MOHS	Multi-Objective Harmony Search
MO	Multi-Objective
MR	Multi-Robot
MRTA	Multi-Robot Task Allocation
MT	Multi-Task
mTSP	multiple Traveling Salesmen Problem
mTSPPC	multiple Traveling Salesmen Problem with Precedence Constraints
ND	No Dependencies
NSGA	Non-Dominated Sorting Genetic Algorithm
OR	Operations Research
PAES	Pareto Archived Evolution Strategy
PC	Precedence Constraint
PCR	Precedence Constraint Reparation
PDDL	Planning Domain Definition Language
RCP	Resource Constrained Planning
RCPSP	Resource-Constrained Project Scheduling Problem
RG	Research Goal
RMTZ	Reformulated Miller-Tucker-Zemlin
SP	Synchronization and Precedence
SR	Single-Robot
ST	Single-Task

TA	Time-Extended Assignment
2CFN	Two-Commodity Flow Network
TSP	Traveling Salesmen Problem
TSPPC	Traveling Salesmen Problem with Precedence Constraints
TW	Time Windows
UAV	Unamnned Aerial Vehicle
VRP	Vehicle Routing Problem
XD	Cross-schedule Dependencies

Contents

I

Thesis

Chapter 1

Introduction

In recent years, Multi-Agent Systems (MASs) have gained popularity due to technological advancements in several fields, from sensors [1], wireless communication [2], to robotics [3], and Artificial Intelligence (AI) [4]. The immediate consequences of these advancements are improvements with respect to the price-performance ratio, which in turn has led to wider availability and usage of robotic agents as well as complete multi-agent systems [5]. In parallel, increased interest in multi-agent systems has created many new research areas directly related to real-world problems [6]. Deploying a group of agents instead of a human team has many advantages such as improving the cost efficiency of a mission, and more importantly, the safety of the workers. In addition, the ability to deploy a group of agents may also be advantageous over the use of a single unit in many missions [7]. More specifically, by introducing a certain level of redundancy in the system, the effects of unexpected events and failures can be mitigated. This in turn leads to the increase of the robustness of the system, thus minimizing the chances of mission failure. On the other hand, with the increased number of agents and tasks in missions, the problem of allocation of tasks to agents arose, and it is one of the most fundamental classes of problems in robotics, formally known as the Multi-Robot Task Allocation (MRTA) problem. MRTA encapsulates numerous problem dimensions, and it aims at providing formulations and solutions to various problem configurations, i.e., complex multi-robot[1] missions.

A mission can be defined as a specific set of tasks that a single, or a group of robots, is in charge of performing. Missions may include a diverse group

[1]Terms *robot* and *agent* are used interchangeably throughout this thesis.

of robots (e.g., underwater, ground, airborne, etc.) of heterogeneous structure (e.g., sensor modalities) that should achieve a variety of sub-goals (perform allocated tasks) and/or global goals (mission objectives) while being constrained by the environment they are being deployed in. Constraints might not come solely from the environment, but from the interrelatedness of tasks, mission objective, or user preferences. These are some of the key high-level aspects of a mission. A list of more detailed aspects may include – but are not limited to – the communication infrastructure, the type of control algorithms, the task decomposition, etc. While this detailed list of deployment aspects may vary from scenario to scenario, the high-level mission model can remain unaffected.

Motivation. A mission can consist of numerous agents, tasks, and constraints, making it very hard and impractical for a human operator to plan. Mission planning implies the allocation of a set of tasks to a set of agents such that the mission makespan is minimized and given constraints are satisfied. Although humans are skilled in solving some type of planning problems, e.g., simpler instances of the Traveling Salesmen Problem (TSP) [8], a multi-agent mission planning problem may have more constraints than a TSP that may not be very intuitive to address. Having human operators solving these kinds of problems may lead to a long planning time or a poor performance, or even both. Additionally, in order to have an operator involved in the planning process, certain training and experience are required in making plans for multi-agent missions. Nevertheless, very small missions are still possible to be planned manually.

On the other hand, some users might want to use planning as a service. For example, a farmer wants to use a set of drones to monitor the crops' health or plan a harvest with autonomous tractors. A user of such a service is not interested in what is happening in the background or how these missions are modeled and solved. For this reason, it is necessary to have an automated planner capable of planning a mission for a large number of agents and tasks and to be able, in the case of unexpected events, to re-plan the mission with the new set of information. More often than not, in the re-planning operations, time is of the essence as the limited autonomy of the agents may affect the time the mission can be in a halt mode.

The increase in the power of available computing platforms in robotic systems has allowed the utilization of concurrent task execution. Moreover, it allowed for possible parallelism in sensing, computation, motion, and manipulation tasks. This in turn had the benefit of allowing the creation of more complex robotic missions. However, it came at the cost of increased complexity for the optimization of the task allocation problem. Although many problem configurations have been addressed previously, the one covering the aforementioned problem has not caught much of the research attention in the past. In particular, problem configurations including agents able to perform multiple tasks concurrently have been neglected.

Goals. By analyzing the aforementioned requirements, it was assumed that it was necessary to provide a framework for different mission configurations, i.e., a taxonomy that will give a structured overview of the existing problem configurations while allowing for the easy incorporation of the possible new requirements. The next step is to derive a specific model that will encapsulate the main attributes of multi-agent missions at hand, on a high level of abstraction such that a given problem formulation can be regarded as domain-independent. In the broad sense, this model should be able to utilize a group of heterogeneous robots to perform a variety of different tasks that require a certain capability, on the robot side, in order to be performed. In addition, tasks may be interrelated, e.g., a certain order among some tasks may need to be maintained or tasks may be executed in parallel. Part of the problem also includes choosing a set of agents to perform the mission, judging the agents' location, capabilities, and the whereabouts of the final destination. This concludes the requirements in the problem domain. Finally, requirements in the solution domain determine the reasoning behind the selection of the planner, i.e., planning algorithm. In the general case, it is assumed that the time for the creation of the initial mission plan is not particularly limited, while the re-planning process should be done as fast as possible, even at the possible expense of the solution quality.

Based on the described motivation, in the following text, we provide the list of contributions aimed at addressing identified requirements in multi-agent mission planning.

Contributions. Based on the different constraint types and their mutual relatedness, different missions or problem configurations can be identified (Section 3). During the last two decades, various taxonomies have been proposed in order to try to systematically describe these different problem configurations by combining different problem dimensions. Generally, newly proposed taxonomies try to add new dimensions to the MRTA taxonomy defined by Gerkey and Matarić [9] that set the basis by proposing three semi-decoupled dimensions. However, adding new dimensions is not a straightforward process, and it may lead to the introduction of coupled dimensions, or a redefinition of existing ones. While some of the less complicated problems are covered by existing taxonomies to a certain extent, more complex ones either cannot be described fully or some ambiguities may arise depending on the used taxonomy. A part of this thesis is dedicated to the survey and identification of previously proposed taxonomies and categorizing those problem configurations that these taxonomies can describe. This work lead to the proposal of TAMER, an Entity-Relationship formalism, that allows representation of problem dimensions in a more structured manner. In addition, during this process, new problem dimensions are identified that can describe even more complex multi-agent missions than previously proposed taxonomies.

After laying the groundwork with the proposed taxonomy and identifying relevant dimensions for a generic multi-agent mission planning problem, the next goal of this thesis is to provide a formal problem formulation of a general case of a real-world mission planning problem that includes the identified attributes and requirements. Some of the attributes necessary for a generic multi-agent mission description, on a high-level, include task requirements, agent capabilities, temporal constraints, task dependencies, etc. First, the focus is set on the multi-agent mission planning problem without concurrent tasks (Section 3.1). For this particular problem configuration, we proposed two different Mixed Integer Linear Programming (MILP) formulations, which are based on the famous TSP and extended to utilize additional constraints and requirements. In particular, the problem is formalized as a generalization of the Colored TSP [10]. The generalization includes: (i) Precedence Constraints (PCs), which are modeled in two ways, specifically, by extending the Reformulated Miller-Tucker-Zemlin (RMTZ) [11] and Two-Commodity Flow Network (2CFN) [12] formulation; (ii) The possibility of having multiple source and destination depots for agents; (iii) The presence of a *duration* associated with the execution of the task; and (iv) A new objective function for the minimization of the total mission duration in presence of multiple robots. This problem mainly falls under the category of routing problems.

With the models being formalized, the next step was to provide a reasonable solution. It is not only necessary to provide a feasible solution, but the problem needs to be solved efficiently. In some missions, there can be a requirement that the solution to the problem needs to be provided quickly at the expanse of optimality, especially in the case of re-planning. One of the proposed solutions is an optimal state-of-the-art commercial MILP solver called CPLEX[2]. The other proposed solution is based on the Evolutionary Algorithm (EA)

[2]https://www.ibm.com/products/ilog-cplex-optimization-studio

paradigm, more specifically the Genetic Algorithm (GA), which is a sub-class of EA. Both solvers are capable of solving the same problem, they differ in the way they search for the best solution. A comprehensive analysis is conducted on the results of the benchmark[3] performed on the set of 10 problem instances with gradually increasing complexity. Both approaches, GA and CPLEX, have been compared and analyzed from the perspective of planning and re-planning.

Finally, the multi-agent mission planning with concurrent tasks is addressed. In order to provide a formal definition of the problem, it is first necessary to define in what cases task parallelism may be achieved. To be able to describe this problem configuration, a distinction between physical and virtual tasks has been proposed that encapsulates their mutual relationships in terms of parallel task execution. In addition, the formal mathematical formulation of the problem is given that is built on top of previously defined multi-agent mission planning problem without concurrent tasks. By introducing concurrency, this problem becomes a mixture of routing and scheduling problems. Hence, in addition to the Integer Linear Programming (ILP) formulation that is implemented and verified in CPLEX, a Constraint Programming (CP) formulation has also been provided, since CP has had a noticeable amount of success in solving scheduling problems. The models are validated in CPLEX and CP Optimizer[4] tools on the set of benchmarks with the goal of exploiting the potential task parallelism of the agents involved while minimizing the makespan of the mission. Finally, a comprehensive performance analysis of both solvers has been provided, which explores their scalability and solution quality on a given multi-agent mission planning problem with concurrent tasks.

[3]Library with 10 instances is available for download at https://github.com/mdh-planner/ECTSP

[4]https://www.ibm.com/analytics/cplex-cp-optimizer

Chapter 2

Background and Preliminaries

In the AI domain, planning can be defined as a search for a set of possible actions, also referred to as **tasks**, which leads from an initial state to the desired state. That set of actions is called a **plan**. Actions affect problem state space. A problem state space can be defined as a set of all configurations that a given problem and its environment could achieve. The simplest planning problem, also known as the Classical Planning Problem [13], has a unique known initial state, actions are always instantaneous, deterministic, and sequential, i.e., actions have no duration, the effect of one action on the state space is always the same, and only one action can be done at a time. Finally, the entire world, including the environment, is considered to be fully observable with a finite number of states.

In more complex problems, which are closely related to the open real-world problems, actions are rarely considered to be instantaneous and a notion of time, i.e., task duration, arises in the planning problem. In these cases, a description of the world state has to contain information about absolute time and the current execution time, thus allowing concurrent actions. This type of planning is called temporal planning problem, and it is closely related to scheduling [14]. Although the terms planning and scheduling are quite often used interchangeably, they are not semantically equivalent. **Planning** answers questions of *"what task"* and *"how"* a certain task should be done, while **scheduling** defines *"when"* and *"who"* should perform a certain task. Scheduling is the problem of assigning a set of actions to a set of resources bound by a set of constraints. To perform an action, different kinds of resources may be required to be used (e.g., tools, space) or consumed (e.g., energy). Time is a resource required by every non-instantaneous action, although it differs from other types of resources. It flows independently from the actions being executed, and it can be shared by independent agents indefinitely, as long as their actions do not interfere with each other.

In this context, agents are considered as a type of resource and if more than one agent is available the classical planning problem becomes **multi-agent planning problem**, i.e., the plan does not need to be sequential anymore. In the general case, agents do not need to be homogeneous, thus they can have different capabilities, sensors, and performances. In other words, not every agent can perform each action, or at least not equally good. Since resources are usually not infinite they represent constraints in the planning process. This type of planning is called **resource-constrained planning**. Constraints can be either soft or hard. Soft constraints can be violated with a certain penalty, while the violation of hard constraints is not permitted.

In addition, missions can be conducted in a harsh and challenging environment where several different unforeseen events may arise and compromise planned task execution. In these cases, usually, the time available for the creation of a new plan is fairly limited, thus an option of performing a fast re-planning is very important. It is important to emphasize that in this context re-planning refers to repeating the planning process with updated initial conditions. Re-planning may also refer to the process of **plan reparation**, i.e., local modification of the current plan to overcome the problem, e.g., failed task, or malfunctioning agent, however, this is out of the scope of this work.

The terminology referring to mission planning is vast and varies, depending on the problem at hand, on the scientific community, and on the techniques used for providing a solution. This is due to the complexity of the problem, and to the fact that several researchers have proposed different techniques to provide solutions in diverse contexts. The literature review is mostly done in the Combinatorial Optimization area and areas it intersects with: MRTA, Operations Research (OR), and EA (see Figure 2.1). Combinatorial optimization can be defined as a process of searching for an optimum of an objective function whose domain is a discrete, but large configuration space [15]. It is important to emphasize that these three sub-areas include problems that are well outside the combinatorial optimization area, however in the context of this thesis, whenever these areas are mentioned, they are mentioned in the context of discrete combinatorial optimization.

In addition, an overview of the related work, covering selected relevant ar-

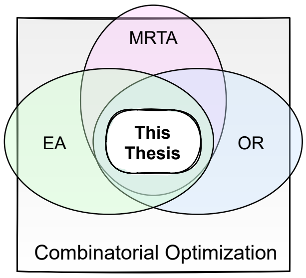

Figure 2.1: A literature review is mostly done on the intersection of these four areas.

eas, is provided. Taxonomy related to MRTA is presented in Section 2.1. After presenting relevant taxonomies and their dimensions of research, concepts of missions, planning, and re-planning are introduced in Section 2.2. Resource-Constrained Planning has been addressed in Section 2.3. Section 2.4 surveys problems from OR that can be applied to mission planning problems. Finally, Section 2.5 presents an overview of commonly used approaches and algorithms for solving mission planning problems presented in the previous sections.

2.1 Multi-Robot Task Allocation Taxonomy

In order to be able to describe a problem and see how it relates to other similar problems, a framework was necessary that would group similar problems into respective categories while providing a clear description of each problem group. Gerkey and Matarić [9] did a formal study of an MRTA that resulted in a domain-independent taxonomy describing MRTA problems. This taxonomy consists of three dimensions *task concurrency*, *task type*, and *assignment type*.

The *task concurrency* axis consists of Single-Task (ST) robots and Multi-Task (MT) robots. ST robots are capable of doing at most one task at a time, while MT robots can perform numerous tasks simultaneously.

The *task-robot type* is divided into Single-Robot (SR) tasks and Multi-Robot (MR) tasks. SR tasks require only one robot, while MR tasks require more than one.

The *assignment type* can be Instantaneous Assignment (IA) or Time-Extended Assignment (TA). In IA, the available information regarding robots, tasks, and the environment permits only instantaneous allocation regardless of future allocations. TA, on the other hand, has information about all the tasks that need to be allocated. In this case, the number of tasks can be greater than the number of robots, even in the SR-ST case.

The three-dimensional MRTA taxonomy has been extended by Landén *et al.* [16], by adding four more dimensions: *task utility*, *task constraints*, *allocation view*, and *dynamism of the environment*.

Korsah *et al.* [17] merged task utility and task constraints dimensions into the degree of interrelatedness. This dimension describes the degree of interrelatedness between tasks within one agent and among other agents. Hence, it can be distinguished between four types of dependencies, i.e., (i) No Dependencies (ND); (ii) Intra-schedule Dependencies (ID); (iii) Cross-schedule Dependencies (XD); and (iv) Complex Dependencies (CD). The first class refers to the simple case (as assumed by Gerkey and Matarić [9]) in which the tasks are independent of one another. The second class covers those cases where two tasks have mutual dependencies and are executed by the same agent. The third class covers those cases in which a task mat not only depend on other tasks allocated to the same agent, but also on other schedules that belong to other agents. The fourth class covers the cases assumed in the other classes, with an additional factor that includes the way a task is decomposed. This assumes that there are multiple ways in which a task could be decomposed.

In addition to the previously mentioned assignment type dimension, Nunes *et al.* [18] distinguish between temporal and ordering constraints, by adding Time Windows (TW) and Synchronization and Precedence (SP) constraints under TA. Furthermore, TW and SP can be divided into hard and soft constraints as well as deterministic or stochastic models.

2.2 Multi-Agent Mission Planning and Replanning

In this work, the mission planning problem concerns temporal resource-constrained multi-agent planning and scheduling problems. Aside from a very small set of trivial problems, mission planning problems are very hard to solve, even sub-optimally [19]. These types of problems are usually NP-hard, meaning that even with a given solution to the problem it cannot be confirmed that the solution is optimal in polynomial time [20], thus making these types of problems computationally expensive, and challenging to solve. One way of overcoming this issue, i.e., to try and solve NP-hard problems, is to use a meta-heuristic approach, since they are computationally less expensive for larger problem instances and provide “any time stop” option, which can be a valuable asset in real-world scenarios. The downside of this approach is that the quality of the solution cannot be guaranteed, moreover, it is usually sub-optimal.

Plans that are to be executed in a distributed fashion can nonetheless be produced by a centralized planner. A planner breaks a mission plan into smaller pieces that are sent to the appropriate agents for execution. In one of the possible approaches, a partial order planner generates plans where the need for a strict ordering between some of the actions can be omitted, and in fact where those actions can be executed concurrently. Boutilier and Brafman [21] define concurrency on actions, specifying which actions can be performed simultaneously. Kvarnström's [22] work focuses on a centralized planning for multi-agent domains and on a loose commitment to the precedence between actions belonging to distinct agents, leading to execution schedules that are flexible where it matters the most.

The opposite approach was taken by Crosby and Patrick [23] where the authors have investigated how centralized, cooperative, multi-agent planning problems with concurrent action constraints, and heterogeneous agents can be encoded to the Planning Domain Definition Language (PDDL). They encode concurrency constraints on objects and determine conditions under which a certain object can be used concurrently. In both aforementioned approaches, it is assumed that there cannot be concurrent actions on a single agent.

A research framework on mission planning for swarms of Unamnned Aerial Vehicle (UAV) has been proposed by Zhou *et al.* [24]. In general, most of the approaches used for UAV mission planning can be used in different scenarios, such as swarms of Autonomous Underwater Vehicle (AUV) in the underwater application or for swarms of terrestrial vehicles. The problem of mission planning for a swarm of UAV can be solved using the evolutionary approach as it is presented by Ramirez-Atencia *et al.* [25, 26]. The problem is modeled as a constraint satisfaction problem and solved using multi-objective GA. This work has been further extended in Ramirez-Atencia *et al.* [27] to utilize re-planning and analysis of operator training in the control center. For a similar problem of mission planning for cooperative UAV teams, a solution was proposed by Bello-Orgaz *et al.* [28] that uses GA with a weighted linear combination of mission's makespan and fuel consumption as an optimization criterion. A simple GA with several enhancements and PDDL modeling language was implemented by Brie *et al.* [29]. The proposed genetic planner utilized the approach of a variable chromosome length. This approach benefits when the length of a plan is not known *a priori*. On the other hand, the proposed approach lacks extension for multi-agent planning and planning concurrent actions. A different approach to a similar group of problems is taken by

Karaman Sertac *et al.* [30] where process algebra is used to model the problem that is later solved with the GA.

Mission planning does not necessarily consist of optimizing only one parameter. Multi-Objective UAV mission planning using an evolutionary approach is presented by Pohl and Lamont [31]. This approach is based on GA. The problem of multi-objective optimization with the evolutionary algorithm is tackled by Khoaudija *et al.* [32], where a way of benchmarking obtained solutions is also addressed. They have developed an evolutionary planner called Divide-and-Evolve that embeds a classical planner and feeds it with a sequence of sub-problems of the problem at hand. Landa-Torres *et al.* [33] compare three multi-objective evolutionary algorithms (Multi-Objective Harmony Search (MOHS), Non-Dominated Sorting Genetic Algorithm (NSGA) II, and Pareto Archived Evolution Strategy (PAES)) on an underwater mission planning problem for a swarm of AUV. Planning constraints include multiple heterogeneous agents and heterogeneous task requirements, while precedence constraints between tasks are not covered. Experiments show that MOHS outperforms the other two algorithms in the majority of scenarios presented. Finally, Torreño *et al.* [34] provide a comprehensive survey of different approaches to cooperative multi-agent planning.

2.3 Resource-Constrained Planning

The need to economize limited resources, such as fuel or money, is a ubiquitous feature of planning problems. Resource Constrained Planning (RCP) can be seen as a special case of mission planning where resources are limited. However, two cases can be distinguished here: (i) it is possible to replenish resources (e.g., recharge batteries); and (ii) resource replenishment is not an option (e.g., a limited amount of building material). Nakhost *et al.* [35] have generalized the notion of constraindness and improved the Monte Carlo Random Walk method to solve different instances of RCP.

Another popular way of solving RCP is by using GA, where chromosome representation is based on random keys. Gonçalves *et al.* [36] have proposed solving project scheduling problems by constructing a schedule using a heuristic priority rule in which the priorities and delay times of the activities are defined by the GA. Note, however, that joint or concurrent actions are not possible. Debels and Vanhoucke [37] proposed a Decomposition Based GA for RCP. This method divides an RCP problem into smaller problems and obtains the solution for the global problem by combining the solution of each such sub-problem. They showed that the decomposition-based approach finds satisfactory near-optimal solutions.

A closely related problem to RCP is Resource-Constrained Project Scheduling Problem (RCPSP). In a broad sense, this problem assumes scheduling of project activities subject to precedence and resource constraints in order to fulfill a given objective or objectives. An extensive overview of the existing variations of RCPSP is given by Habibi *et al.* [38].

2.4 Operations Research

Many different problems from the area of Operations Research are used for modeling multi-agent missions. The accent here is on the TSPs and Vehicle Routing Problems (VRPs). TSP expressed as an ILP was introduced by Dantzig *et al.* [39]. This definition is later extended to the multiple Traveling Salesmen Problem (mTSP) by Kara and Bektas [40]. Kalmar-Nagy *et al.* [41] proposed an approach using sub-tours to solve mTSP. The idea is to divide a graph into sub-graphs, which are solved using GA. Each sub-graph represents a tour for one of the salespersons. Rather than distance, time is being optimized, therefore, the objective is to minimize the longest makespan of a sub-tour over all sub-tours, i.e., a min-max optimization. Another TSP variant including PC called Traveling Salesmen Problem with Precedence Constraints (TSPPC) has been presented by Kubo *et al.* [42]. The above-mentioned TSP variants have been combined into an multiple Traveling Salesmen Problem with Precedence Constraints (mTSPPC) by Zhong [43], although a formal problem formulation was not given in the paper.

A branch-and-cut algorithm is used to solve Asymmetric Traveling Salesmen Problem (ATSP) with a precedence constraint of size of up to 200 nodes [44]. The real-world application of air transport is modeled using a time-dependent ATSP with time windows and PC. Problems in this application domain are solved by a modified nearest neighbor heuristic with a local search [45]. Roberti and Toth [46] provided an experimental comparison of models and algorithms for ATSP. Generalized ATSP with precedence constraint is applied in the coordinated-measuring machine inspection process [47]. In this work, two possible solutions are compared, CPLEX and Ant-Colony Optimization. While the former provides solutions for small to mid-sized problems only, the latter performs well also on larger instances. This problem formulation was later extended to use multiple salespersons [48]. These results correspond to our findings after comparing CPLEX and GA in

Paper C [49].

A mixed-integer nonlinear problem formulation is given by Fügenschuh *et al.* [50] and used to model mission planning for UAVs. This formulation is then approximated by MILP and solved by GUROBI[1]. Problem instances of 2 AUVs and 15 waypoints are routinely solved to optimality, while for larger problem instances only sub-optimal solutions were provided. A problem formulation of the real-world routing problems was provided and solved with different greedy algorithm variations by Yuan *et al.* [51]. A Mixed Integer Programming (MIP) formulation of a multi-robot mission planning problem was given by Flushing *et al.* [52]. In this work a two-layer solution was proposed: (i) the selection of sequences of tasks with GA and (ii) the service scheduling with iterative local search. We adopted a similar paradigm in Paper C.

Recently, serial [53], radial [10], and a more complete version of a Colored Traveling Salesmen Problem (CTSP) [54] to solve multiple bridge machine planning problems in the industry have been proposed. Algorithms used to tackle these problems are Population-based incremental learning, GA with local search (Hill climbing and Simulated Annealing), and Variable Chromosome search, respectively. These CTSP models were used as the basis for our model, described in the C2 of Section 6. Recently, in addition to our proposed extension of the CTSP, there has been proposed a General CTSP (GCTSP) [55] that uses a hypergraph to represent the problem. This formulation has been extended to include Precedence Constraints, called PCTSP [56].

A survey on the use of VRP instances for military multi-UAV mission planning problems is presented by Adbelhafiz *et al.* [57]. The authors show that each military multi-UAV mission has its corresponding VRP variant. Another instance of VRP with metric temporal logic is used for modeling and solving multi-UAV missions by Karaman and Frazzoli [58]. A MILP based algorithm is used to solve the given problem optimally, however, the problem size is quite small—two UAVs and 5 tasks. A survey of the problem variants and proposed solutions of the heterogeneous VRP is given by Koç *et al.* [59]. Quttineh *et al.* [60] provide a MILP formulation of the generalized VRP problem with cross-schedule synchronization and precedence constraints for military aircraft mission planning. The results of this approach are tested on problems of the size of at most 6 aircraft and 8 targets. A hybrid EA [61] is successfully used to solve heterogeneous VRPs with TWs. The proposed algorithm combines several metaheuristics and is able to solve different variants of the VRP.

[1] https://www.gurobi.com/products/gurobi-optimizer/

2.5 Planning Algorithms

A large number of conventional planning algorithms handle planning by mapping the search space into a graph or a tree, searching through the nodes using heuristic functions, cutting infeasible branches, or backtracking from dead-ends (e.g., CPLEX using branch-and-cut). One of the main advantages of this approach is the guarantees that the algorithm can provide. It can guarantee the optimal solution is found, or it can guarantee what is the maximum gap between the found feasible (sub-optimal) solution and the best bound. Exact methods are effective on small problem instances, while larger problems are usually tackled with the use of meta-heuristics. EAs are among the most popular meta-heuristic optimization algorithms. EAs approach problem solving by mimicking mechanisms found in nature. The fundamental idea behind all EA techniques is that the environmental pressure causes natural selection (survival of the fittest) in the population of individuals, which leads to the improvement of population fitness over numerous generations.

Among the most popular EAs approaches, GAs have been widely used in different contexts ranging from airlines revenue management [62], vehicle routing problems [63], multiple criteria production scheduling [64], to multi-agent mission planning [65], and power electronics design [66]. GA fully inherits the previously described properties of EA. It works by starting with an initial generation of chromosomes (population), where each chromosome represents a candidate solution. Reseeding of the population is done according to the probabilistic selection, crossover, and mutation operations. The crossover operator combines the genetic information of two or more parents to create offspring. Mutation tries to preserve diversity in the population by randomly altering one or more gene values in a chromosome. Probabilistic distribution guides the chromosomes through the search space, performing an uninformed search. The fitness of the individuals plays the main role in the selection process, where fittest individuals have a higher chance of reproducing and creating offspring.

It is important to mention that the optimization problem can be either single or Multi-Objective (MO). In a non-trivial case of MO optimization, objectives are conflicting, i.e., one objective cannot be improved without degrading another one(s), thus trade-off solutions must be sought. A common approach to handle multiple objectives is to create a weighted (biased) linear combination of them.

The objective function used throughout this thesis will have a single optimization criterion and that criterion is time.

Chapter 3

Problem Formulation

Based on a specific application scenario, the general mission planning problem can have different realizations, which can be classified according to three main dimensions. These dimensions are the *Task Type*, the *Concurrency*, and *Task Dependency*, as shown in Figure 3.1. *Task Type* describes how many agents are necessary for the successful completion of a certain task (SR tasks vs. MR tasks). *Concurrency* is related to the ability of an agent to perform multiple tasks concurrently (ST robots vs. MT robots). Finally, *Task Dependency* defines if a task has a relation to any other task, either within the same agent's

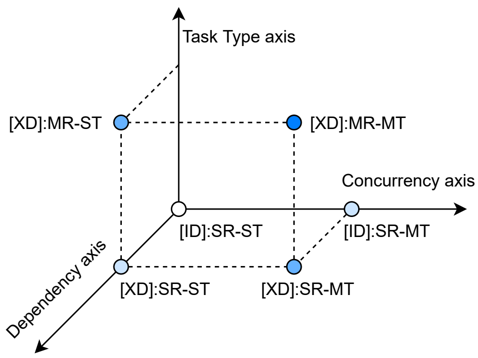

Figure 3.1: An illustration of three dimensions and 6 different problem configurations. Darker shades indicate more complex problem configurations.

schedule or across different agents' schedules (ID dependency vs. XD dependency). *Task Dependencies* can be synchronous [67] or precedence constraints (ordering). A more detailed description of these dimensions is given in Section 2.1.

By exploring these dimensions, 6 different problem configurations can be identified. These problem configurations are marked in Figure 3.1 with blue shaded circles. Darker shades represent more complex problems. The two missing vertices are problem configurations [ID]:MR-ST and [ID]:MR-MT, as MR tasks always impose certain dependencies over multiple robot schedules. Hence, we cannot have a problem configuration with ID and MR as they contradict each other. In addition to the presented dimensions, there is another dimension related to the *Allocation Type*, and it consists of IA and TA. In this thesis, only TA is considered, since mission planning consists of planning and scheduling, and scheduling of more than one task implies Time-Extended allocation of tasks.

A few examples of relevant problem configurations as real-world application scenarios are the following. Scheduling jobs for a factory production line can be seen as a [ID:SR-ST] problem. If tasks within a job are done on different machines, and completion of one task depends on the successful completion of the other task on another machine, the problem is defined as [XD:SR-ST]. In a case where some of the tasks of a job require more than one agent (machine) for its completion (e.g., one robot arm holds two metal parts, while another robot arm welds them), the problem is extended to [XD:MR-ST]. Furthermore, if one of the machines can do two tasks concurrently, the problem becomes [XD:MR-MT].

This thesis focuses on two problem configurations. The first one is [ID:SR-ST-TA] in papers B and C. The second one is [XD:SR-MT-TA] that is in the focus of paper D. All problem configurations in this work have the additional assumption that agents are heterogeneous.

3.1 [ID]:SR-ST-TA Problem Configuration

In a general sense, missions belonging to this problem category assume of a set of m heterogeneous agents $\mathbb{A} = \{a_1, \ldots, a_m\}$ and a set of n tasks $\mathbb{T} = \{t_1, \ldots, t_n\}$. Tasks are assumed to be atomic and non-preemptive at the mission planning level. Due to the heterogeneity among agents, regarding different physical capabilities, not all agents in $\mathbb{A}$ can perform all tasks in $\mathbb{T}$. In addition, the environment can prevent some agents from fulfilling certain tasks. For example, a surface vehicle cannot perform a task below the surface of the water, or an underwater vehicle cannot send data to the control center while being underwater. A set of tasks that an agent $i \in \mathbb{A}$ can perform can be denoted as $\mathbb{T}_i \subseteq \mathbb{T}$. Analogously, a set of agents that can perform task $j \in \mathbb{T}$ can be defined as $\mathbb{A}_j \subseteq \mathbb{A}$. In this work, it is assumed that all agents that can perform a task $i \in \mathbb{T}$ have equally good performance. Formally, the utility function U for a task i performed by an agent $j \in \mathbb{A}$ is defined as

$$U_{ij} = \begin{cases} 1, & \text{if } t_i \in \mathbb{T}_j, \\ 0, & \text{otherwise.} \end{cases}$$

However, in general case, agents may have different velocities and/or may consume a different amount of energy. For example, in the case of spatially distributed tasks, the overall performance estimate of two different agents over the same set of tasks might be different, since some agents can perform the same task set more efficiently – in terms of time or energy consumption – than others.

The mathematical formulation of [ID]:SR-ST-TA problem configuration can be found in Papers B and C [49, 68], and it is called Extended Colored Traveling Salesperson Problem (ECTSP). The formulation is given as an extension of the TSP, more specifically, CTSP, with the addition of PC, and multiple source and destination depots. Given that the problem is a variant of TSP, it is clear that the problem is, in its essence, a routing problem. Nevertheless, the mapping between ECTSP and MRTA is quite straightforward.

In MRTA, salespersons map to agents, while cities correspond to tasks. Every salesperson has a color set that maps into its equipment, e.g., camera, gripper, different sensor modalities. In the same manner, the color that is assigned to the city indicates the equipment the agent needs to have to be able to perform that task. Opposite to the TSP, city visits are not instantaneous, i.e., tasks have a predefined duration. The PCs are also part of the problem, however, the mapping is not necessary as they have the same name and meaning both in ECTSP and MRTA. It is important to stress out that the task interrelatedness is defined in the context of a single agent's schedule, i.e., there cannot be any task interrelatedness between tasks allocated to different agents. Following Korsah's definition [17], it can be concluded that ECTSP has only intra-schedule dependencies.

A graphical example of a mission is given in Fig. 3.2. Tasks are represented with colors blue, red, and green, with each color type having a special shape. To simplify, there is only one agent per source depot, so **X** marks both the

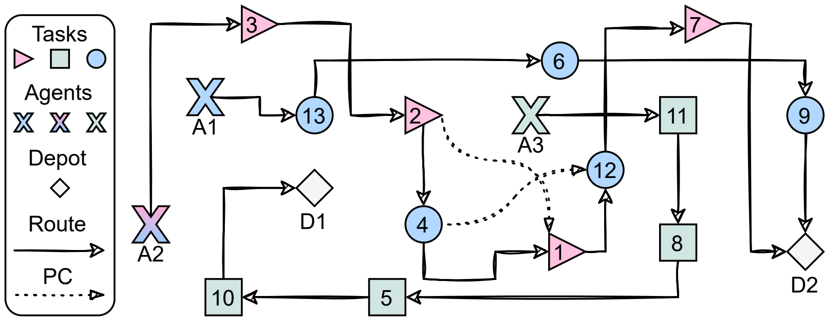

Figure 3.2: An illustration of an ECTSP plan.

starting location of an agent and a source depot. Agents have specific colors that map to given tasks. Agent two has two colors, red and blue, which means it is capable of doing two different types of tasks. Finally, PC are shown with a dashed line, $4 \prec 12$ and $2 \prec 1$. In this example the routes of the agents are $A1 = \{13, 6, 9, D2\}$, $A2 = \{3, 2, 4, 1, 12, 7, D2\}$, $A3 = \{11, 8, 5, 10, D1\}$. This example serves the purpose of providing intuition on the problem and solution of [ID]:SR-ST-TA problem configuration, since the problem in the Sect. 3.2 is built on top of the one described in this section.

3.2 [XD]:SR-MT-TA Problem Configuration

In order to address this problem configuration, it is necessary to have MT agents, i.e., agents that can perform multiple tasks in parallel. In recent years, robotic systems have become more powerful thanks to the adoption of novel computing platforms, enabling an increased level of parallelism, in terms of sensing, actuation, and computation. As a result, more complex missions can be achieved, at the cost of increased complexity for the optimization of the mission planning.

To utilize the full power of the MT approach, the distinction between virtual and physical tasks has been introduced. We can reason about physical tasks as tasks that are bound to a certain spatial location, e.g., moving an object, surveillance of an area, etc. In contrast, virtual tasks have no such constraints, i.e., they can be executed at any time of the mission, even in parallel with some other tasks, as long as other constraints are satisfied, e.g., precedence constraints. Having two different task types lead to multiple possible relations of these tasks, in particular, (i) relation between two or more physical tasks; (ii) relation between physical and virtual tasks; and (iii) relation between two or more virtual tasks.

In case (i), to be able to execute two or more physical tasks at the same time means that those tasks are at the same physical location. An example of this can be a dual-arm robot manipulating two objects at the same time. Although this case is certainly interesting, at the level of abstraction that is assumed in this thesis, concurrent physical tasks are seen as one monolithic physical task. The reasoning is that this monolithic task can be decomposed into necessary actions, in the lower level of abstraction, as actions are performed at the same location. On the other hand, cases (ii) and (iii) are more interesting from the perspective of multi-agent mission planning. In the case of mixed parallelism, only one of the tasks may have a spatial constraint (constraint related to a certain location), whereas the other tasks are not bound to the physical location of the agent. An example of this is the task of scanning an area and concurrently sending the data to the command center. The sending data task has no constraints on the location from where it has to be performed. A physical task may be executed in parallel with more than one virtual task. The number of virtual tasks that can run in parallel is limited with functional dependencies among the tasks, the contention of the required resources, or simply because the level of parallelism provided by the computing platform is not enough to support the amount of concurrent virtual tasks. Nevertheless, when parallelism can be achieved, it can lead to mission makespan reduction. In addition, it is also assumed that a virtual task can be performed during the transition between two physical locations.

We formulate the [XD]:SR-MT-TA problem configuration on top of the ECTSP formulation with three main distinctions. Firstly, there is a distinction between task types, i.e., we introduce virtual tasks (tasks without a physical location in the environment). Secondly, task parallelism is allowed between a physical task and virtual tasks, or only between virtual tasks. Lastly, instead of allowing only intra-schedule dependencies, both physical and virtual tasks can have cross-schedule dependencies. It can be reasoned about the described problem as a mixture of routing and scheduling problems. Where the amount of physical or virtual tasks in a mission determine if the problem is closer to a routing or scheduling problem. For example, a mission with more physical tasks is closer to a routing problem, while a mission with more virtual tasks can be seen as closer to a scheduling problem. Both routing and scheduling problems, except for a few trivial cases, are NP-hard. Consequently, [XD]:SR-MT-TA is also at least NP-hard. This means that the algorithm's performance exponentially decreases with the increase in the problem size. Moreover, the ratio between the two task types may affect the performance of the selected algorithm. As this is the mixture of routing and scheduling, the selected solvers are the ones commonly used for respective types of problems. The problem is tackled with both CPLEX and CP Optimizer. In addition, both ILP and CP formulation of the problem is given. CPLEX is commonly used to solve routing problems [69,70], while CP Optimizer, and constraint programming in general, are preferred choices when it comes to solving scheduling problems [71, 72].

An example of parallel task execution, within a single agent's schedule, is given in Figure 3.3. In this case, Tasks 1, 2, and 4 are virtual tasks, while Task 3 is a physical task. Task 0 represents the necessary time (transit) to reach a physical task from the previous location. Tasks 1 and 2 can be executed in parallel with Task 3, however, Task 1 cannot be run in parallel with Task 2, nor can any other combination of tasks. Task 4 has precedence constraint with Task 3, i.e., $T_3 \prec T_4$. Since Tasks 2 and 4 cannot be executed in parallel, nor can Tasks 3 and 4, Task 4 has to be scheduled to start when Task 2 ends. This in turn postpones the start of the second instance of Task 3, hence, instead of at time step τ_5 Task 3 starts at τ_6, even though the robot reached the second instance of Task 3 at time step τ_5. The purpose of this example is to show some of the possible relations between virtual and physical tasks in a single agent's schedule.

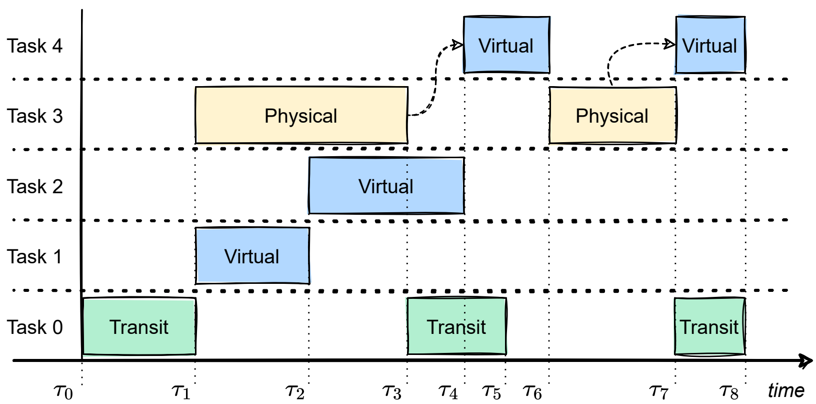

Figure 3.3: An example of a schedule of an agent with virtual and physical tasks and task parallelism.

3.3 Objective Function

The goal is not just to satisfy mission constraints, but to optimize an objective function as well. In this thesis, the optimization criterion is time. Time is incorporated in the objective function through the mission duration, i.e., a makespan of the mission that is being minimized. Mission duration (makespan) is defined as the time passed from when the first agent leaves a source depot until the last agent reaches a destination depot. In this sense, a minMax objective function is commonly used, as it minimizes the maximum makespan over all the agents. However, this objective function is not suitable for problems where tasks do not have the same duration, more specifically in scenarios where one task may dominate other tasks. This means that one task can take longer to finish than all other tasks combined, thus, in that case, other agents' plans will not get optimized at all. On the other hand, if the objective is to minimize the sum of all agents' plans, this can lead to one agent doing all the tasks, while the rest are unused. To circumvent this issue, we proposed a different objective function, which is a linear combination of the weighted sum of all tasks added to the weighted minimum of the longest makespan over all the agents. More details can be found in Paper B [68].

3.4 General Assumptions

Tasks are executed by physical agents (robots) within an environment $\mathcal{E}$. Specific characteristics of the environment $\mathcal{E}$ are not taken into consideration during the mission planning process. It is assumed that there are no obstacles in environment $\mathcal{E}$, i.e., all the tasks are accessible by straight path from any other task. Communication limitations are out of the scope of this work, and we assume that robots have infinite range, and that communication is instantaneous, which means that in the same moment a possible event happens, the planner gets that information. All the states are fully observable, which means there are no uncertainties about task execution or a location of a robot during the mission execution. The physical properties of the robots are ignored, except for its velocity. This means that every robot is modeled as a mathematical point moving freely in the environment and limited only by its velocity, which is constant. No partial task execution is possible, robots either finish the task successfully or in case they fail (robot breakdown) the task is repeated by another robot from the beginning. Tasks properties are known *a priori*, and they are not changeable during the execution of a mission. These properties include (i) task duration; (ii) task location; (iii) required equipment; and (iv) precedence relatedness to other tasks. Additionally, tasks can only start at (i) time *zero*, (ii) the beginning of some other task, or (iii) the end of some other task. In this context, transiting between two tasks is also considered as a task, i.e., a task can start at the end of transit tasks, as well.

Finally, to sum up, the environment $\mathcal{E}$ is fully observable and accessible, only agents can make changes in the environment, and the communication among robots/planner is perfect. Robots have constant velocity and no other physical property. Task properties are known before the mission, and they do not change during the mission execution.

The aforementioned assumptions and constraints lay down the basis for the work done in this thesis, which focuses on extending this basic problem formulation to encompass other constraints found in real-world application scenarios. Although the presented work can be seen as domain-independent, the predominant part of this thesis deals with robotic systems. Moreover, this thesis tackles High-Level planning of different robotic missions, however, some parts of the planning problem (path planning, motion planning, communication, obstacle avoidance, etc.) are out of the scope of this work. In order to shed more light on the position of this work in the robotics context and the position of the addressed problem in the abstraction hierarchy, a diagram of different levels of abstractions in robotic missions is provided in Fig. 3.4. As it is shown, the mission planning is a part of the High-Level planning, which receives the mission as an input and outputs sets of tasks allocated to robots. This is the

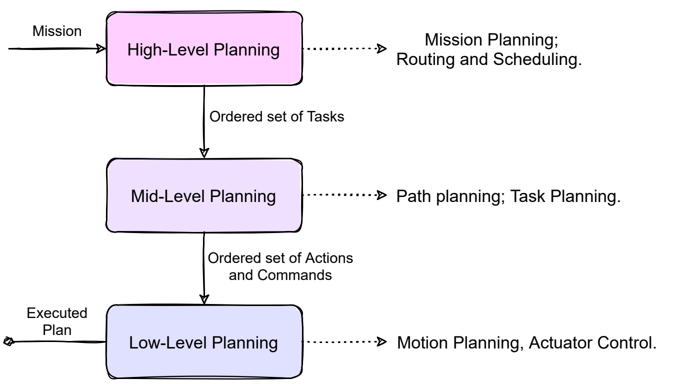

Figure 3.4: Different levels of abstraction of planning in robotic missions.

input for the Mid-Level planning, which handles the path planning including the environmental constraints, and task planning and decomposition into simple actions and commands that the robot can understand and execute. Finally, Low-Level planning is performed, which is usually done on the robot itself. The robot takes action by action from the Mid-Level planning and executes them. When they are all executed, the mission is complete.

This chapter offered an insight into the basis of problems this thesis aims to address. On top of the basic mission planning definition and MRTA taxonomy, additional problem dimensions are added in order to allow more complex problems to be expressed. These dimensions include concurrency, dependency, and task type. In this thesis, such dimensions and problem configurations are explored and addressed separately, in the attempt of identifying commonalities that can be exploited to provide a general approach to tackle the mission planning problem. Another aim of this thesis is directed towards the systematization of the MRTA taxonomy by providing a solution for stating the mission's constraints and requirements in a more structured manner. A detailed and exhaustive survey of the MRTA taxonomy was performed to identify and classify the aforementioned problem configurations. In addition, it also leads to the identification of two new research dimensions, i.e., *environment* and *mission*, which will allow more complex missions to be expressed. Furthermore, two problem configurations are formally addressed with mathematical problem formulation and their models implemented in various solver solutions. Obtained results were compared in order to understand the usability of proposed solution approaches.

Chapter 4

Research Goals

In this chapter, the overall research problem, with specific research goals, will be defined based on the state-of-the-art. The overall research goal will be decomposed into three smaller research goals, and they will be mapped to the papers addressing them.

Multi-agent mission planning can be interpreted very broadly, i.e., many different problems may be regarded as missions. Therefore, a taxonomy that can represent different problem dimensions in a structured and systematic manner is desired. Based on the different constraint types and their mutual dependencies, different problem configurations can be identified. These problem configurations have different key aspects and complexity levels, thus it is not possible to provide a unified solution to all of the identified problems. One part of this thesis aims at identifying constraints and requirements that are relevant to describe real-world mission planning problems on a high level of abstraction such that they can be applied to different domains. This does not mean that the aim is defining a single model to unify all possible problem configurations, but rather to recognize key aspects that multi-agent missions have in common. The types of the missions covered by the model are driven by real-world applications, involving very different technologies, such as different communication constraints, autonomy levels, and capabilities of the involved agents, just to mention a few. The second part of this thesis research problem is to design an efficient way of solving complex missions while addressing the issues of scalability and efficiency.

Figure 4.1 is provided in order to better show where these problem configurations fit in the overall picture of MRTA. Problem configurations are depicted

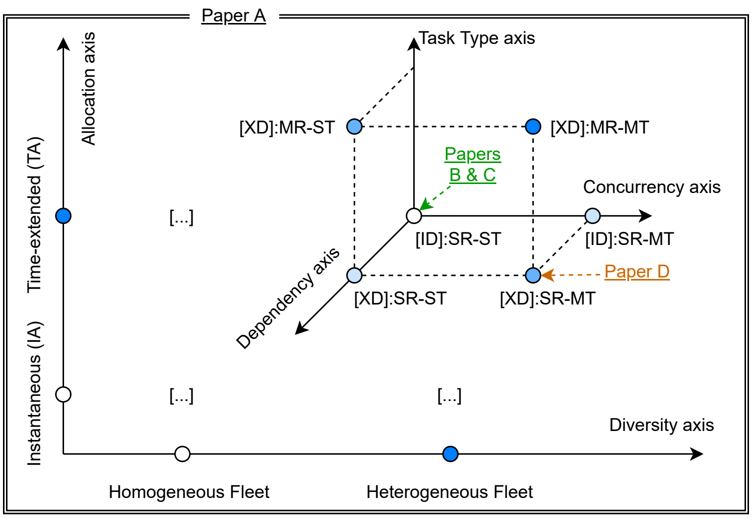

Figure 4.1: An illustration of selected MRTA problem configurations with five different dimensions.

as blue-shaded circles. The mapping of the papers A – D, included in this thesis, to problem configurations is depicted as well. The figure shows some of the other problem configurations, not covered in this thesis, and their relation to the research goals presented in this section.

In order to group the aforementioned problems, the overall Research Goal (RG) of this thesis can be summarized as follows:

> **Overall RG:** ***To formulate models that capture key aspects of multi-agent missions and develop effective solutions for the identified high-level mission planning problems.***

Moreover, this overall RG can be further decomposed into three more specific research goals that will now be explained in more detail.

RG1: Provide a taxonomy model for multi-agent mission problems that allows systematic and structured addition of new dimensions.

RG1 aims to provide a formal taxonomy model that incorporates all of the previously defined dimensions in a non-ambiguous way. This has the advantage of preventing the reintroduction of already existing concepts. Moreover, extending such taxonomy with additional dimensions, requires a global vision of the MRTA problems, to avoid the introduction of redundant dimensions that can be reduced to already existing ones. In addition, the goal is to be able to add new research axes, not covered in MRTA and MRTA-related taxonomies, thus allowing for more complex problem configuration (missions) to be expressed using the proposed taxonomy.

RG2: Give a formal problem definition and solution of a [ID:SR-ST-TA] with the addition of precedence constraints for a heterogeneous fleet of agents.

The outcome of addressing RG2 should be a formal problem formulation of multi-agent mission planning problems expressed as MILP problems. Having a well-defined problem formulation helps to focus on the solution of the problem. Hence, the second part of this research goal is solving the aforementioned problem and comprehensive analysis of the gathered results.

RG3: Provide a problem formulation and solution of a [XD:SR-MT-TA] with the addition of precedence constraints for a heterogeneous fleet of agents.

RG3 targets providing formal formulation to task parallelism in multi-agent mission planning problems. As the problem addressed is a mixture of routing and scheduling problems, the goal is to provide both the ILP and CP formulation. In addition, both formulations will be implemented in commercially available software and their efficiency and solution quality will be compared.

The mapping of the aforementioned research goals into published and submitted publications, that are included in the thesis, is shown in Table 4.1. Paper A addresses the RG1 with the additional goal of providing a background for

Table 4.1: The mapping of the research goals to the included publications.

	Paper A	**Paper B**	**Paper C**	**Paper D**
RG1	✓			
RG2		✓	✓	
RG3				✓

the problem formulation in RG2 and RG3. Papers B and C are mutually connected, and one is the continuation of the other. In both papers, the problem from RG2 is addressed but in different ways. Paper B is more focused on providing the original formulation and a possible solution, while Paper C is about the comparison between the meta-heuristic solver and MILP solver. Paper D addresses problem formulation defined in RG3 and focuses on the task parallelism in multi-agent mission planning.

Chapter 5

Research Process and Methodology

This chapter will present an overview of the research process and methods used to achieve the research goals. The research methodology helps to solve research problems systematically by using an assortment of widely accepted scientific methods and rules [73]. The main part of the research methodology is the research process. The research process used in this thesis is depicted in Figure 5.1.

The critical analysis of both state-of-the-art in theory and practice was conducted to formulate research goals and objectives. In particular, the literature

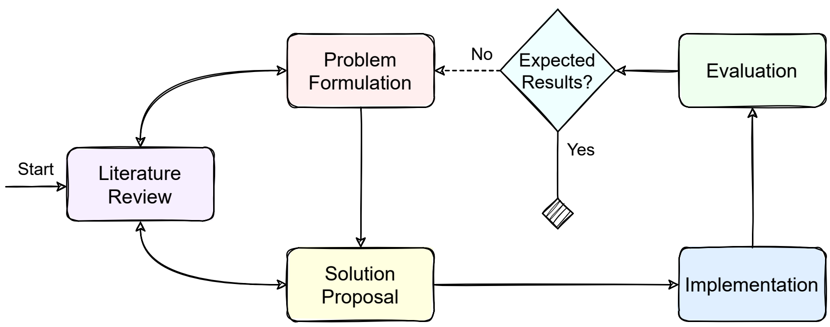

Figure 5.1: The main steps of the research process.

review helped with the understanding of how and if the desired topic has been addressed by other researchers, how it compares to similar notions, and where there are gaps that allow for scientific contribution. The rest of the research process is done repetitively, starting from the problem formulation. It was not only enough to formulate the research problem to cover the gap found in the literature review. The problem had to be relevant from the standpoint of the state of practice. This was ensured through collaboration with industrial partners in ECSEL JU [1], [2] projects. In addition, through this collaboration, the evaluation of the proposed solution in a real-world environment is done. Therefore, the proposed theoretical solution to the identified problem has to be implemented in order to be evaluated in practice. After the evaluation step, it is decided whether the repetitive approach should stop (evaluation showed desired results) or continue if the proposed solution did not satisfy set research goals. The research process is described in more detail in the next section.

5.1 Research Process

The main objective of the proposed research is to define and evaluate new methods, techniques, and theoretical foundations in the context of multi-agent mission planning, considering the research goals in Section 4. A constructive research [74, 75] is a type of research that combines the design and development of the solutions, rather than discovery. A constructive research process consists of the following steps.

After the initial literature review, the first step is problem formulation. The problem formulation describes the problem that is being solved and its relevance from both an academic and practical point of view. In addition, in this step, the current state-of-the-art with regard to the given problem needs to be addressed. In this thesis, the problem that is being addressed arose from the practical perspective in the first place, i.e., there was a need for a multi-agent mission planning solution in a multi-agent underwater scenario to reduce cost and safety risks, and increase efficiency. However, the solution to this problem is majorly shaped by the state-of-the-art, and that is the next step.

Now that a problem has been formulated, and its significance established, it is important to identify what existing knowledge can be utilized to solve the problem. If the problem is novel, it means that there is a void in the knowledge that needs to be filled with a theoretical solution. In our case, we first formulate

[1] http://www.swarms.eu

[2] https://www.ecsel.eu/projects/afarcloud

and model the problem at hand based on the found related problems. Secondly, possible solutions to the problem are identified, which need to be implemented and evaluated for their effectiveness. This process can reveal new voids in knowledge, as was the case in this thesis, where the lack of systematic multi-agent taxonomy was identified and addressed.

Both of these steps play a major role in the identification of research problems and the definition of research goals. Nevertheless, these goals may be changed and revised based on the results of the next two steps.

The next step is the implementation of the proposed solution, i.e., the construction of a practical solution out of theoretical knowledge. In this thesis, this step mainly refers to the development of a solver for computing a solution to the problem. More specifically, the problem is first formalized as an optimization problem, as MILP or CP models of identified configurations, and then solvers are implemented. Finally, the solvers are integrated into the planner of a mission management tool. As the identified problems, in their general formulation, are typically NP-hard, the implementation of solvers is done in C++ programming language, favoring the performance of the implemented solutions with respect to other programming languages, such as Java or Python. CPLEX and CP optimizer have been chosen as the solvers for MILP and CP models, respectively, as they are commonly used for verification and benchmarking of different models, and they implement state-of-the-art algorithms for the solution of such kinds of optimization problems. Other solvers are also available (e.g., Gurobi[3], SCIP[4] Xpress[5]), however a general comparison of different MILP/CP solvers is beyond the scope of this work. Moreover, this thesis develops different GAs to compute solutions to some of the formalized problems, as an alternative to the (exact) solutions provided by the state-of-the-art solvers. Such GAs explore the possibility of computing sub-optimal, yet feasible, solutions in shorter time, opening the opportunity to be used for re-planning purposes.

In the fourth and final step, the evaluation of the implemented solution is conducted. In the evaluation process, it is first checked if the solver can provide a solution to the given problem. Secondly, the proposed solution is compared over a benchmark to other solutions from the literature, if such solutions exist, and among implemented solutions. The focus of the evaluation is twofold (i) verify that the proposed model is correct; and (ii) comprehensive analysis of the performance, in terms of the solution quality and scalability, of the imple-

[3] http://www.gurobi.com/
[4] https://www.scipopt.org/
[5] https://www.fico.com/fico-xpress-optimization/docs/latest/overview.html

mented solutions. If the problem solution solves the problem within the set research goals, the work is done, otherwise, the research process cycle continues until such condition is met.

It is worth mentioning that the benchmarks over which the solvers are evaluated are inspired by, or come from, real-world scenarios. However, the quality of the generated plans is not assessed in terms of the actuation of the plan by the multi-robot system, as this thesis focuses only on high-level planning. The high-level plans are generated under the assumptions described in Section 3.4, but the executed plan will generally deviate from the original plan due to existing non-idealities, e.g., the kinematic constraints of the robots, the presence of obstacles, potential external disturbances, etc. Such aspects are typically taken care of by the path planners (mid-level planning) and the motion controllers of the robot (low-level planning), and therefore are not considered in the evaluation of the proposed algorithms.

Chapter 6

Thesis Contributions

In this chapter, a compact overview of the contributions that address the research goals in Section 4 is given. This thesis consists of three contributions:

Contribution 1 (C1): This contribution is directed towards the systematization of the MRTA taxonomy by providing a solution for stating a given mission's constraints and requirements in a more structured manner. For this contribution, first, a survey of the existing taxonomies had been performed, which has led to the identification of the important dimensions of MRTA problem configurations, isolating ambiguities, and understanding differences and similarities.

The final result is the Task Allocation in Multi-Robot System Entity-Relationship (TAMER) model that aims at covering the relevant aspects of the multi-agent mission planning problems, by adopting Entity Relationship (ER) paradigm [76] of representing knowledge and modeling relations between attributes and entities. As the name suggests, the relevant dimensions of MRTA problems are modeled through entities, and the relationships between them, according to the ER model. Four main entities have been proposed: *Robot*, *Task*, *Environment*, *Mission* and appropriate relationships that connect these entities. More details in Paper A [77].

The goal of TAMER is to provide a unified view of the existing taxonomies. The very structure of the ER model helps to avoid unnecessary overlapping of dimensions and provides a deeper understanding of how newly proposed dimensions fit within the big picture. Newly proposed aspects may not only overlap, but they may be coupled with existing ones. TAMER helps simplify the process of adding new dimensions, by providing a more formal approach to tame the complexity of the MRTA taxonomy problem.

It is not only that TAMER unifies dimensions of previous taxonomies, but it also brings two additional research dimensions to light: Multi-Mission problems and Multi-Environment problems. These aspects have not been in the focus of previous taxonomies and in general have not been extensively explored. Nevertheless, they might be of crucial importance in representing missions with a shared environment, robots, tasks, or resources. The Multi-Mission aspect provides an interesting perspective when several missions share some of the robots or some of the tasks, and the MRTA problem needs to take into account this additional constraint. On the other hand, the Multi-Environment aspect allows more complex problem configurations to be expressed with the TAMER model.

Contribution 2 (C2): This contribution can be decomposed into two sub contributions.

C2.1 The first goal is to encapsulate the main attributes of multi-agent missions on a high level of abstraction such that the given problem formulation can be regarded as domain-independent. The proposed model can utilize a group of heterogeneous agents being allocated to perform a variety of different tasks that require certain capabilities, on the agent side, to be performed. Moreover, there might be interrelatedness between tasks, i.e., a certain order among some tasks may need to be maintained. Thus, besides allocating tasks to agents, a good solution should include an optimal choice of a set of agents to perform the mission, judging on the agents' source depots, capabilities, and the whereabouts of destination depots. This problem can be categorized, by using previous taxonomies (Section 2.1), as [ID]:ST-SR-TA with PC, where agents have different capabilities and tasks have different capability requirements. In addition, agents may start and end their tours in different depots. The proposed model is expressed as a novel variation of a classical TSP that we named ECTSP, and it was cast as a MILP problem. We derived two MILP formulations, one based on the 2CFN model and the other one based on the RMTZ model. The main difference between these two formulations is in the way precedence constraints are expressed and modeled. The two models are both implemented in the state-of-the-art MILP solver CPLEX and results are published in Papers B and C. In addition, a comparison with the meta-heuristic approach, defined in C2.2, is given.

Regarding the hardness of the problem, in this case, we start from the routing problem, i.e., TSP, which is proved to be NP-hard. Since TSP is a special case of ECTSP, i.e., the latter can be reduced to the former. We can thus conclude that ECTSP is at least NP-hard. The scalability poses one of the main issues when dealing with this kind of problem. We tried to circumvent this issue by using a GA-based solver described in paragraph C2.2.

C2.2 This contribution focuses on solving the problem formulated in RG2. Since we have established that the problem described in RG1 is NP-hard, a meta-heuristic approach, specifically, GA is used to try and solve this problem more efficiently. The solver is called Genetic Mission Planner (GMP) and it follows the well-established model of the GA, with specifically tailored variation operators and a newly introduced Precedence Constraint Reparation (PCR) algorithm. Chromosomes consist of two arrays of integer identifiers. They are used to represent different types of genes, namely task, agent, parameter, and dummy genes.

The variation operators that are used, are adapted to the problem at hand. The Edge Recombination Crossover (ERX) has shown the best results among other tested crossover operators. The underlying mechanism of preserving edges between nodes, i.e., tasks, from parents and passing them to the offspring is responsible for a good performance of ERX. The crossover operator works in combination with mutation operators. The mutation is the foundation of variability, as it leads to genetic diversity in the population. Four different mutation operators are developed, out of which two operate on task genes and the other two on agent genes. Task gene mutation consists of swapping genes and inserting genes mutation operations. Agent genes mutate in two different ways, by adding agent genes to the chromosome (growth mutation) or by removing agent genes from the chromosome (shrink mutation).

Precedence constraints violations are repaired once after the creation of the initial population, and every time after the crossover and mutation are done since PCs are not taken into account during these processes. The PCR algorithm works by identifying the conflicts in the chromosomes and repairing them based on the type of detected conflict.

The local refinement is done by a Greedy Search (GS) algorithm. GS was applied after every generation. While the GA performs allocation of cities to salespersons, the GS reorders cities within the salesperson's plan based on the nearest neighbor heuristic. In this approach, if the newly produced candidate solution is better than the original one, it is inserted into the population, otherwise, it is discarded.

The final part of this contribution is the objective function that is specifically tailored for multi-agent mission planning scenarios where tasks have different durations. The objective function is formulated as the sum of two parts.

The first part is the maximum makespan of an agent over all the agents. The second part is a weighted sum of all makespans. The advantage of having an objective function formulated in this way is discussed in detail in Paper B [68].

Contribution 3 (C3): In this contribution, we address the multi-agent mission planning with parallel task execution. The first part of the contribution is the distinction between virtual and physical tasks. Physical tasks are defined as a task that has spatial constraints, i.e., that have to be executed at a specific location in the environment. Virtual tasks have no such constraints. Their execution is only limited by task dependencies and the computational power of the system. Virtual tasks can be executed in parallel with other tasks, both physical and virtual. They also can be executed solo or while transiting between two physical locations. Allowing for parallel task execution may reduce the total makespan of a mission. The upside is that with this distinction more complex missions can be described, the downside is that having parallel tasks increases the optimization complexity. These days, with the increase in the power of computing platforms, it is quite possible and realistic to utilize parallel task execution. Nevertheless, in the robotics domain, this particular problem configuration remains neglected, as there is very little work done that addresses this type of problem. We believe that the first step, in introducing this problem to the scientific community, is to provide a formal problem formulation. And that is the second part of this contribution.

By defining the distinction between physical and virtual tasks, we set the basis for a formal problem definition of multi-agent mission planning with parallel task execution. The formulation is built on top of the previously defined problem in RG2 that has no parallel task execution. By introducing parallelism, this problem becomes a mixture of routing and scheduling problems. Hence, in addition to the ILP formulation that is implemented and verified in CPLEX, a CP formulation has also been provided, since CP has had a noticeable amount of success in solving scheduling problems. The models are validated on the set of benchmarks with 10 test instances and different mission settings with the goal of exploiting the potential task parallelism of the agents involved while minimizing the makespan of the mission.

The last part of this contribution is a comprehensive performance analysis of both CPLEX and CP solvers, which explores their scalability and solution quality on a given multi-agent mission planning problem with parallel task execution, both in terms of initial plan creation and re-planning.

The mapping of the aforementioned thesis contribution to published and

Table 6.1: Mapping of the thesis contributions to the different included publications.

	Paper A	Paper B	Paper C	Paper D
C1	✓			
C2		✓	✓	
C3				✓

submitted publications, that are included in the thesis, is shown in Table 6.1. Paper A is focused on the first contribution of this thesis (C1). Papers B and C address the same type of problem; however, contributions from the papers are different. Both papers present a MILP formulation of the same problem (ECTSP). However, MILP formulations are different, and they are being evaluated in paper C in different contexts. Paper B gives a detailed overview of the GA-based solver that is further extended in paper C. Also, in paper B it is discussed and explained why the proposed objective function is used. Paper C makes a comparison between the improved GA solver, updated with local search, and CPLEX implementation of ECTSP. Paper C can be seen as the continuation of paper B. Finally, C3 maps to Paper D.

Chapter 7

Overview of the Included Papers

Included papers are not presented in the chronological order, but rather contextual. Four papers are included in the thesis, referred to as paper *A–D*.

Paper A: *TAMER: Task Allocation in Multi-robot Systems Through an Entity-Relationship Model*

Abstract. Multi-robot task allocation (MRTA) problems have been studied extensively in the past decades. As a result, several classifications have been proposed in the literature targeting different aspects of MRTA, with often a few commonalities between them. The goal of this paper is twofold. First, a comprehensive overview of early work on existing MRTA taxonomies is provided, focusing on their differences and similarities. Second, the MRTA problem is modeled using an Entity-Relationship (ER) conceptual formalism to provide a structured representation of the most relevant aspects, including the ones proposed within previous taxonomies. Such representation has the advantage of (i) representing MRTA problems in a systematic way, (ii) providing a formalism that can be easily transformed into a software infrastructure, and (iii) setting the baseline for the definition of knowledge bases, that can be used for automated reasoning in MRTA problems.

Authors. **Branko Miloradović**, Mirgita Frasheri, Baran Çürüklü, Mikael Ekström, and Alessandro V. Papadopoulos.

Status. Published at the 22nd International Conference on Principles and Practice of Multi-Agent Systems (PRIMA'19).

Contributions. The work done on this paper is equally split between Mirgita Frasheri and I. My contribution to the paper is related to topics regarding task allocation and high-level view of MRTA problems, while Mirgita Frasheri contributed to agent's architecture and low-level side of MRTA problems. The other co-authors contributed by discussions and reviewing the paper.

Paper B: *A Genetic Algorithm Approach to Multi-Agent Mission Planning Problems*[†]

Abstract. Multi-Agent Systems (MASs) have received great attention from scholars and engineers in different domains, including computer science and robotics. MASs try to solve complex and challenging problems (e.g., a mission) by dividing them into smaller problem instances (e.g., tasks) that are allocated to the individual autonomous entities (e.g., agents). By fulfilling their individual goals, they lead to the solution to the overall mission. A mission typically involves a large number of agents and tasks, as well as additional constraints, e.g., coming from the required equipment for completing a given task. Addressing such a problem can be extremely complicated for the human operator, and several automated approaches fall short of scalability.

This paper proposes a genetic algorithm for the automation of multi-agent mission planning. In particular, the contributions of this paper are threefold. First, the mission planning problem is cast into an Extended Colored Traveling Salesperson Problem (ECTSP), formulated as a mixed-integer linear programming problem. Second, a precedence constraint reparation algorithm to allow the usage of common variation operators for ECTSP is developed. Finally, a new objective function minimizing the mission makespan for multi-agent mission planning problems is proposed.

[†]This article is an extended version of the following conference paper: *Extended Colored Traveling Salesperson for Modeling Multi-Agent Mission Planning Problems*, Branko Miloradović, Baran Cürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. In Proceedings of the 8th International Conference on Operations Research and Enterprise Systems (Vol. 1, pp. 237-244).

Authors. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro V. Papadopoulos.

Status. Published in: Parlier G., Liberatore F., Demange M. (eds) Operations Research and Enterprise Systems. ICORES 2019. Communications in Computer and Information Science, vol 1162. Springer, Cham.

Contributions. I was the main driver of the work. I did the implementation and wrote the paper. Baran Cürüklü was involved in the design of the Generic Algorithm and use case scenarios. The ECTSP problem formalization was carried out in close collaboration with Alessandro V. Papadopoulos. All co-authors contributed by discussions, feedback, and reviewing the paper.

Paper C: *GMP: A Genetic Mission Planner for Heterogeneous Multi-Robot System Applications*

Abstract. The use of Multi-Agent Systems (MASs) in real-world applications keeps increasing, and diffuses into new domains thanks to technological advances, increased acceptance, and demanding productivity requirements. Being able to automate the generation of mission plans for MASs is critical for managing complex missions in realistic settings. In addition, finding the right level of abstraction to represent any generic MAS mission is important for being able to provide general solution to the automated planning problem. In this paper, we show how a mission for heterogeneous MASs can be cast as an extension of the Travel Salesperson Problem (TSP), and we propose a Mixed-Integer Linear Programming formulation. In order to solve this problem, a Genetic Mission Planner (GMP), with a local plan refinement algorithm, is proposed. Additionally, comparative evaluation of CPLEX and GMP is presented in terms of timing and optimality of the obtained solutions. The algorithms are benchmarked on a proposed set of different problem instances. The results show that, in presence of timing constraints, GMP outperforms CPLEX in the majority of test instances.

Authors. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro V. Papadopoulos.

Status. Published in IEEE Transactions on Cybernetics, May 2021. doi: 10.1109/TCYB.2021.3070913.

Contributions. I was the main driver of the work. I did the implementation and wrote the paper. The problem formalization was carried out in close collaboration with Alessandro V. Papadopoulos. Baran Cürüklü contributed to the GA design. All co-authors contributed by discussions, feedback, and by reviewing the paper.

Paper D: *Optimizing Parallel Task Execution for Multi-Agent Mission Planning*†

Abstract. Multi-Agent Systems have received a tremendous amount of attention in many areas of research and industry, especially in robotics and computer science. With the increased number of agents in missions, the problem of allocation of tasks to agents arose, and it is one of the most fundamental classes of problems in robotics, formally known as the Multi-Robot Task Allocation (MRTA) problem. MRTA encapsulates numerous problem dimensions, and it aims at providing formulations and solutions to various problem configurations, i.e., complex multi-robot missions.

One dimension of the MRTA problem has not caught much of the research attention. In particular, problem configurations including Multi-Task (MT) robots have been neglected. However, the increase in computational power, in robotic systems, has allowed the utilization of parallel task execution. This in turn had the benefit of allowing the creation of more complex robotic missions; however, it came at the cost of increased problem complexity.

To overcome the aforementioned problem, we introduce the distinction between physical and virtual tasks and their mutual relationship in terms of parallel task execution. To fill in the gap in the literature related to MT robot problem configurations, we provide a formalization of the mission planning problem, using MT robots, in the form of Integer Linear Programming and Constraint Programming (CP), to minimize the mission makespan. The models are validated in CPLEX and CP Optimizer on the set of benchmarks. Moreover,

†This article is an extended version of the following conference paper: *Exploiting Parallelism in Multi-Task Robot Allocation Problems*. Branko Miloradović, Baran Cürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC 2021)

we provide a comprehensive performance analysis of both solvers, exploring their scalability and solution quality.

Authors. **Branko Miloradović**, Baran Çürüklü, Mikael Ekström, and Alessandro V. Papadopoulos.

Status. Submitted to the Journal of Intelligent & Robotic Systems on 29th of September 2021. Revised version submitted in December 2021.

Contributions. I was the main driver of the work. I did the implementation and wrote the paper. All co-authors contributed by discussions, feedback, and by reviewing the paper.

Other Papers, related to Ph.D. Thesis

The publications are listed in reverse chronological order.

1. *Exploiting Parallelism in Multi-Task Robot Allocation Problems*. Branko Miloradović, Baran Cürüklü, Mikael Ekström, and Alessandro Vittorio Papadopoulos. IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC 2021).

2. *Planning and supervising autonomous underwater vehicles through the mission management tool*. Afshin Ameri, Baran Cürüklü, Branko Miloradović, Mikael Ekström. IEEE Global Oceans 2020: Singapore – U.S. Gulf Coast (2020).

3. *Extended Colored Traveling Salesperson for Modeling Multi-Agent Mission Planning Problems*, Branko Miloradović, Baran Cürüklü, Mikael Ekström, and Alessandro V. Papadopoulos. In Proceedings of the 8th ICORES (Vol. 1, pp. 237-244), 2019.

4. *A Genetic Mission Planner for Solving Temporal Multi-Agent Problems with Concurrent Tasks*, Branko Miloradović, Baran Cürüklü, Mikael Ekström, 8^{th} International Conference on Swarm Intelligence (ICSI), 2017.

5. *A Genetic Planner for Mission Planning of Cooperative Agents in an Underwater Environment*, Branko Miloradović, Baran Cürüklü, Mikael Ekström. 9^{th} IEEE Symposium Series on Computational Intelligence (SSCI), 2016.

Chapter 8

Conclusion

The ambition of this thesis is to provide formal models that capture key aspects of generic multi-agent missions and develop effective solutions for identified high-level mission planning problems.

The first step consisted of surveying and classifying existing problem configurations, and providing a way for extending the initial classification. In other words, the first contribution provides a unified view of existing taxonomies and a way for a structured representation of different problem characteristics and constraints, thus allowing representation of more complex problem configurations to be expressed in a systematic manner. The main result of this contribution is the proposed TAMER model, which offers a general model that (i) includes existing dimensions from previous taxonomies presented by others, (ii) provides a unified approach to the MRTA taxonomies, and (iii) allows for the addition of new dimensions in a non-redundant manner. Similar to other taxonomies, TAMER does not aim at completeness, however, it utilizes the Entity-Relationship model, which requires a clear understanding of how newly proposed aspects relate to each other.

In the second step, we used the outcome of the first contribution to identify the most important aspects of real-world applications of multi-agent systems. This approach is driven by the European (ECSEL JU) project demands. Three main research axis have been isolated: Task Type, Concurrency, and Dependency axis. Two problem configurations are addressed in this thesis. The first multi-agent mission planning problem consists of allocating a set of tasks to a set of heterogeneous agents. Every task has its parameters, which are defined as (i) required capabilities from an agent, (ii) the physical location of the task, and (iii) possible relation with other tasks (precedence ordering constraints). Every agent starts from a source depot and ends its mission in a destination depot. Multiple agents can start from a single depot and finish at the same depot. This problem has been formally described, by introducing a novel TSP variation called ECTSP. Two different ECTSP MILP formulations are provided. In addition, we proposed a solution that had to fulfill several criteria to (i) provide a solution reasonably fast, (ii) have "any stop" option, (iii) satisfy imposed constraints, and (iv) optimize (in this case minimize) the given objective function. The need for obtaining a solution fast is not evident during the initial planning, however, in the re-planning phase it might be crucial for the success of the mission. Two approaches were tested, for a problem described in Section 3.1, meta-heuristic (GA) and exact (CPLEX) solver. Results show that in time-limited situations, for other than small problems, GA outperforms CPLEX. GA also has the option to be stopped anytime, and use the best solution found thus far.

Finally, we addressed the dimension of the MRTA problem that has been rather neglected by the scientific community. In particular, it is the problem formulation that includes MT robots. In order to formalize this problem, first, we had to define a distinction between virtual and physical tasks, and their mutual relationship in terms of parallel execution. In addition, the ILP and CP formulation have been provided and verified in the state-of-the-art commercial software, CPLEX and CP Optimizer, respectively. A comprehensive evaluation has been conducted in order to evaluate the efficiency and scalability of the used solvers. The benchmark has been done on a set of test instances with gradually increasing complexity. It can be concluded that except in the case of small problem instances, CP formulation used in CP Optimizer outperforms ILP formulation implemented in CPLEX. Both in terms of the time taken to find a feasible solution and the gap between the lower bound and found solution. This also makes CP more suitable for missions that may require mission re-planning.

Future Work. This thesis sets up the basis for further research on multi-agent mission planning, especially, with parallel task execution. However, we just scratched the surface with this work, and there are many paths that can be followed. The first one is the extension of [XD]:SR-MT-TA to [XD]:MR:MT:TA, i.e., to problem configuration that includes MR tasks in its definition. The second possible direction to follow is to dive deeper into the meta-heuristic for ECTSP, by trying different approaches and using a more sophisticated local search. Another possible direction is to try and provide a heuristic for solving larger problem instances for [XD]:SR-MT-TA problem configuration that can compete with solutions provided by CP Optimizer.

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II

Included Papers