Synthesis and Verification of Mission Plans for Multiple Autonomous Agents under Complex Road Conditions

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Mission planning for multi-agent autonomous systems aims to generate feasible and optimal mission plans that satisfy given requirements. In this article, we propose a tool-supported mission-planning methodology that combines (i) a path-planning algorithm for synthesizing path plans that are safe in environments with complex road conditions, and (ii) a task-scheduling method for synthesizing task plans that schedule the tasks in the right and fastest order, taking into account the planned paths. The task-scheduling method is based on model checking, which provides means of automatically generating task execution orders that satisfy the requirements and ensure the correctness and efficiency of the plans by construction. We implement our approach in a tool named MALTA, which offers a user-friendly GUI for configuring mission requirements, a module for path planning, an integration with the model checker UPPAAL, and functions for automatic generation of formal models, and parsing of the execution traces of models. Experiments with the tool demonstrate its applicability and performance in various configurations of an industrial case study of an autonomous quarry. We also show the adaptability of our tool by employing it in a special case of an industrial case study.

Additional Key Words and Phrases: mission-plan synthesis, autonomous agents, path planning, task scheduling, UPPAAL

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1 INTRODUCTION

Autonomous robotic systems are becoming common in our society. These systems can take different forms, e.g. vehicles used for transportation in a factory or in a construction site, mobile robots used for entertainment in our homes, or

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a mobile communication platform for the elderly. These robotic systems are associated with different requirements, and have various shapes and overall designs. Despite the differences, these systems share a common feature: the ability to function in an environment, with minimum human intervention, if any at all. This feature can be referred to as *autonomous operation*. However, the environment where these systems operate could include humans and other obstacles, hence it is varying. To realize the autonomy feature, the autonomous robotic systems must be able to perceive the environment, reason based on known facts, and act to meet the requirements associated with their goals (for the sake of brevity autonomous robotic agents are called “autonomous agents”, or simply “agents” [FG96] in the rest of the paper).

One key challenge of designing agents that move and operate in a confined environment is *mission planning* (a.k.a., mission plan synthesis), which includes *path planning* and *task scheduling*. A mission is a set of tasks to be completed in different positions in the environment with constraints, such as the prerequisites of the tasks. When obstacles are present in the environment, the ability to reach a destination without colliding with them is a problem that has been solved by existing path-planning algorithms, such as A* [Rab00] or rapidly-exploring random tree (RRT) [LaV98] algorithms. However, a real environment might impose complex restrictions to path planning, stemming from obstacles that are temporary, or from existing special areas, like crowded or desired areas. Consequently, the *path-planning* algorithm should provide means to calculate a path plan for an agent that chooses to wait, circumvent, or cross the respective areas, “wisely”. Furthermore, agents must visit different positions (a.k.a. *milestones*) in the environment as part of their tasks, e.g., within a quarry, autonomous wheel loaders visit stones piles to load stones. Being able to guarantee that agents carry out the right tasks at the right milestones is important for the overall success of a mission. Additionally, tasks can have complex and temporal constraints, for instance, autonomous wheel loaders must keep digging stones until trucks arrive, and then load the stones into the trucks before the latter transport the stones to crushers. Some applications require the agents to keep a certain level of productivity, e.g., autonomous trucks must transport all the stones to a crusher within a maximum time window of a few hours. Path-planning algorithms alone are not able to calculate *mission plans* that accomplish the tasks respecting such requirements. They must be combined with *task-scheduling* algorithms for synthesizing mission plans that ensure that the agents travel safely, that is, without any collision with static obstacles, and satisfy the requirements of tasks.

Task-scheduling algorithms aim to calculate an order of task execution to achieve the global goal, e.g., a pile of stones is dug and loaded, then transported to crushers, and then crushed into fractions. Based on the position of each agent, task scheduling assigns milestones and visiting orders to the agents, respectively, so that the agents can finish their mission within a given time window. A classic presentation of this problem is called the *job-shop* problem, which is described as follows:

“*Given a set of jobs and a set of machines, assume that: (i) Each machine can handle at most one job at a time, and (ii) Each job consists of a chain of operations, each of which needs to be processed during an uninterrupted time period of a given length on a given machine. The purpose is to find a schedule, that is, an allocation of the operations to time intervals on the machines, which has minimum length.*” [Len92]

Being an NP-hard problem, even a simple instance of the *job-shop* problem with very restrictive constraints remains difficult to solve [AAM+06]. Furthermore, the task schedules that we aim to compute must not only “have the minimum length”, that is, accomplish the tasks in the quickest way, but also satisfy the complex temporal requirements aforementioned. In a nutshell, in this paper, we address the following challenges:

(1) *Path planning*: considering an environment with various road conditions, such as static obstacles (e.g., forbidden areas and temporary obstacles), crowded areas, and desired/undesired areas, how to calculate a path that reaches the required milestone without a collision?
(2) *Task scheduling*: given a set of tasks and milestones where the tasks are supposed to be carried out, as well as a set of task execution constraints, how to synthesize a task-execution schedule that finishes tasks at their respective milestones and satisfies the task execution constraints?
(3) *Mission planning*: how to combine path planning with task scheduling and produce a time-optimal mission plan?
(4) *Automation*: given a mission-planning problem that matches the problem definition (Definition 1), how to easily configure the scenario of the problem and automatically calculate mission plans that combine the results of path planning and task scheduling?
(5) *Adaptability*: When the goal of the mission changes, such as new tasks appearing, after a mission plan is computed, how to leverage the existing result and quickly generate a new plan based on that.
(6) *Reusability*: when the mission-planning problem does not match the problem definition, how to maximize the reuse of models to solve the problem?
(7) *Visualization*: how to visualize mission plans for demonstration purpose?

As path planning and task scheduling influence each other, we need to develop a holistic solution to solve all the mentioned problems. To develop such a framework is non-trivial because our goal is not only generating mission plans but also providing a correctness guarantee on the results despite the complex environmental conditions, i.e., temporary obstacles, and preserving the possibility to adapt to changes via replanning. As far as we know, such a framework does not exist in academia or industry. In this paper, our main contribution is a methodology and tool support for addressing challenges (1) - (7) collectively, with an optimal result, that is, a correctness-guaranteed mission plan that not only meets various requirements but also reaches the goal in the fastest manner.

In particular, we adapt and tune up the DALI algorithm [CFL+15] for path planning, which takes into account both environmental constraints and user preferences (challenge (1)). We adapt a method called TAMAA (Timed-Automata based Mission planner for Autonomous Agents) [GES19] for task scheduling, which uses the well-known timed automata (TA) [AD94] formalism for modeling, and model checking in UPPAAL [HYP+06] for generating results with a correctness guarantee (challenge (2)). TA is a formalism suitable for modeling real-time systems, and model checking a TA model against a reachability property gives us a witness trace showing how the model satisfies the property. In particular, TAMAA generates a TA model of agents, automatically, including the movement TA and task execution TA, and checks the model to find the execution trace that reaches the goal state the fastest, while satisfying other requirements too. The contribution of the new version of TAMAA is the combination with DALI, assuming environments not tackled before. Previously, TAMAA used the result of path planning once, and generated a mission plan that considered only the permanently existing obstacles. In this article, complex road conditions such as temporary obstacles are considered as part of the environment. Hence, the initially correct mission plans may become invalid when temporary obstacles are activated. We design a validator in MALTA to check if the temporary mission plan meets the complex road conditions, and an iteration of execution between DALI and TAMAA until a correct mission plan is produced (challenge (3)). When new tasks or milestones appear after a mission plan is computed, we leverage the existing plan by encoding it in the new model that contains the new tasks or milestones, and then synthesize a new plan. As the new plan reuses the old plan, the synthesizing time is much reduced while the correctness guarantee is preserved (challenge (5)).

The design and implementation of our methodology, i.e., a toolset named *MALTA*, addresses challenges (4) - (7). MALTA has a client-server architecture, which integrates a graphical user interface (GUI) called *MMT* [ACME20] for mission management in the client, data exchange modules, and path-planning and task-scheduling algorithms in the server. In MMT, users can configure the environment, missions for the agents, and parameters of agents, like their speeds, respectively. The server side has two modules: the middleware and a back end. The middleware is responsible for obtaining the mission information from the GUI, running a path-planning algorithm, and generating agent models by using the path-planning results and mission information. Next, the middleware sends the agent models to the back end, where TAMAA runs for task scheduling. As our methodology is designed to cope with complex road conditions, such as temporary obstacles, MALTA possibly runs more than one round between the middleware and the back end until a time-optimal mission plan is produced.

If a mission plan exists, it is visualized by MALTA so that users can check the details of the mission plan, such as when and which agent starts to execute a certain task, and how temporary obstacles can affect the plan (challenge (7)). MALTA generates models and parses traces automatically, which eases the work of model and mission plan construction, especially for cases where the amount of agents or the size of the environment is large (challenge (4)). One can also modify the models according to one's own applications and still enjoy the facility of other automation provided by MALTA, such as trace parsing and information extraction from the map (challenge (6)). MALTA has been applied to an industrial use case of an autonomous quarry that exposes the challenges of synthesizing time-optimal mission plans for several autonomous vehicles with various requirements.

The rest of the paper is organized as follows. In Section 2, we introduce the industrial case study. Section 3 describes the preliminaries including timed automata and UPPAAL, and the DALI algorithm for path planning. Our methodology for solving the mission-planning problem for multiple agents is introduced in Section 4, followed by the description of the toolset in Section 5. In Section 6, we conduct experiments on a normal use case taken from the industrial case study, which matches our problem definition, for the evaluation of our methodology. Section 7 demonstrates how the method can be adapted to a special use case of our industrial case study. After the experiments and case studies, we discuss the scope of our methods and the possible use of MALTA in self-adaptive systems, in Section 8. In Section 9, we present and compare to related work, whereas in Section 10, we conclude the paper and outline some directions of future work.

2 AN INDUSTRIAL CASE STUDY: THE AUTONOMOUS QUARRY

In this section, we introduce an industrial use case of an autonomous quarry provided by VOLVO Construction Equipment (CE) in Sweden. This use case serves as a running example through Sections 2 to 6, and as concrete motivation for our research. In the quarry, there are several machines such as crushers that crush stones into certain sizes, wheel loaders that dig stones, and autonomous trucks that transport stones into crushers. In the use case we assume that the crushers are stationary and manually controlled. Other examples of static obstacles are holes over a certain size and temporarily forbidden areas. Wheel loaders are non-autonomous construction equipment that moves. They can become static obstacles, as can autonomous trucks, if they stop functioning for some reason. Our goal is to synthesize mission plans for the autonomous trucks that are not necessarily identical, which means that they can have different speed limits (e.g., 50 – 80 km/hour) and capability of transportation (e.g., 10 – 50 m^3). The vision is to deploy autonomous trucks that perform certain tasks, e.g., loading and refueling or charging, in order to fulfill the objectives defined by the operators of the quarry. The collection of such tasks together defines a *mission*, which we show how to synthesize automatically.

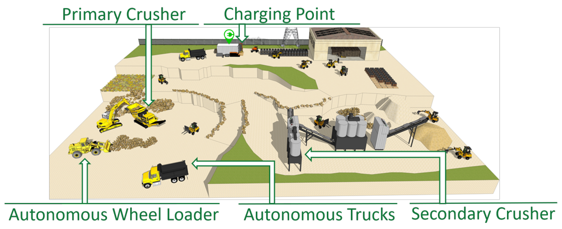


Fig. 1. An example of an autonomous quarry

A simple quarry is illustrated in Figure 1. In this example, the stones should be dug up and loaded into the autonomous trucks by wheel loaders. Then trucks transport the stones and unload them into a primary crusher first, then later to a secondary crusher that is the destination of the stones. The milestones are the positions where the tasks are carried out, e.g., at stone piles, crushers, and charging poles. A mission in this use case can be to dig, crush, and transport 1000 m^3 of stones in 24 hours.

The environment of a mission may have static obstacles, that is, areas that are impassable by the vehicles (buildings, sizable holes in the road, etc.), and different road conditions that may cause the vehicles to slow down, e.g. muddy or bumpy roads, or form a temporarily inaccessible area, such as during human intervention for maintenance, the corresponding area should not be crossed by any vehicle. Navigation must ensure collision-free transportation in the presence of all environmental constraints. The execution of tasks, e.g., loading, unloading, and charging, must be scheduled correctly and efficiently such that the trucks are guaranteed to accomplish the mission. In the autonomous quarry, all the planning work must be done automatically. Therefore, we need a tool-supported methodology that generates mission plans automatically, and ensures the completion of the mission while satisfying the requirements.

Based on this use case, we formulate several requirements. We group the requirements for *task scheduling* into the following categories:

- **Requirement Category I** (*milestone matching*): Tasks must be executed at the correct milestones, e.g., loading stones into primary crushers must be executed at a primary crusher.
- **Requirement Category II** (*task sequence*): Tasks must be executed in the right order, e.g., loading stones from stone piles must precede unloading stones into crushers.
- **Requirement Category III** (*timing*): Tasks can be executed multiple times and must be finished within a time frame in order to maintain a certain level of productivity, e.g., quarrying 1500m^3 stones per day.

Path planning takes care of finding safe and fast paths for agents between milestones in complex environments. We consider the following types of environmental abnormalities that should be taken into account by the path planner:

- **Environmental Abnormality I** (*obstacles*): permanent and temporary obstacles must be avoided by agents. Permanent obstacles are always present, while temporary ones appear at known time points and disappear later on. Within this work, we assume that all obstacles are static.
- **Environmental Abnormality II** (*road conditions*): muddy or bumpy roads cannot be passed at full speed. The planner must decide whether it is faster to take a detour than to travel on these roads at lower speed.
- **Environmental Abnormality III** (*soft constraints*): some abnormalities may not be as critical as the ones that influence safety. For example, if an area is undesirable for driving for some reasons, e.g., comfort, the planner

must attempt to avoid it if there exists an alternative path. Such constraints should be satisfied unless they prevent the satisfaction of critical requirements, such as safety. In the latter case, soft constraints can be ignored.

Note that path planning and task scheduling are not independent. Traveling time among milestones is needed by our task scheduler, while the presence of temporary obstacles can influence the starting time of travel. Therefore, path planning and task scheduling must work together to produce efficient mission plans. When new tasks or milestones appear after a mission plan is synthesized, we utilize the existing mission plan and synthesize a new plan based on it such that the computation time is reduced and the correctness guarantee is preserved.

Path following and collision avoidance among agents and moving obstacles are not the problems of mission-plan synthesis and thus are outside the scope of this paper. However, we have a two-layer framework that separates mission planning from path following and dynamic collision avoidance, and we refer the interested reader to our previous work [GMSL19] for these topics. In addition, the order of visiting milestones only depends on the constraints of a task sequence. For example, for a mission containing two tasks A and B that must be carried out at milestones a and b, respectively, the order of visiting the milestones only depends on the task sequence of A and B. In other words, if tasks A and B can be executed in any order, then visiting milestones a and b can be in any order too. To define the scope of the automation of our methodology, we informally define the mission-planning problem and its solution as follows. The set of (non-negative) real numbers is denoted as $\mathbb{R}$ ($\mathbb{R}_{\geq 0}$).

Definition 1 (Mission Planning). *A mission-planning problem is a tuple:*

$$\mathcal{P} =< \mathcal{E},\ Ab,\ \mathcal{M},\ \mathcal{T},\ f,\ Req >, \tag{1}$$

where $\mathcal{E} \subset \mathbb{R}^n$ is a confined environment, $n \in \{2, 3\}$, $Ab \subseteq \mathcal{E}$ is a set of areas that belong to one of the mentioned Environmental Abnormalities I, II, III, $\mathcal{M} \subset \mathcal{E}$ is a set of milestones, $\mathcal{T}$ is a set of tasks, $f : \mathcal{M} \to \mathcal{T}$ assigns each of the tasks to one or multiple milestones, and Req is a set of task requirements that matches the Requirement Categories I, II, III described previously.

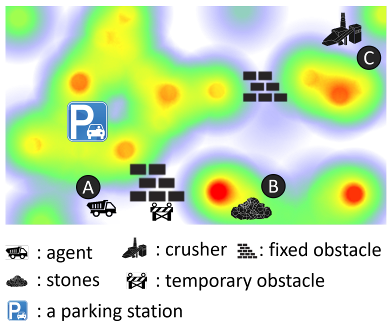
Figure 2(a) illustrates the mission-planning problem in a small quarry. The autonomous truck is an agent that originally locates at milestone A and the quarry is its confined working environment. Two stationary obstacles (brick walls in the figure) as well as the area next to the stationary obstacle at the bottom are temporarily blocked. These are examples of environmental abnormality I. Roads in bad condition are examples of environmental abnormality II, where the color scheme indicates speed reduction (white areas can be passed at full speed while red areas slow down the agents the most). A parking station is an area that is recommended to be avoided (environmental abnormality III). The agent's mission consists of two tasks: loading stones at milestone B, and delivering them to a crusher at milestone C (requirement categories II and III). To maintain a level of productivity, the autonomous truck is required to transport all the stones within 2 hours (requirement category III).

Assuming an agent is equipped with the ability to do two types of actions: moving to a milestone and executing a task, a solution to the mission-planning problem is informally defined as follows:

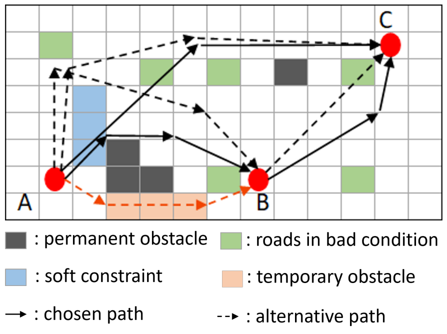
Definition 2 (Solution of Mission Planning). *Given a set of autonomous agents $\mathcal{V}$, a solution that enables the agents in $\mathcal{V}$ to solve a mission-planning problem $\mathcal{P} =< \mathcal{E},\ Ab,\ \mathcal{M},\ \mathcal{T},\ f,\ Req >$ is a tuple:*

$$plan =< schedule,\ path >, \tag{2}$$

where schedule is a set of pairs $(st,\ ft)$, $st,\ ft \in \mathbb{R}_{\geq 0}$ are the starting and finishing time of an agent's action, respectively, path is a set of sequences of points $p \in \mathcal{E}$ that the agents must tract in order to reach the milestones $m \in \mathcal{M}$. Let $E1$, $E2$,



(a) An example of the autonomous quarry



(b) A grid of the example

Fig. 2. An example of the autonomous quarry and a grid that discretizes the environment.

and $E3$ *be the sets of environment constraints belonging to Environmental Abnormalities I, II, and III, respectively, s.t.,* $Ab = E1 \cup E2 \cup E3$*, and* $E3' \subseteq E3$ *be the subset of* $E3$*, which does not contradict* $E1$ *and* $E2$*, that is, the paths that meet* $E3'$ *do not violate* $E1$ *and* $E2$*. Then, a plan must fulfill the following two conditions:*

- $\forall e \in E1 \cup E2 \cup E3'$, *path* $\models e$*, that is, the paths must meet environmental constraints in* $E1$*,* $E2$*, and* $E3'$*,*
- $\forall r \in Req$*, schedule* $\models r$*, that is, the task schedule must satisfy all the requirements in* Req*.*

Again, Figure 2(b) depicts path plans associated with a mission plan that finishes the truck's tasks. Solid arrows are the paths chosen by the mission plan and dotted arrows are the alternative paths that are considered by the path-planning algorithm but abandoned in the end. For instance, going through the blue areas clearly violates environmental abnormality III, i.e., a soft constraint. However, the overall performance of the mission plan satisfies the requirement of productivity, which has a higher priority, so the soft constraint is neglected, that is, $E3' = \emptyset$. In addition, there are two solid paths from A to C in Figure 2(b), meaning that the agent can choose to go to C directly or via B, depending on whether the task at B is finished or not.

In the rest of this paper, we introduce our methodology for automatically generating solutions for mission-planning problems, defined in Definitions 1 and 2, respectively. We also demonstrate the adaptability of the methodology to solve problems that do not match Definition 1, with a slight change of the models.

3 PRELIMINARIES

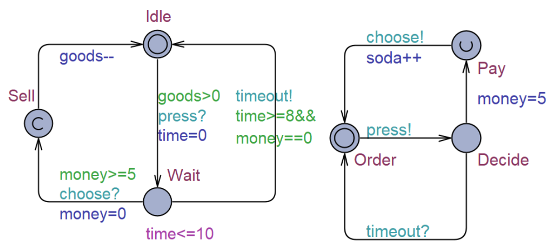
In this section, we introduce UPPAAL - the modeling, simulation, and verification tool that uses *Timed Automata* as the modeling formalism, which we apply for modeling agents' movement and task execution. We also briefly describe the path-planning algorithm DALI that we employ in MALTA. We denote the set of natural numbers as $\mathbb{N}$.

3.1 Timed Automata and UPPAAL

Definition 3. *A* Timed Automaton *(TA) [AD94] is a tuple:*

$$\mathcal{A} = < L, l_0, X, \Sigma, E, Inv >, \tag{3}$$

where L *is a finite set of locations,* l_0 *is the initial location,* X *is a finite set of non-negative real-valued clocks,* Σ *is a finite set of actions,* $E \subseteq L \times \mathcal{B}(X) \times \Sigma \times 2^X \times L$ *is a finite set of edges, where* $\mathcal{B}(X)$ *is the set of guards over* X*, that is, conjunctive*



(a) A UTA of a vending machine (b) A UTA of a customer

Fig. 3. An example of UTA modeling a customer ordering food from an impatient vending machine.

formulas of clock constraints of the form $x \bowtie n$ *or* $x - y \bowtie n$*, where* $x, y \in X$*,* $n \in \mathbb{N}$*,* $\bowtie \in \{<, \leq, =, \geq, >\}$*,* 2^X *is a set of clocks in* X*, which are reset, and* $Inv : L \rightarrow \mathcal{B}(X)$ *is a partial function assigning invariants to locations.* □

The semantics of a TA $\mathcal{A}$ is defined as a *timed transition system* over states (l, v), where l is a location and $v \in \mathbb{R}^X$ represents the valuation of the clocks in that state, with the initial state $s_0 = (l_0, v_0)$, where v_0 assigns all clocks in X to zero. There are two kinds of transitions:

(1) $(l, v) \xrightarrow{d} (l, v \oplus d)$, where $v \oplus d$ is the result obtained by incrementing all clocks of the automaton with the delay amount $d \in \mathbb{R}^+$ such that $v \oplus d \models Inv(l)$, and
(2) $(l, v) \xrightarrow{a} (l', v')$, corresponding to traversing an edge $l \xrightarrow{g,a,r} l'$ for which the guard g evaluates to *true* in the source state (l, v), $a \in \Sigma$ is an action, r is a set of clocks that are reset over the edge, and clock valuation v' of the target state (l', v') are obtained from v by resetting all clocks in r such that $v' \models Inv(l')$.

UPPAAL [HYP+06] is a state-of-the-art model checker for real-time systems. It supports modeling, simulation, and model checking, and uses an extension of TA with data variables, synchronization channels, urgent and committed locations, etc., as the modeling formalism, which we call UPPAAL TA (UTA). In UPPAAL, UTA can be composed in parallel as a *network* of UTA synchronized via *channels* (an edge decorated with channel $a!$ is synchronized with one decorated with $a?$ by handshake). An example of UPPAAL model is depicted in Figure 3, consisting of two automata: a customer ordering sodas and an impatient vending machine kicking its customers out of the system when they do not order quickly enough (i.e., 10 time units is the maximum waiting time). A UTA of the vending machine shown in Figure 3(a) has 3 locations named `Idle`, `Sell`, and `Wait`. *Edges* are the direct lines that connect *locations*, which can be decorated by *guards*, *channels*, and *updates*. A clock variable `time` measures the elapse of time and is used in the *invariants* on locations (e.g., `time<=10`) and in the *guards* on edges (e.g., `time>=8`). In UTA, locations can be labeled as *urgent*, denoted by encircled ∪, which forbids delaying in the locations (e.g., `Pay` of the customer TA in Figure 3(b)), or *committed*, denoted by encircled C, which not only forbids time from elapsing but also requires the network of UTA to transit the next edge from one of the committed locations. Such an example of committed locations is *location* `Sell` of the vendor UTA in Figure 3(b). UTA also extends TA with data variables (integer and Boolean variables), which can be updated via C-code functions or assignments on edges. For example, on the *edge* from *locations* `Decide` to `Pay` of the customer TA, an integer variable `money` is updated to 5, meaning that the customer has paid 5 Swedish crowns to the vending machine.

UPPAAL can verify properties formalized as queries in a subset of *Timed Computation Tree Logic* (TCTL) [BY03]. Given an atomic proposition p over the locations, clocks, and data variables of the UTA, the UPPAAL queries that are used in this paper are: (i) **Invariance**: $A[]\ p$ means that for all traces and all states in each trace, p is satisfied, (ii) **Reachability**: $E\text{<>}\ p$ means that there exists a trace where p is satisfied in at least one state of the trace, and (iii) **Time-bounded Reachability**: $E\text{<>}_{\leq T}\ p$ means that there exists a trace where p is satisfied in at least one state of the trace within T time units.

3.2 Devices for Assisted Living (DALI)

The DALI algorithm has been proposed previously in the literature [CFL+15] and is designed to provide motion planning in complex environments. The planner takes into account environmental constraints and user preferences.

DALI consists of two parts: long-term and short-term planners. The former one is performed prior to actual navigation and searches for paths accounting for area topology, user goals, and foreseen obstacles or problems along the way. During navigation unforeseen obstacles can appear, e.g. a group of people obstructs the path, their detection starts a short-term planner attempting to find a minimal deviation from the path that preserves all the constraints. Short-term planning is often required to operate on low resources and to provide a quick response, therefore long-term planning cannot be used for a quick search for path deviations.

In this paper, we are interested in a long-term planner of DALI. In the first step, the algorithm transforms the area into a graph with sufficient granularity to represent paths between points. Permanent obstacles are excluded from the graph. Other environmental constraints and user preferences are stored within nodes and edges of the graph with one of the following options:

- Soft constraints taken from users' preferences and indicating zones that the planner would try to visit or avoid. Each soft constraint is characterized by a triple (*center, radius, intensity*): it affects paths within the *radius* from its *center* and its intensity is the highest at the *center* decreasing with the distance from the *center*. A proposed path is deviated towards or outwards of the center within the radius based on the intensity level.
- A heat map of the environment indicating areas with high occupancy; navigation through such areas is slower by a specified factor.
- Anomalies or temporary obstacles that are areas inaccessible during certain periods of time. The long-term planner considers foreknown anomalies, assuming that their appearance and disappearance time is provided.

The long-term planner of DALI is based on Dijkstra's shortest path algorithm [D+59]. The algorithm maintains a set of nodes to which the shortest distances from a source node are computed. Starting from the source node, at each step, the algorithm selects a new node that has the shortest distance from the source node and adds it to the set. DALI modifies Dijkstra's algorithm by taking into account environmental constraints and users' preferences during the choices of the nodes to be added to the set. Temporary obstacles prevent the selection of the nodes inside these obstacles during the inaccessibility time. Heat maps affect the actual lengths of the edges. Soft constraints add virtual coefficients to the distances inside the zones covered by these constraints. Note that soft constraints do not affect the real travel time (the coefficient is virtual), thus DALI might return a path that is not the shortest. The coefficients of the soft constraints bound the extra length of the returned path, that is, if a detour for satisfying a soft constraint is too long to satisfy the time limit of reaching the destination, the constraint would be ignored.

4 MISSION PLANNING METHODOLOGY

In this section, we introduce our methodology for automated mission planning for multiple agents. We describe the overall procedure followed by a detailed description of each step.

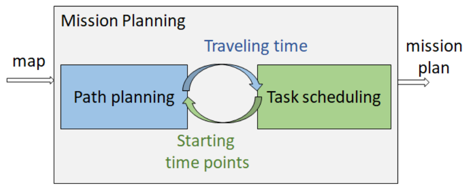


Fig. 4. Iterative process of mission planning

Mission planning is composed of two main aspects: task scheduling and path planning. The former defines which tasks should be executed, in which order, at what time, and by which agent. The latter indicates the traveling path between milestones. Note the dependency of task scheduling on path planning: the knowledge of the traveling time is needed for task scheduling.

We propose a *UTA-based mission planner* for agents. The path-planning aspect is based on an adapted version of the DALI algorithm. The DALI-based path planner takes the information of the map, including the navigation area, special areas (e.g., forbidden areas), milestones, tasks, and agents, and computes paths connecting milestones to each other, regardless of the visiting order. The task-scheduling aspect is an adapted version of TAMAA (Timed-Automata-based Mission Planner for Autonomous Agents) [GES19]. The TAMAA-based task scheduler employs UPPAAL to synthesize an optimal schedule satisfying all the task constraints such as the correct order of task execution. In general, a task schedule sets up the skeleton of the mission plan, which orders the actions of movement and task execution, and path planning fills in the generated concrete routes between every pair of milestones. Though it is theoretically possible to employ UPPAAL for both path planning and task scheduling, in practice full mission planning in UPPAAL is infeasible due to the scalability problem, and the separation into two aspects is designed to simplify the computations [GES19].

To ensure the correct mission planning, path planning, and task scheduling have to interact with each other: task scheduling requires the traveling time between milestones, respectively, while path planning needs to know when the trip would take place in order to generate paths avoiding temporary obstacles. Therefore, both parts are executed in a loop until all constraints are satisfied by the resulting mission plan. The **overall workflow** consists of the following steps (Figure 4 illustrates the steps):

(1) Mission planning receives input information about the navigation area (map) and its abnormalities, as well as required tasks and their constraints.
(2) Path planning calculates potential paths between every pair of milestones.
(3) TAMAA builds UTA models that are verified in UPPAAL. In case of successful verification, UPPAAL provides execution traces of the models that satisfy all task constraints. Subsequently, a task schedule is generated from the traces.
(4) Path planning checks whether the scheduled travels cross temporary obstacles when they are active. If a conflict is found, the planning returns to step 2 where the affected paths are updated.
(5) If both task and path constraints are satisfied, the iteration ends and a resulting mission plan is returned.
(6) (Optional) if new tasks or milestones appear, repeat steps (2) - (5) with the following differences: i) path planning only calculates the paths between the new milestones and the existing ones; ii) TAMAA builds a new UTA model that contains the existing mission plan.

In the following subsections, we provide detailed descriptions of the path planner (DALı) and of the task scheduler (TAMAA), as well as their integration. To illustrate the following models and algorithms, we use a running example in Figure 2, Section 2.

4.1 Improved DALı for Path Planning

The path planning algorithm is utilized to compute paths between all milestones. The traveling time of the paths is used by TAMAA for task scheduling. Note that not all paths are included in the final mission plan: only travels scheduled by TAMAA would be used. In the running example in Figure 2(a), the path planning algorithm computes paths between every pair of milestones, three in total (i.e., A to B, B to C, and A to C), yet the final mission plan would use only two of them (i.e., A to B and B to C).

Path planning has to be capable of providing navigation in complex environments, considering obstacles, road conditions, and users' additional preferences. The DALı algorithm supports different types of environmental constraints, thus we select it for our methodology. To adapt DALı to our use case, we transform DALı environmental constraints to be applicable in a quarry. In addition, we tune the algorithm with several optimizations as shown below.

The preliminary step of the DALı algorithm is a transformation of the navigation area into a graph and annotation of graph elements with environmental conditions. Figure 2(b) illustrates a discretization of the area with a Cartesian grid where each cell represents a node in the graph and neighbor cells are connected by edges. Each edge has a length equal to the distance between the centers of cells connected by the edge. The initial positions of agents as well as milestones are assigned to the nodes corresponding to the cells where they are located, respectively. Environmental constraints are encoded into the graph as follows.

- Permanent obstacles or areas that are always impassable (dark grey in Figure 2(b)) are excluded from the graph. There are no nodes corresponding to such areas and no edges connecting them.
- Temporary obstacles or areas that are impassable for a specified time interval (light orange in Figure 2(b)) are kept in the graph, unlike permanent obstacles. Nodes in such areas are annotated with periods of inaccessibility that would be used by path planning.
- Areas with bad road conditions are specified with a heat map used in DALı (green in Figure 2(b)). Following the naming convention from the literature [CFL$^+$15], we refer to such areas as *heat areas*. Agents in a heat area have to reduce their respective speeds by a given factor that is stored within the edges connecting nodes inside the area.
- Soft constraints marking some areas as "undesirable" (blue in Figure 2(b)) are defined differently from the soft constraints in DALı. Agents are allowed to pass through such areas however a virtual coefficient is added to the lengths of edges making them less preferential to the path planner. Contrary to the original DALı where the coefficient depends on the distance to the area center, we consider the uniform coefficient in the whole undesirable area discouraging the traverse even close to its boundary. Note that, contrary to the heat areas that also affect the edges' lengths, this coefficient is virtual and only applied during the pathfinding but does not influence the actual traveling time on the paths.

The core step of the algorithm is a computation of the path between each pair of milestones on a graph. The original DALı is a single-source single-target algorithm, i.e., it computes a path between a *source* and a *target*, and is based on Dijkstra's shortest path algorithm [D$^+$59]. Algorithm 1 is called for each pair of milestones computing the shortest path between them while considering the environmental constraints. Each node stores a distance to the *source*, initially

Algorithm 1: Path Planning Algorithm

```
1  class Node
2      Edge edges[]                                      // Outgoing edges
3      Double distance, vDistance       // Distance to source (virtual - with soft constraints)
4      Node previous                                     // Previous node on the path
5      Double softConstraint             // Soft constraint coefficient; 1 if no constraint
6      TimeInterval temporaryObstacle      // Inaccessibility time for temporary obstacles
7
8  class Edge
9      Node start, end
10     Double length
11     Double heat                        // heat map speed reduction factor; value ∈ [0, 1)
12
13 Function FindPath(Node source, Node target, Double speed, Double startTime)
14     priorityQueue.add(source)
15     source.distance := 0
16     processed := ∅
17     while priorityQueue ! = ∅  &  target ∉ processed do
18         curNode := priorityQueue.remove()
19         foreach edge ∈ currentNode.edges do
20             if edge.end ∉ processed  & !IsInsideTemporaryObstacle(edge, speed, startTime) then
21                 newDistance := curNode.distance + edge.length × edge.end.softConstraint/(1 − edge.heat)
22                 if edge.end.vDistance > newDistance then
23                     //update edge.end distances and previous node
24                     priorityQueue.add(edge.end)
25         processed.add(curNode)
26     return ExtractPath(target)            // traversal from target to source via node.previous
27
28 Function IsInsideTemporaryObstacle(Edge edge, Double speed, Double startTime)
29     time := startTime + (edge.length + edge.start.distance)/speed
30     return time ∈ edge.end.temporaryObstacle
```

infinite. A priority queue orders nodes by their current distances to the *source* (line 14). The main loop (lines 17-25) takes a node with the smallest distance and updates the distances from all its neighbors to the *source*. The update ensures the avoidance of temporary obstacles (line 20) and calculates the distances taking into account soft constraints and heat areas (line 21). The algorithm terminates when the distance to the *target* node is computed and the path is obtained by moving in the graph via references to the previous nodes (line 26).

Within this work, we propose two optimizations of the original DALI algorithm. The first optimization takes into account that our method requires computing paths between every pair of milestones and that Dijkstra's algorithm on which DALI is based can be modified into a single-source multiple-target path planner. The extension of DALI is straightforward: the algorithm continues the main loop until the distances to all milestones are computed. This optimization reduces the number of calls to the path planner.

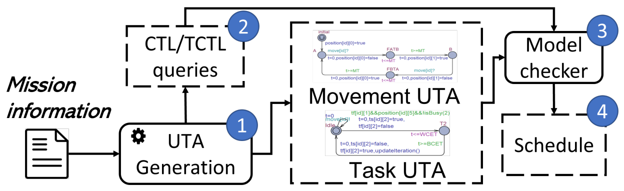


Fig. 5. Overview of the workflow of model generation and mission plan synthesis in TAMAA

The second extension is inspired by the heuristics from the A* algorithm [HNR68]. Whenever the algorithm updates the distance of a node (line 21), it considers not only the distance to the *source* but also a distance estimation to the *target*. In particular, each node stores an estimation of the entire path length from the *source* to the *target* passing through the node and the priority queue sorts the nodes based on the estimation. For a node n the estimation is computed as $n.distance + dist(n,\ target)$, where $dist$ returns the Euclidean distance. Such heuristic guides the exploration of the graph towards the *target* and, in general, finds the shortest paths faster, especially in areas with few obstacles. In the remainder of the paper, we call the DALI extension with the A* heuristic as DALI*. Note that the two extensions above are incompatible: an A* heuristic assumes that the algorithm is single-source single-target. The selection between the two optimizations must take into account the number of milestones, which affects the number of paths to compute, and the size of the Cartesian grid that discretizes the environment (Fig. 2(b)).

At step (2) of the overall workflow described earlier, a path planning algorithm computes the path between every pair of milestones. Since the path planner does not know at which time a path would be used, temporary obstacles are not considered during this step, i.e., the call to IsInsideTemporaryObstacle function on line 20 is ignored. In our running example in Figure 2(b), the red path between A and B through the temporary obstacle would be selected. A path between B and C would not be direct: a heat area on the way would significantly slow down the agent and make a deviation faster. The path between A and C is also deviated due to the soft constraint, yet such a path is far from optimal and may affect the timing constraints of the mission plan.

Temporary obstacles are considered during step (4) of the overall workflow. At this point the selected paths and their starting time points are known, thus making it possible to check whether such obstacles have been passed at the wrong time when the temporary obstacles exist. If that is the case, such paths are recomputed with a consideration of the temporary obstacles. In the running example (see Fig. 2(b)), the path between A and B is recomputed due to the temporary obstacle and a new and longer path avoiding both the temporary obstacle and the area with a soft constraint is computed. The new path and its length are then given to TAMAA for model generation.

It might be the case that paths avoiding areas with soft constraints are too long, which causes the timing constraint of a global mission to be violated. In this case, paths are recomputed by the path planner with soft constraints ineffective (i.e., `edge.end.softConstraint` is ignored on line 21). This recomputation may improve some paths and the updated traveling time is passed to TAMAA for task rescheduling. In the running example, such recomputation would output a faster path between A and B.

4.2 TAMAA for Task Scheduling

Now, we recall the mission-related requirements of agents, mentioned in Section 2, which agents need to fulfill. To ensure the correct work of the agents, we need a method that guarantees to meet all the desired requirements, including correct task scheduling. Model checking can provide such guarantees given a modeling formalism for agents and constraints. We propose a method named *TAMAA (Timed-Automata-based Mission planner for Autonomous Agents)* that is able to automatically generate models and synthesize task schedules that satisfy the formalized requirements by using model checking. TAMAA employs UPPAAL as the model checker that uses the UPPAAL timed automata (UTA) formalism for modeling the timed behavior of agents and Timed Computation Tree Language (TCTL) for formalizing the requirement specification.

Figure 5 depicts the workflow of our approach:

(1) *UTA generation*: mission information, e.g., the topology of the map, and information about the agents and their tasks, are input into the model-generation module, where a set of UTA that models the agents' movement and task execution are generated automatically.
(2) *Query generation*: TCTL queries for synthesizing schedules are generated automatically. Based on our templates of queries, users can manually modify the queries according to their own requirements.
(3) *Trace generation*: The UTA models are verified with UPPAAL against the TCTL queries. If the model checker finds an execution trace of the model that meets all the requirements, the trace is returned; otherwise, a verdict that the query is not satisfied is returned.
(4) *Schedule generation*: The returned trace is parsed and a schedule of actions (i.e., movement and task execution) is generated based on the trace.

The method automatically generates models, formalizes requirements, and synthesizes traces. The automation of TAMAA requires no action from the user after setting up the tasks, milestones, and navigation area, which simplifies the application of the method significantly. Nevertheless, we leave the possibility to modify models and add requirements, so that our method can be used in applications with individual needs that are not considered in the existing models. We show an example of such modifications in Section 7. In the following, we introduce the theoretical and technical details of TAMAA, including formal definitions of the concepts and the templates of queries that formalize the requirements presented in Section 2.

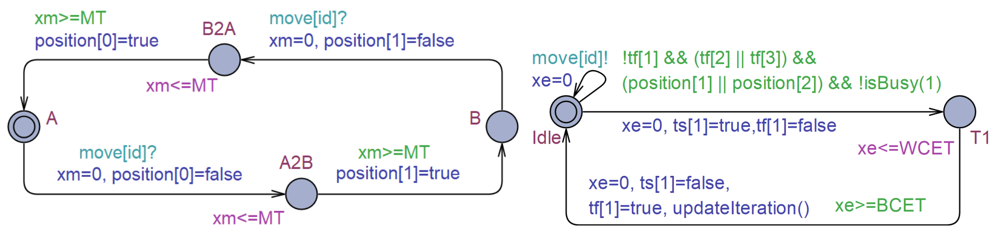
4.2.1 Definitions of Concepts. In our approach, autonomous agents are characterized by their speeds and a set of tasks that they are supposed to execute for accomplishing the entire mission. The environment where agents work contains a number of milestones where the tasks are supposed to be carried out. Therefore, agents should visit the right milestones to execute particular tasks. To accomplish the mission, there are two types of actions that agents can perform, namely *moving* and *executing* tasks. Therefore, we split the agent model into two UTA, one taking care of the movement and one of the task execution. We formally define the movement and task-execution UTA in Definitions 4 and 6. For understanding the definitions easily, we illustrate these two kinds of UTA in Figure 6.

Definition 4 (Agent's Movement UTA). *Given an autonomous agent AA, the movement of AA is defined as a UTA in the following form:*

$$MV = < P_m, p_0, U_m, \Sigma_m, E_m, I_m >, \tag{4}$$

where:

- $P_m = P_m^s \cup P_m^t$ *is a finite set of locations, where* P_m^s *represents the set of milestones in the environment, and* P_m^t *represents the travel between two milestones;*
- $p_0 \in P_m^s$ *is an initial location representing the milestone where the agent is initially positioned;*



(a) Agent movement as an UTA

(b) Agent execution of tasks as an UTA

Fig. 6. Examples of agent movement UTA and task-execution UTA.

- *U_m = {x_m, position}, where x_m is a clock variable for measuring the traveling time, and "position", which is shared with other UTA, is an array of Boolean variables that stores whether the agent is at a milestone or not;*
- *$\Sigma_m = \{move, \tau\}$ is a set of channels, where "move" models the synchronization with task execution automaton described below in Definition 6, and τ denotes internal or empty actions without synchronization;*
- *$E_m = E^c_m \cup E^u_m$ is a finite set of edges connecting locations, where $E^c_m \subseteq P^s_m \times \{true\} \times \{move\} \times F_m \times P^t_m$, where F_m is a set of functions that update the value of the Boolean array "position" and reset the clock x_m, and $E^u_m \subseteq P^t_m \times B_m(x_m) \times \{\tau\} \times F_m \times P^s_m$, where $B_m(x_m)$ is a set of guards containing clock constraints of the form $x_m \geq \delta$, where $\delta \in \mathbb{R}_{\geq 0}$ is the traveling time between two milestones;*
- *$I_m : P^t_m \rightarrow B_t(x_m)$ is a function that assigns invariants to locations in P^t_m, where $B_t(x_m)$ contains clock constraints of the form $x_m \leq \delta$, where $\delta \in \mathbb{R}_{\geq 0}$ is the traveling time between two milestones.*

Figure 6(a) illustrates the movement UTA for two milestones A and B. The UTA has four *locations*: two *milestone* locations representing the milestones, i.e., $P^s_m = \{A, B\}$, and two *traveling* locations representing intermediate positions necessary to capture traveling between milestones, i.e., $P^t_m = \{A2B, B2A\}$. Edges in E^c_m that connect the milestone locations with the traveling locations are labeled with a *channel* `move`, in our example, the edges from *locations* `A` to `A2B` and from *locations* `B` to `B2A`, respectively. The *channel* `move` is used to synchronize the movement UTA with the task execution UTA, when the latter informs that the movement has started. A second group of edges (i.e., E^u_m) models the arrival to the destination. To model the traveling time, we use invariants of the form $x_m \leq$ `MT`, and guards in the form of $x_m \geq$ `MT`. The clock variable x_m is for measuring the traveling time between two milestones. The set F_m in this UTA contains the assignments that reset the clock x_m and modify a specific element in the Boolean array `position`. We use the array `position` to keep track of the current position of an agent, which can be accessed by other UTA.

The second part of an agent model formalizes task execution. First, we define tasks as follows:

Definition 5 (Task). *A task is defined as a tuple, as follows:*

$$TS = (\mathtt{BCET}, \mathtt{WCET}, \mathtt{isStarted}, \mathtt{isFinished}, \mathtt{Func}, \mathtt{pre}, \mathtt{Mil}), \quad (5)$$

where:

- `BCET` *is the best case execution time;*
- `WCET` *is the worst case execution time;*
- `isStarted` *is a Boolean variable denoting if the task has started;*
- `isFinished` *is a Boolean variable denoting if the task has finished;*
- `Func` *is a set of functions that update the variables in the task-execution UTA (Definition 6) after the task finishes;*

Table 1. An example of tasks for the autonomous trucks in Figure 2.

	BCET (mins)	WCET (mins)	isStarted	isFinished	Func	pre	Mil
Loading	5	10	false	false	load()	/	B
Unloading	8	14	false	false	unload()	Loading.isFinished	C

- `pre` *is a precondition that must be met to start the task, which can take into account the execution status of other tasks and global variables. Formally,* $\texttt{pre} = p \mid \neg\texttt{pre} \mid \texttt{pre} \vee \texttt{pre} \mid \texttt{pre} \wedge \texttt{pre}$*, where* p *is an atomic proposition over* $\mathcal{S} \cup \mathcal{F} \cup \mathcal{V}$*, where* $\mathcal{S}$*,* $\mathcal{F}$*, and* $\mathcal{V}$ *are three sets consisting of Boolean variables* `isStarted`*,* `isFinished`*, and the variables updated in* `Func` *of all tasks, respectively;*
- `Mil` *is a set of milestones where the task is allowed to be executed. A task can be executed at multiple milestones.*

Table 1 shows two examples of tasks, which we use to illustrate Definition 5. Initially, an agent starts to load stones near the stone piles at milestone B (*loading.isStarted* turns *true*). When the loading task is finished (*Loading.isFinished* turns *true*, while *Loading.isStarted* turns *false*), a function *load()* updates a Boolean variable named *isLoaded* to *true*, indicating that the agent is fully loaded. At the next step, the agents are supposed to unload the stones into the primary crusher at milestone C. Therefore, the unloading task has a precondition *loading.isFinished*. Note that preconditions can be much more complex Boolean expressions, e.g., $A.pre = (B.isFinished \mid\mid \neg C.isStarted)\ \&\ D.isStarted$, which means task A can start only when task B is done or task C has not started, and after task D has started. When the unloading task is done, a function *unload()* is called, which increases the number of crushed stones.

The execution time of a task is usually specified with a time interval (i.e., [`BCET`, `WCET`]). In a 1-player game [Jen18], the environment is under the total control of agents, which means agents can choose any time point within the time interval to finish the task. The goal of task scheduling in this paper is to find the schedules that finish tasks in the quickest way. Notably, the quickest schedules do not necessarily mean always using BCET for all tasks. In some cases, prolonging the execution time of some tasks can be more efficient for the entire mission, especially when multiple agents are working in the same environment. Additionally, some applications require the tasks to be executed multiple times before the final goal is reached. Like the example in Table 1, autonomous trucks are asked to repeat the trip of loading and unloading until all the stones are transferred to the primary crusher, and the tasks should be executed once and only once during one trip, i.e., before all tasks are completed. With all the requirements, how to assign starting time and ending time of tasks to each of the agents is the question that is answered by task scheduling. Now, we define the task execution UTA based on the definition of tasks.

Definition 6 (Task Execution UTA). *Given an agent AA and a set of tasks* $\mathcal{T}$*, task execution of AA is defined as a UTA of the form:*

$$TE = (N_e, n_0, U_e, \Sigma_e, E_e, I_e), \tag{6}$$

where:

- $N_e = \{n_0\} \cup N_e^t$ *is a set of locations, where* $N_e^t = \{n_t \mid t \in \mathcal{T}\}$*;*
- n_0 *is the initial location, which stands for the idle status of AA;*
- $U_e = \{x_e, t_s, t_f, ite\}$*, where* x_e *is a clock that is reset whenever a task finishes,* t_s *and* t_f *are Boolean arrays that store the statuses of tasks (*$isStarted$ *and isFinished in Definition 5, respectively), and* $ite \in \mathbb{N}$ *stores the current iterations of all tasks. At the end of each iteration,* ite *is incremented by 1, while* t_s *and* t_f *are reset to false for a new round of tasks execution;*

- *$\Sigma_e = \{move, \tau\}$ is a set of channels;*
- *$E_e = E_i^d \cup E_e^d \cup \{e_s\}$, where $E_i^d \subseteq \{n_0\} \times B_e^i(U_e) \times \{\tau\} \times F_e \times N_e^t$ is a set of edges from n_0 to $n_t \in N_e^t$, F_e is a set of functions updating the variables in U_e, $B_e^i(U_e)$ is a set of guards consisting of the preconditions and milestone requirements of tasks, $E_e^d \subseteq N_e^t \times B_e^d(x_e) \times \{\tau\} \times F_e \times \{n_0\}$ is a set of edges from $n_t \in N_e^t$ to n_0, $B_e^d(x_e)$ is a set of guards containing clock constraints of the form $x_e \geq BCET$ of a task, e_s is a self-loop edge on n_0 that is labeled with channel move and an assignment $x_e = 0$;*
- *$I_e : N_e^t \to B_i(x_e)$ is a function assigning invariants to locations in N_e^t. The invariants are of form $x_e \leq WCET$ of a task.*

An example of the task execution UTA is depicted in Figure 6(b), where *location* `Idle` is the initial *location* n_0, and *location* `T1` represents a task. The *channel* `move` labels the self-loop *edge* on *location* `Idle`, which synchronizes the movement UTA and the task execution UTA. Due to the synchronization, movement cannot start during task execution but only when the agent is idle. *Location* `T1` and its outgoing *edge* are labeled with an invariant (`t<=WCET`) and a *guard* (`t>=BCET`), respectively, to ensure the execution time within *BCET* and *WCET*. Function `updateIteration` on the edge from `T1` to `Idle` is for incrementing the variable *ite* when an agent finishes all its tasks. For a specific case, additional functions can be added to this edge too, for example, the function `unload()` in Table 1. Moreover, the guard `!tf[1]` forbids the multiple executions of the task during a single round of tasks iteration; the next execution of this task can be done only in the next iteration after the reset of the arrays `ts` and `tf`. The guard on the edge from *Idle* to `T1` presents the precondition (i.e., `!tf[1]` && (`tf[2]` || `tf[3]`)), the milestone requirement (i.e., `position[1]` || `position[2]`), and the mutual-exclusive requirement of task *T1* (i.e., `!isBusy(1)`). The function `isBusy(1)` checks if `T1` is being executed by other agents or not. As preconditions defined in Definition 5, the function `isBusy(1)` uses the "isStarted" and "isFinished" variables of the same task executed by other agents to see if task *T1* is being executed. Definitions 4 and 6 define the UTA of agent movement and task execution, respectively. A network of these UTA models the behavior of multiple agents working collectively to reach a common goal respecting a given set of constraints, such as mutual exclusiveness of tasks.

The definitions present the foundation for describing multi-agent systems with a formal modeling language. Based on these definitions, we design a method for generating UTA models of movement and task execution and implement it in our tool MALTA. Essentially, the method takes in the information of tasks (Definition 5) and the traveling time between every two milestones. Then it generates locations, edges, and the labels on them based on Definitions 4 and 6.

4.2.2 Formalizing Requirements as UPPAAL Queries. In Section 2, we provide a list of typical requirements of our use case. In this section, we describe how they are formalized for model checking. Queries for verification of each agent are created based on the templates presented below (formulas (7) to (10)). We use index '`a`' to denote an agent in queries. We use $\texttt{task}_a$ (respectively, $\texttt{move}_a$) to denote the task execution UTA (respectively, movement UTA) of an agent `a`, and `Ti` (respectively, `Pi`) to denote any *location* in the task execution UTA (respectively, movement UTA). A clock variable `x` is used to measure the global time. Two Boolean arrays named `ts` and `tf` indicate whether tasks have been started and finished, respectively. Two constant integers `ALL` and `LIMIT` denote the requested number of iterations of tasks and the time constraint to accomplish the entire mission, respectively.

- *Milestone matching*: Agents must be located at the right milestone while executing a task. Assuming task T_i must be carried out at one of the milestones: P_i, P_{i+1}, ..., P_k, the following queries are checked for each agent `a`:

$$\texttt{E<> ts}_a\texttt{[i]} \tag{7}$$

$$\texttt{A[] task}_a\texttt{.Ti imply (move}_a\texttt{.Pi} \parallel \texttt{...} \parallel \texttt{move}_a\texttt{.Pk)} \tag{8}$$

Query (7) is for verifying whether task T_i ever starts, after which Query (8) checks whether task T_i is carried out at the right milestone.

- *Task sequence*: Tasks must eventually be executed, and to start the execution, their preconditions must be satisfied. Assuming task T_i can start only after task T_j finishes, and at the beginning of each task iteration, all elements in both `ts` and `tf` are set to *false*, the corresponding queries are designed:

$$\texttt{A[] ts}_a\texttt{[i] imply tf}_a\texttt{[j]} \tag{9}$$

The first part of the requirement, i.e., whether task T_i ever starts, is verified in the requirement of *milestone matching* by checking Query (7). Query (9) checks the second part of the requirement: task T_i never starts before the required preceding task T_j has finished.

- *Timing*: Tasks must be finished within a time frame in order to maintain a certain level of productivity. The following query is used to capture this requirement:

$$\texttt{E<> iteration[a]>=ALL and gClock <= LIMIT,} \tag{10}$$

where *gClock* is a global clock that is not reset by any transition. Query (10) checks the reachability of a state where all tasks are executed for `ALL` rounds within `LIMIT` time units, and UPPAAL returns the trace reaching that state, in case the query is satisfied.

Note that satisfaction of Queries (7-9) is guaranteed by the construction of movement and task execution UTA. The queries can still be verified for a given mission, but they are not used in mission planning. If Query (10) is satisfied, UPPAAL outputs the trace reaching the goal state. The trace is processed by TAMAA and a schedule is generated following the steps of the trace. We always look for the fastest trace. When the task execution time is a time interval rather than a fixed value, we assume the environment to be under the control of the agents, which means that the agents can choose any task execution time during the time intervals, respectively. If the environment reacts competitively or possibly antagonistically, we need a comprehensive schedule that considers all possible scenarios. We refer interested readers to our previous work [GJP+22], in which we propose a method combining model checking and reinforcement learning to deal with uncooperative environments.

4.3 Mission Planning with DALı and TAMAA

Path planning and task scheduling aspects of mission planning depend on each other. One of the task scheduling parameters is traveling time between pairs of milestones. Temporary obstacles affect the shortest paths between milestones, therefore path planning requires knowing the starting time points of travels in order to ensure the avoidance of temporary obstacles. In this section, we introduce the algorithm that combines TAMAA with DALı for mission planning. In addition, in the second part of the section, we show how an existing mission plan can be adapted to incorporate additional tasks and milestones that could appear during an execution.

4.3.1 Mission Planning Algorithm. Dependencies between scheduled tasks and paths between milestones do not allow generating a mission by a single run of the path planner and the task scheduler. Paths are affected by temporal obstacles and, therefore, by starting time points of travels, i.e. the task schedule which depends on travel time and, consequently, selected paths. Algorithm 2 describes the steps of mission planning. During the first step (line 6), DALı discretizes the entire environment into a Cartesian grid shown in Figure 2(b) and builds a graph of the environment which is

Algorithm 2: Mission Planning Algorithm

```
1  Function MissionPlanning(Environment env, TS tasks[], Agent agents[], Query query)
2      $model := empty$                                          // A network of UTA
3      $startTimes[][][] := 0$                // Depart time for each agent and pair of milestones
4      $ignoreTempObst := true$        // Ignore temporary obstacles while start times are unknown
5      $useSoftConstr := true$
6      $Discretize(env)$                      // Discretize the continuous environment into a grid
7      foreach $agent : agents$ do
8          foreach $m1, m2 : milestones$ do
9              $paths[m1][m2] := FindPath(m1, m2, agent, startTimes[agent][m1][m2])$
10         $movementUTA := CreateMovementUTA(paths, agent.speed)$
11         $taskExeUTA := CreateTaskUTA(agent.ID, tasks)$
12         $model.add(movementUTA, taskExeUTA)$          // Compose the models into a network of UTA
13     $schedule := Scheduling(model, query)$
14     if $schedule == null$ then
15         if $softExist$ then
16             $useSoftConstr := false$       // If scheduling is impossible with soft constraints
17             $startTimes[][][] := 0$                           // Retry without soft constraints
18             goto line 8
19         else
20             return $false$                                              // No mission plan found
21     if $!CheckTemporaryObstacles(schedule)$ then
22         $ignoreTempObst := false$
23         $updateTimes(startTimes, schedule)$                   // Update the start time of each path
24         goto line 8                              // Recomputes affected paths with path planning
25     foreach $agent : agents$ do
26         $agent.schedule := distribute(schedule)$    // Dissolve and distribute the plan to each agent
27     return $true$
28
29 Function Scheduling(NUTA model, Query query)
30     $trace := check(model, query)$             // Call UPPAAL to check the model against Query (10)
31     return $traceParser(trace)$                          // Extract action sequence from the trace
```

used in all consequent path-planning calls. DALı computes the path between every pair of milestones while ignoring temporary obstacles during the first computation (lines 8-9). Indeed, at this point, neither the order nor the starting time points of travels are known and the shortest paths between every two milestones are returned. In Figure 2(b), the red path between milestones A and B would be selected as the shortest even if it passes through a temporary obstacle (orange cells).

At the next step, the model generation module of TAMAA automatically generates the network of UTA that models the agents' movement and task execution (lines 10-12), after which a function named `Scheduling` is invoked to schedule the tasks taking into account the traveling time of the paths (line 13). In the `Scheduling` function, UPPAAL checks the existence of a model execution trace satisfying the Query (10) (line 30). Note that queries that formalize other requirements, e.g., Queries (7) - (9), can also be checked, which ensure the satisfaction of other requirements but do not contribute to the mission plan synthesis. Next, if the query is satisfied and a trace is obtained, we convert the trace into a schedule ordering the movement and task execution actions (line 31). In the `traceParser` function, a schedule that orders the actions of movement and task execution for all the agents is generated (line 13). Note that the returned result of the schedule can be empty (i.e., `null`), which indicates the non-existence of mission plans. Since the model checker exhaustively explores the entire state space of the model, the non-existence of mission plans is guaranteed. In such case, the mission planning tries to recompute the paths and the schedule ignoring soft constraints (line 18). If the Query (10) cannot be satisfied even without soft constraints (line 20), the algorithm terminates and suggests the users to modify their environment configuration or requirements.

If the `Scheduling` function returns a non-empty result, DALI checks whether the plan happens to cross any temporary anomalies and at which time (line 21). The function *CheckTemporaryObstacles* looks at all the paths involved in the schedule, and, with the knowledge of the starting time of travel, checks that no temporary obstacle is entered during its inaccessibility period. If at least one path crosses a temporary obstacle during its existence, recomputation is run (line 24). Given the scheduled starting time of actions, DALI updates paths that are used to enter the temporary obstacles. New paths might become longer than the original paths, requiring TAMAA to reschedule tasks. For example, in Fig. 2(b), if a temporary obstacle is enabled then a different path between A and B is selected (dashed black lines). The new path is longer and might affect the satisfaction of timing constraints. In this case, another path is computed ignoring the soft constraint (solid line). TAMAA is called after each path modification and regenerates a new task schedule (line 13).

Next, the entire action plan is dissolved into several individual mission plans for the agents and distributed to each of them (line 26). The function `distribute` dissolves the entire schedule and puts the actions into the corresponding individual mission plan according to which agent they belong to. Finally, a mission plan that satisfies all constraints imposed on the tasks and paths is returned by the mission planner that integrates DALI and TAMAA. Again, since the satisfaction of constraints is guaranteed by the model checking technique used in the `Scheduling` function, the resulting mission plan is *correct-by-construction.*

4.3.2 Adaptability. When new tasks and milestones appear after the synthesis of a mission, a modification of the mission plan is required. A naive solution is to recompute a mission plan from the beginning, but it is inefficient. If the new tasks do not influence the execution of the existing tasks, the original mission plan can be largely reused. For example, in our running example (Figure 2), when a new stone pile appears, the agent should keep digging the old stone pile and continue executing the existing mission plan while adding the digging at the new stone pile as a new task. In addition, the precondition of the task that follows the digging task is now changed to incorporate the new digging task. Therefore, a good solution should leverage the existing mission plan and inject a new plan into the existing one in order to reduce the computation time. As properties of the old plan are preserved and the new plan is also based on the fastest trace satisfying Query (10), the result preserves the guarantee of correctness.

Concretely, when new tasks and milestones appear, we run the path-planning algorithm for calculating the paths involving the new milestones. Next, we generate new UTA models that incorporate the existing mission plan as a constant array, which does not increase the state space of the model. Each element of the array is a pair of a state and an action and the code of the array in UTA is as shown below.

```
typedef struct {
    int locations[AgentNum][2]; //current locations of the UTA
    bool positions[AgentNum][MilestoneNum]; //current milestones of the agents
    bool ts[AgentNum][TaskNum]; //if the tasks are started
    bool tf[AgentNum][TaskNum]; //if the tasks are finished
    int iteration[AgentNum]; //the iteration of finishing all tasks
}PState;
typedef struct {
    int agentID; //ID of the agent
    int type; //movement or task execution
    int source; //source milestone or task
    int target; //target milestone or task
}PAction;
typedef struct {
    PState variables; //state of the agent
    PAction action; //action at the state
}Pair;
```

The state (`PState`) consists of locations and the discrete variables of the UTA (Definitions 4 and 6). On the edges of the UTA, we add functions for changing the value of `PState`. For example, when a movement UTA transfers its location, variables `locations` and `positions` in `PState` are changed. To force the UTA to follow the existing mission plan, we add guards on the edges of starting an action, i.e., moving or task execution. The guards check if the existing mission plan allows that action in the current state. However, we do not check the existing mission plan when the UTA is at a milestone of a new task, which means the agents can choose to execute the new task or move to other milestones. Consequently, when model-checking such new UTA, part of the model state space executing the existing mission plan is restricted. The fastest and satisfactory trace of Query (10) depicts how the agents should continue carrying out the existing mission plan while incorporating the new tasks. The execution of the new tasks is interleaved or concatenated with that of the existing mission plan, depending on which way is the fastest. Again, from the fastest witnessing trace satisfying Query (10), we can extract a new mission plan that is guaranteed to be correct and fastest.

5 MALTA FOR MISSION PLANNING

In this section, we present our toolset called *MALTA*[1] that consists of three main components: a GUI called Mission Management Tool (MMT), a path planner implementing DALI, and a task scheduler implementing TAMAA.

5.1 Overall Description

The toolset consists of 3 parts: a front end providing the graphic user interface (GUI), a middleware providing path planning and building mission plans from paths and schedules, and a back end dedicated to task scheduling. The toolset design adopts a Client/Server architecture. The reason is twofold: first, the front end of the toolset is a GUI that has been independently designed. Besides the GUI, the front end also provides a group of programming interfaces and data structures for extension and communication. Therefore, the front end is open for extension without touching its code. Second, the computation of mission plan can be quite expensive, therefore it is preferable to perform them on a dedicated server. Therefore, the separation of the front-end GUI from the mission plan synthesis allows the users to move computations to a dedicated server, which is a user-friendly and efficient design pattern.

[1] *MALTA* installation package and source code of path planner and task scheduler can be found at https://github.com/rgu01/MALTA

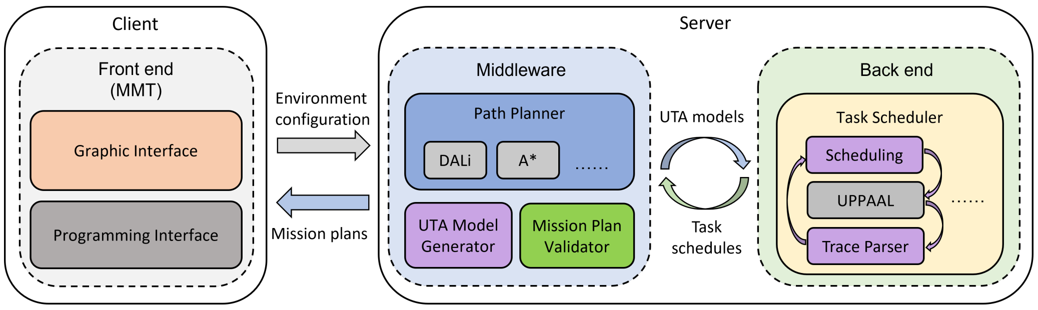


Fig. 7. Architecture and the information flow of the toolset

In the front end, users can configure their environment including the navigation areas, milestones, tasks, agents, etc., after which, the environmental configuration is transferred to the middleware. The *Mission Management Tool (MMT)* described in the following subsections provides the front-end GUI.

The middleware receives the environmental configuration and passes it to a path planner. Any path-finding algorithm that supports the desired environmental constraints can be used. In our implementation, we offer a choice between A* and DALI algorithms described in Subsection 4.1. In the second step, the middleware generates UTA models based on Definitions 4 and 6. The *UTA model generator* is based on an open source library *j2uppaal*[2].

These UTA models are transferred to the back end, where we implement the TAMAA scheduler to synthesize schedules. The `Scheduling` module implementing the `Scheduling` function in Algorithm 2 invokes the model checker UPPAAL to check the UTA models against Query (10) and, in case of successful verification, UPPAAL generates an execution trace containing the sequence of actions that can be translated into a schedule by the *trace parser*, which uses the library for parsing traces provided by UPPAAL[3]. The back end can use other model-checking-based schedulers, for example, missions in uncertain environments could use another scheduler combining model checking and reinforcement learning [GESL20b, GJP+22].

The resulting schedule is stored in a standard format of Extensible Markup Language (XML) and sent to the middleware, where the schedule is combined with the paths to generate a mission plan. A module called *Mission Plan Validator* is designed to check if the mission plan happens to come across temporary obstacles when they still exist. If the collision does happen, a new path plan that circumvents the collision is calculated by the *Path Planner* and the corresponding UTA models that reflect the new paths are generated and sent to the task scheduler again. The iteration of computation continues until a valid mission plan is generated or no valid path exists. The final mission plans are shown in the front-end when the *Mission Plan Validator* confirms that the results are correct, or a warning informs the users that no mission plan can be generated and suggests a configuration modification.

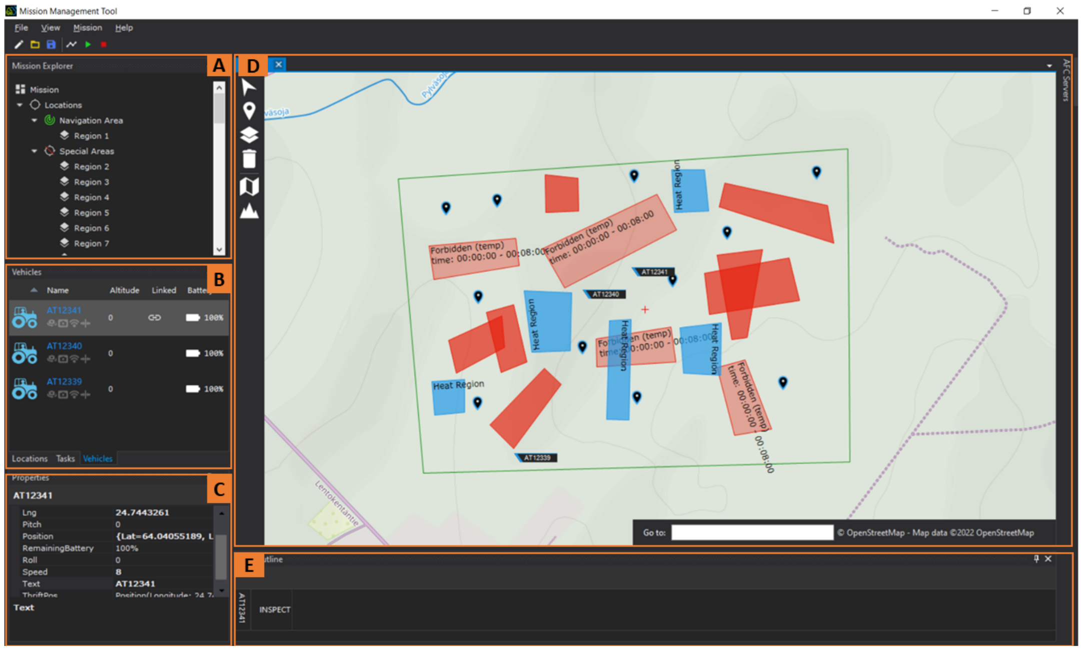
In the following subsections, we introduce MALTA's GUI and demonstrate how can one configure the environment, and visualize the resulting mission plan.

[2]https://github.com/predragf/org.fmaes.j2uppaal
[3]https://github.com/UPPAALModelChecker/utap/wiki

5.2 Mission Management Tool

The Mission Management Tool (MMT) is a GUI that allows the operator to plan, execute and supervise missions involving multiple autonomous vehicles [ACME20]. In the context of this paper, the focus is mission definition and plan visualization, hence we do not discuss the plan execution and supervision functionalities.

MMT's main window contains five main panels: (A) mission explorer, (B) assets, (C) properties, (D) map, and (E) plan outline (Fig. 8). The map shows an overall view of the mission area and the vehicles. It also provides tools to the operator for defining areas of interest for a mission. The mission explorer (Fig. 8.A) represents different assets involved in a mission and their relationship in a tree structure. The assets panel contains three sub-panels that contain vehicles, locations, and tasks. These are either physical assets that the operator has access to (vehicles), or entities that the operator has defined himself/herself (tasks and locations). The properties panel shows different properties of a selected asset and allows the operator to set their values if necessary. Finally, the plan outline provides a Gantt chart representation of the whole plan for a mission (Fig. 9). MMT communicates with the mission planner through the



Vehicles

	Name	Altitude	Linked	Batte
	AT12341	0		100%
	AT12340	0		100%
	AT12339	0		100%

Properties

AT12341

Lng	24.7443261
Pitch	0
Position	{Lat=64.04055189, L
RemainingBattery	100%
Roll	0
Speed	8
Text	AT12341
ThriftPos	Position(Longitude: 24.7

Text

Fig. 8. Mission Management Tool. (A) Mission Explorer, (B) Assets, (C) Properties, (D) Map, and (E) Plan Outline.

Apache Thrift Framework[4]. This allows MMT and the planner to share definitions of different assets and communicate mission data as well as the final mission plan.

5.2.1 Environmental Configuration with MMT. Missions in MMT are defined by setting up and selecting assets and by configuring requirements and constraints. Mission assets include vehicles, tasks, locations, and areas. Locations and areas are placed on the map either by placing a marker or by drawing a region. The locations/areas are added to the

[4]https://thrift.apache.org/

locations sub-panel, where they can be accessed to set their visualization or mission-related properties. For areas, there are some important properties that can be set, which affect the planning phase:

- *Region Type*: This can be set to a forbidden area (vehicles should not go through that region), a preferred area (vehicles are preferred to go through that region), a less preferred area (vehicles can go through there but it is better to avoid it) and a heat area (hard to pass area).
- *Intensity*: This parameter indicates the intensity of heat areas and (less-)preferred areas. For heat areas it affects the speed drop in the area; for (less-)preferred areas it affects the decision for entering the areas.
- *Start and End Time*: These parameters define the time interval relative to the mission start when the area is active, e.g., temporary obstacles appear and last a while.

Defining the tasks of a mission is done through the tasks sub-panel. This panel allows the operator to define a new task or re-use a predefined one. Defining new tasks requires the operator to define the task type (either *inspect* or *survey*) and the equipment required for it. Inspect tasks are tasks that should be performed on a location (i.e. digging), whereas, survey tasks are performed on a whole area (i.e. spraying a field).

When all the assets are defined, the operator can define the mission by dragging and dropping the assets to the mission explorer. The mission explorer contains several entry points for mission assets as follows:

- *Navigation Area*: This is the main area of the mission. No vehicle will be allowed to move outside this area. The navigation area is visualized as a polygon with green borders in MMT (Fig. 8.D).
- *Special Areas*: These are the areas that have specific roles in the mission but are not part of a task. Examples include forbidden areas, preferred areas, and heat areas. In MMT, forbidden areas are displayed with a red background and if they are temporarily forbidden a lighter shade of red is used. Temporarily forbidden areas are also annotated with a timespan during which they become inaccessible by vehicles. Heat and preferred areas are displayed in light blue (Fig. 8.D).
- *Task Areas*: These are areas that are related to a task. For each task involved in the mission a new entry point is added, allowing the operator to add the locations/areas related to it. It is possible to add several locations/areas to a single task. If a task requires a specific sensor/actuator, this information is also written next to it on the map (Fig. 8.D).
- *Home Locations*: These are the locations where the vehicles should move to after finishing their mission.
- *Vehicles*: This part contains all the vehicles that are allowed to participate in the mission. This means that the operator is allowed to only drag some of the vehicles to this section which in turn means the planner can only use those for planning (Fig. 8.B).
- *Tasks*: This contains a list of all the tasks that should be performed in the mission. When the operator drags a task to this section, a new sub-section for this task is also added to the *Task Areas* section, allowing the operator to define the areas for this specific task (Fig. 8.B).

The final step in mission definition is defining location/area properties after they are added to a task. Please note that these properties are not directly bound to the location or the task itself, but are properties that represent that specific task while being done at that specific location. These properties are only accessible by clicking on the location/area under the task in the task areas section of mission explorer (Fig. 8.C). These properties allow the operator to define task preconditions, BCET and WCET.

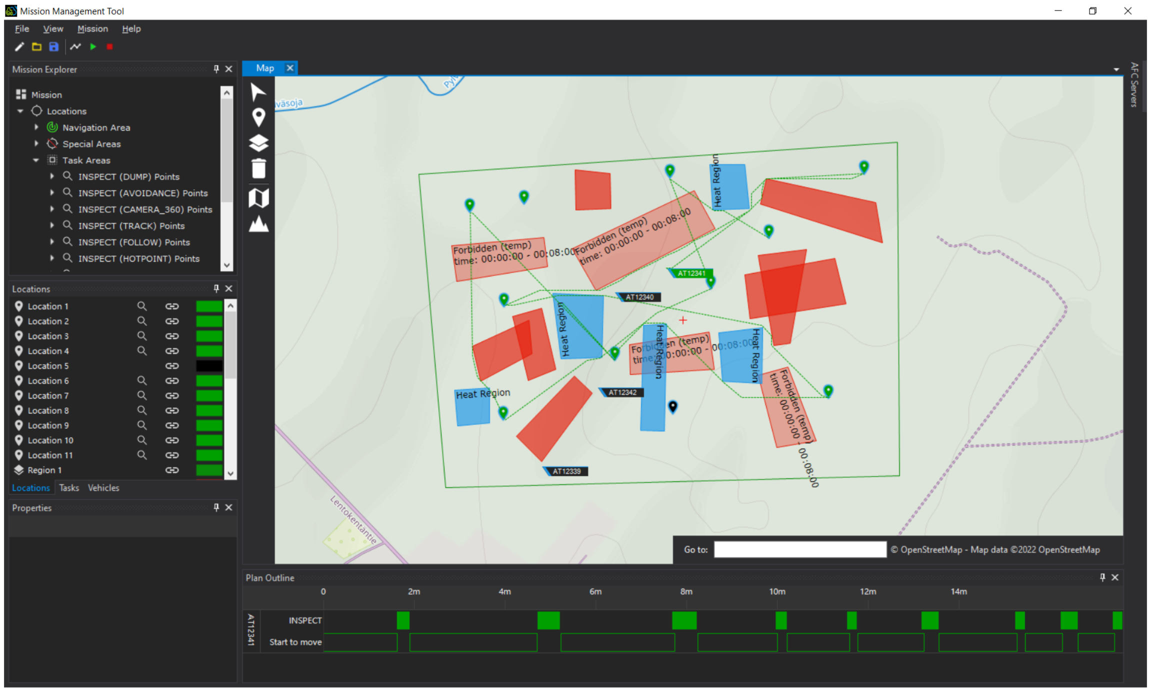


Fig. 9. A generated mission plan in Mission Management Tool (MMT).

After defining the mission, the operator can save it for later use or send it to the planner using the plan button on the toolbar. This sends the plan to the planner and awaits a result. The final mission plan is then visualized on the map and in the plan outline.

Fig. 9 shows a plan visualized in MMT. The plan contains only one vehicle and nine tasks. The vehicle and its related path are color-coded (in this case they are all green). In cases with multiple vehicles, each vehicle, its related path, and tasks will get a separate color. It can be observed that red areas are always avoided by the green lines (vehicle's path), while the light-red areas are sometimes avoided (during the related time span) and sometimes crossed (when the area is not forbidden anymore). The blue regions indicate areas with bad roads: vehicles can pass them but at a slower speed. The plan outline at the bottom also shows the order of actions to be taken by the vehicle and the amount of time each action consumes.

The mission starts from the initial location of the vehicle and the path shows the milestones that the vehicle will visit during its mission. Some milestones are visited several times as this is part of the task and mission definition. The milestone locations are marked with markers matching the color of the vehicle and a text shows the actual action which will be performed at that location.

6 EVALUATION

To test our prototype implementation, we conduct a series of experiments directed to evaluate the performance of the proposed approach by exploring the effect of different parameters on the runtime of the mission planning steps[5].

[5]The mission configurations of the experiments are published so that one can replicate the experimental results: https://github.com/rgu01/MALTA.

The first aspect of the evaluation is the utilization of the DALI algorithm: while it provides additional features for the mission specification, it should not degrade the performance significantly. The second aspect is the scalability of the approach. We are considering the following research questions:

- RQ1: Can A* algorithm [Rab00], which is originally used in MALTA, be replaced with DALI or one of its optimizations without a significant loss of performance?
- RQ2: Does MALTA scale with an increase in the numbers of tasks and road abnormalities?
- RQ3: How do additional constraints such as heat areas and temporary obstacles affect the performance of mission planning in MALTA?
- RQ4: Does MALTA scale with the number of agents?

In this section, we design a set of experiments to answer the research questions and present their results.

6.1 Methodology

For the experiments, we consider the following set of parameters:

- *Path-planning algorithm*: we compare A*, DALI without optimizations (in the remainder of the section we refer to it as DALI), and DALI* discussed in Section 4. To minimize the bias caused by implementation details, we use similar implementations in the same language, relying on the same data structures, for all three algorithms.
- *Granularity*: this parameter defines the size in meters of Cartesian grid cells during the construction of a graph from the navigation area. The graph size is inversely proportional to the square of granularity.
- *Number of tasks/milestones.*
- *Number of permanent obstacles.*
- *Presence of temporary obstacles.*
- *Number of heat areas.*
- *Number of agents.*

We measure the runtime of each part of the mission planning: graph generation time, total time of the path-planning algorithm calls, and total time of task scheduling (i.e. TAMAA) calls. For each combination of parameters we perform multiple runs and consider the mean time.

We use a mission adapted from the one in Figure 8, which contains multiple milestones, permanent and temporary obstacles, and heat areas[5]. The overall area is approximately 1.5 square kilometers. Depending on the current parameter set, certain elements of the mission might be ignored, for example, if the number of permanent obstacles is set to 5, then 5 obstacles are deterministically selected from the mission. If the algorithm used is A*, then heat areas are ignored and temporary obstacles are considered as permanent. For the tasks, we ensure that all their precondition can be met while selecting the subset for the current experiment.

During our evaluation, we consider the following groups of experiments.

- *Preliminary:* In the preliminary experiment we compare two optimizations of DALI discussed in Section 4 and select the fastest one for the remaining experiments. We use a single agent and consider different levels of granularity (between 3 and 10) and numbers of tasks (between 1 and 10). For each combination of parameters, we perform 5 runs. We measure the total time used by the path-planning algorithm in each run. The results show that for the selected parameter range DALI* is faster than the single-source multiple-target optimization and, therefore, it is used in the remaining experiments. Detailed description of the results are shown in Subsection 6.2

- *Group 1:* Within this group we consider a simple setting with a single agent, without heat areas, and with temporary obstacles considered as permanent. It is designed to answer RQ1 and RQ2. We test three path planning algorithms: A*, DALI, and DALI*. The number of tasks and permanent obstacles are varied in the range between 1 and 10, and the granularity in the range between 3 and 10. For the additional evaluation of the granularity effect on performance, we additionally run the mission planning with granularity levels 1.5, 2, and 2.5, but a fixed number of permanent obstacles (10 obstacles).
- *Group 2:* The second group is designed to answer RQ3. Since A* cannot take into account heat areas and temporary obstacles, it is excluded from this group. A single agent and all obstacles are used in this group. The number of tasks, granularity, and the number of heat areas are varied in this group.
- *Group 3:* RQ3 is answered by the third group. We increase the number of agents and use A* and DALI* algorithms. The granularity is set to 4, and the number of permanent obstacles is set to 10.

The experiments have been run on a PC with Intel-i5 CPU, 16 GB RAM, and Windows 10. The front end and the middleware have been run directly in Windows, while the back end has been run in a virtual machine (Oracle VirtualBox 7.0) hosting Ubuntu 20.04 LTS on the same PC. The timeout of computation is set to be 1 hour in the experiments.

MALTA has been run 5 times on each combination of parameters in the preliminary and third groups, and 50 times for the first and second groups. Some of the parameter combinations showed similar runtime results; for such cases, we employ *statistical analysis* to check whether they have the same mean computation times. Since the results of the experiments did not have equal variances, we use Welch's t-test [Wel47] (pairwise if the number of options is greater than 2). The test checks the null hypothesis, that is, two sets of results have equal means. With a large number of runs we have performed, the normality assumption on the means approximately holds due to the Central Limit Theorem. In the analysis, we consider a significance level, i.e. a probability of falsely rejecting the null hypothesis, set to 0.05. In Figures 10-21, we show the influence of 1 or 2 parameters on the execution time of our tool, while the remaining parameters are set to default values: 1 agent, 10 milestones, 10 obstacles, 0 heat areas, and granularity 4.

6.2 Comparison of DALI optimizations

In this preliminary experiment, we compare the path-planning time of the basic DALI algorithm and two optimizations proposed in Subsection 4.1. The first optimization converts DALI into the single-source multiple-target algorithm. Considering that our methodology requires computing paths between every pair of milestones, such optimization drastically reduces the number of calls to the algorithm. The second optimization referenced as DALI* uses a heuristic from the A*.

The results show that both optimizations are significantly faster than the original DALI algorithm. Among the two optimizations, the DALI* is the fastest. On any considered combination of parameters the slowest run of DALI* was faster than any run of DALI or of single-source multiple-target optimization. The results for the granularity set to 4 are shown in Figure 10. Considering the results of this experiment, we do not use the single-source multiple-target optimization in the following experiments.

6.3 Evaluation in Simple Environments

In the first group of experiments, we consider a simple setting with a single agent and without temporary obstacles and heat areas. This setting allows us to compare A* with DALI and its optimizations and check whether performing

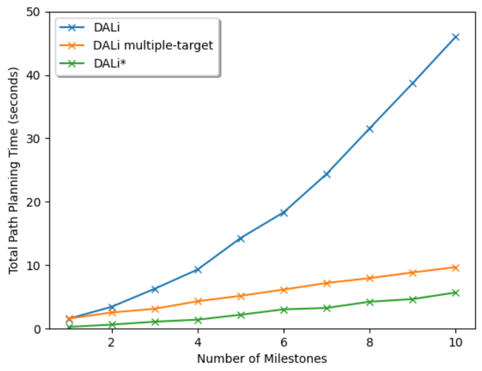


Fig. 10. Comparison of DALı and its optimizations

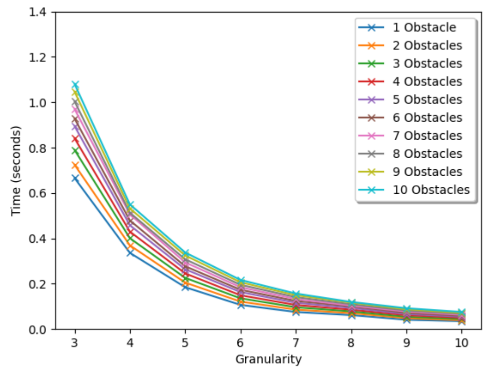


Fig. 11. The first group of experiments: the graph generation time w.r.t. the granularity and the number of obstacles

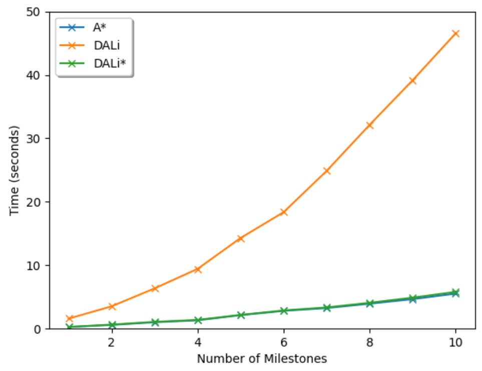


Fig. 12. The first group of experiments: the path-planning time w.r.t. the number of milestones

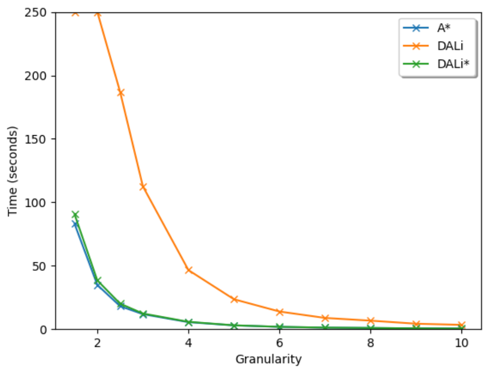


Fig. 13. The first group of experiments: the path-planning time w.r.t. the granularity. For the granularities 1.5 and 2, DALı take 1003 and 418 seconds on average, respectively.

path-planning in complex areas imposes high overhead. We vary the number of milestones, the number of permanent obstacles, and the granularity. This group of experiments is focused on RQ1 and RQ2 in the single-agent case.

The first step of MALTA is the discretization of the navigation area, which generates a graph of the area. Its implementation is independent of the number of agents and path-planning algorithms but depends only on the granularity since the number of nodes in a graph is inversely proportional to the square of the granularity. The results are illustrated in Figure 11. With finer granularity, the construction time increases: for granularity values 2.5, 2, and 1.5 the average construction time is 1.6, 3, and 5.8 seconds respectively. Permanent obstacles are excluded from the graph and each additional obstacle reduces the construction time. Pairwise Welch's t-test rejects the null hypothesis of equal means, indicating the difference between the graph construction times for various levels of granularity.

In the first experiment the generated plan can satisfy all constraints after the single scheduling (Line 13 of Algorithm 2) without recomputations caused by soft constraints and temporary obstacles. The number of calls to the path-planning

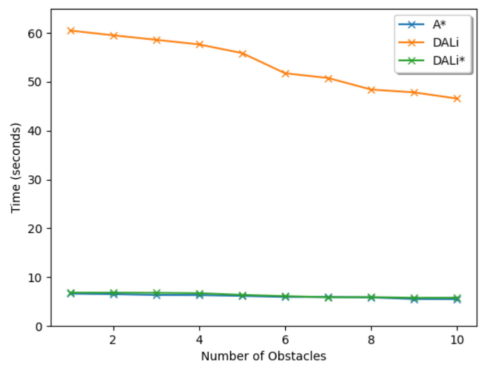


Fig. 14. The first group of experiments: the path-planning time w.r.t. the number of obstacles

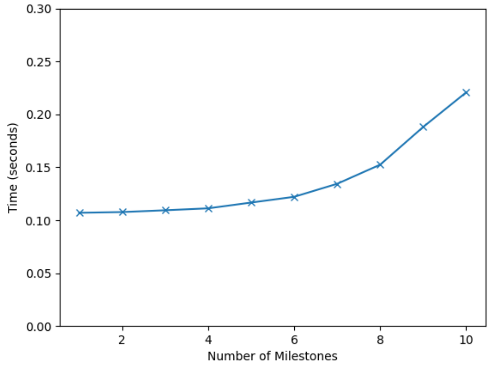


Fig. 15. The first group of experiments: TAMAA computation time w.r.t. the number of milestones

and, consequently, total path-planning time increases with the number of milestones as shown in Figure 12. Finer granularity results in a more accurate representation of obstacle boundaries and more precise paths and travel time estimations at a price of path-planning time. In Fig. 13, we can see that the graphs with a granularity of 2, that is 400,000 nodes in the graphs, can still be handled efficiently by A* and DALI*, but the original DALI requires much more time than the other two methods. Considering all combinations of parameters, the difference between A* and DALI* is statistically insignificant in 37% of parameter combinations, while for the remaining ones A* is faster. It is important to note that insignificant results are obtained for coarse granularity, where the runtime is below 1 second and, therefore, noise has a strong effect on the results. Nevertheless, the performance loss of DALI* is not high: for 98% of parameter combinations, the mean computation time of DALI* is less than 10% higher than the mean time of A*.

The number of obstacles also affects the path planning time. For 81% of parameter combinations, there is a statistically significant difference between two sets of parameters with different numbers of obstacles, but equal other parameters. A higher number of obstacles reduces total time, the mean relative difference of path-planning between 1 and 10 obstacles is 18%. Figure 14 illustrates the effect of the number of obstacles on execution time. Note that while the relative difference is similar for all three algorithms, in absolute values the effect on DALI is more significant due to a much slower execution.

The number of milestones affects the size of our UTA model and, consequently, the time needed for mission-plan synthesis. Figure 15 shows the TAMAA computation time in the first experiment. Excluding a few outliers (less than 1%), all schedules have been constructed within 0.3 seconds.

Answer to **RQ1**: DALI is significantly slower than classic algorithms like A*. Its optimized version DALI* is much faster, and the performance difference between DALI* and A* is below 10% on almost all combinations of parameters.

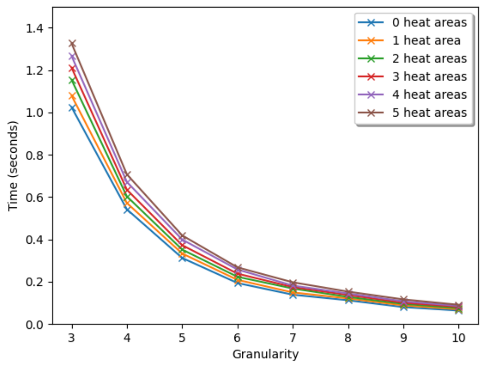


Fig. 16. The second group of experiments: the graph generation time w.r.t. the number of heat areas

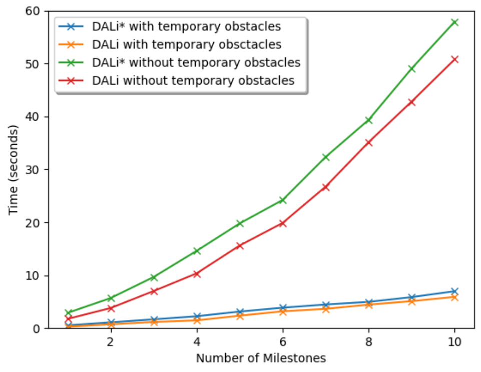


Fig. 17. The second group of experiments: the path-planning time w.r.t. the number of milestones

Answer to **RQ2**: The number of obstacles, the number of milestones, and granularity affect the performance of MALTA. The most significant is granularity, since its square is inversely proportional to the graph size. Nevertheless, even with 400,000 nodes in the graph the overall computation with DALI* or A* takes less than 1 minute.

6.4 Evaluation in Complex Environments

For the evaluation of **RQ3**, we add heat areas and convert several obstacles into temporary ones. A* does not support such constraints, therefore the evaluation has been limited to DALI and DALI*. The mission has been specifically designed to ensure that paths computed before the first call to the task scheduler would cross the temporary obstacles during their active time. Therefore, the generation of a correct mission plan requires at least one path recomputation and additional calls to TAMAA.

The presence of temporary obstacles has minimal effect on graph generation: the areas inside temporary obstacles are always included in the graph, but we precompute the list of nodes inside each temporary obstacle. On average, this costs several milliseconds depending on the granularity: 4 milliseconds for granularity 10 and up to 68 milliseconds for granularity 3. For heat areas we also precompute affected edges: Figure 16 illustrates a slight increase in graph generation time with the number of heat areas. For granularity 3, the time difference between 0 and 5 heat areas is just 0.3 seconds on average.

Figure 17 shows the results for the two versions of DALI. For comparison, we add the corresponding results from the previous group of experiments without temporary obstacles. Due to the presence of temporary obstacles, MALTA requires several additional calls to the path-planning algorithm and to TAMAA, thus requiring extra computation time. For granularity 4, DALI requires several seconds to recompute several paths, while DALI* can do that within a second. Note that path-planning during these additional calls is known to encounter at least one temporary obstacle during the graph exploration and requires additional checks at each step to ensure the avoidance of the obstacle. Therefore these calls are slower and increase mean time per call as shown in Figure 18. The mean time increase depends on a proportion of extra calls: for a single milestone where we have two calls in the beginning and 1 recomputation call, the

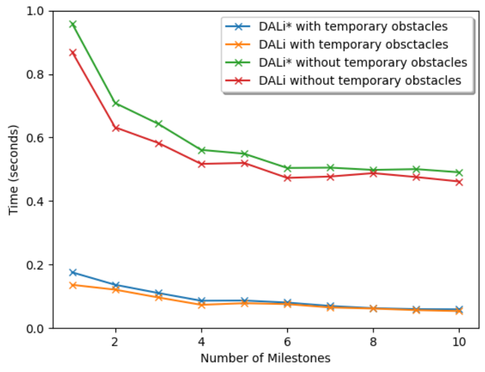


Fig. 18. The second group of experiments: the mean time of a single path-planning call at granularity 4

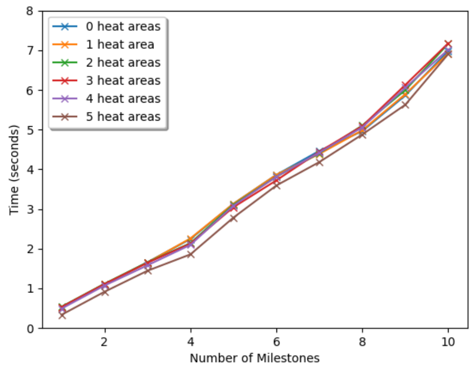


Fig. 19. The second group of experiments: the path-planning time w.r.t. the number of heat areas

mean time increase per DALɪ* call could reach 0.1 second (0.2 for DALɪ) for granularity 3, while for 10 milestones the increase is below 0.01 second (0.05 for DALɪ).

Heat areas can potentially affect the performance of path planning. They can increase the length of the shortest path and the time for the search. More importantly, their combination with temporary obstacles may affect the number of recomputations of paths: a path around a heat area can lead towards a temporary obstacle or, conversely, can help to avoid it. In the experiment, we have the latter case: one of the heat areas changes the shortest path between two milestones and avoids a temporary obstacle. As a result, the recomputation is not called, reducing the total computation time. Figure 19 shows the effect of heat areas on path-planning time. Considering all pairs of parameter sets that differ only in the number of heat areas, only 30% pairs show significant differences in the total path planning time including all cases with different number of recomputations. Thus, the length increase of the shortest path is mostly insignificant unless a temporary obstacle is encountered or avoided.

The computation time of TAMAA does not depend on heat areas or temporary obstacles, therefore, the time for a single call to TAMAA remains the same as in the previous group of experiments. The difference is not statistically significant in 76% of parameter combinations, while in the remaining combinations the difference does not exceed 0.07 seconds and for the majority is below 0.01.

Answer to **RQ3**: The introduction of additional constraints may require MALTA to recompute paths and consequent tasks rescheduling. Their impact on performance is low and does not significantly affect the scalability of the solution.

6.5 Evaluation on Missions with Multiple Agents

In the third group of experiments, we evaluate how the tool performs with multiple agents (**RQ4**). Within this group, we use A* and DALɪ* and missions without temporary obstacles. We ignore the case when two agents might cross their paths and assume that the shortest path between a pair of milestones can be the same for all agents.

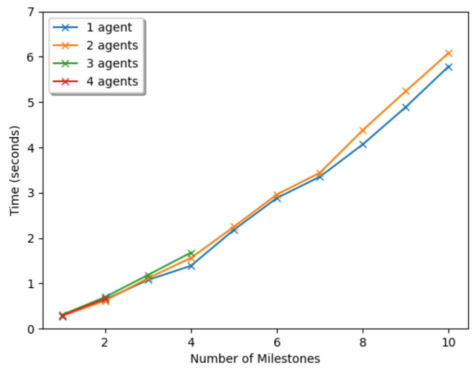


Fig. 20. The third group of experiments: the path-planning time w.r.t. the number of milestones

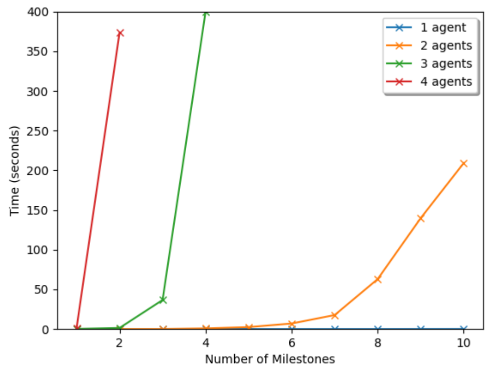


Fig. 21. The third group of experiments: the TAMAA time w.r.t. the number of milestones. The point at the tp boundary corresponds to 924 seconds.

The involvement of multiple agents in the mission has a low effect on the path-planning algorithm performance, and on 5 runs the difference is not statistically significant. The assumption above on the common shortest paths for agents allows us to reuse paths between milestones for all agents. In the experiment all agents started from the same point, therefore all paths were reused between the agents. In the case of different starting points, additional calls would be required to compute paths from their respective starting points, yet considering a single call time, they could be completed within a second. Figure 20 shows the DALı* path-planning time for multiple agents.

The number of UTA used in TAMAA and, consequently, the complexity of the composed model of multiple agents depend on the number of agents. Figure 21 show the TAMAA calls time. Our tool timed out for 3 agents with 5 milestones and 4 agents with 3 milestones.

The introduction of temporary obstacles would require additional calls to the task scheduler and would roughly multiply the computation time by the number of calls to TAMAA. This experimental result reflects the limits of MALTA: task scheduling model must not become too large to be handled by the model. Our previous experiments with TAMAA have also reported this phenomenon [GES19]. We discuss this limit further in Section 8.

Answer to **RQ4**: MALTA does not scale with the number of agents due to the state-space explosion problem in model checking.

7 ADAPTABILITY AND REUSABILITY OF MALTA: SPECIAL INDUSTRIAL USE CASES

The variability of mission planning problems is immense. Even within the autonomous quarry case study, there is a huge spectrum of requirements starting from safety properties to liveness properties [BK08], such as: agents must never go across a certain area when humans are working there (safety property), and agents should repetitively enter the charging points until they accomplish the mission (liveness property). Due to high variability, it is infeasible to build a fully automated solution that covers all possible cases efficiently. Therefore, the adaptability of a solution plays a crucial role, which requires an easy way of adapting the agent models and queries to different applications and their

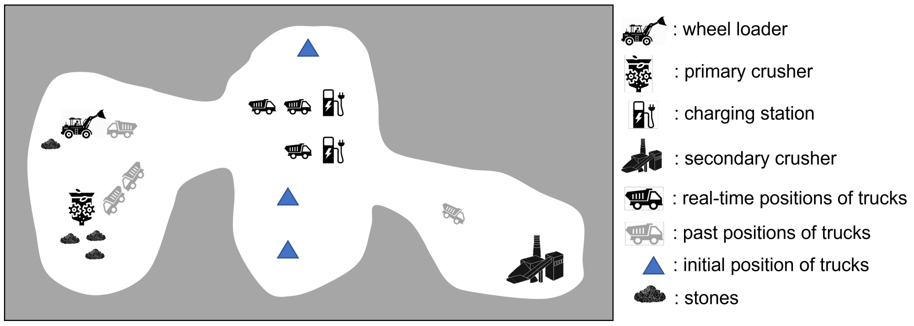

: wheel loader
: primary crusher
: charging station
: secondary crusher
: real-time positions of trucks
: past positions of trucks
: initial position of trucks
: stones

Fig. 22. An example of the autonomous quarry

Table 2. Machine parameters in the autonomous quarry

	Machine	Speed	Rate	Capacity
Mobile	Autonomous truck	35 km/h	1.5 tons/s	15 tons
Stationary	Wheel loader	/	1.5 tons/s	/
	Primary crusher	/	0.25 tons/s	/
	Charging station	/	30 s/time	/

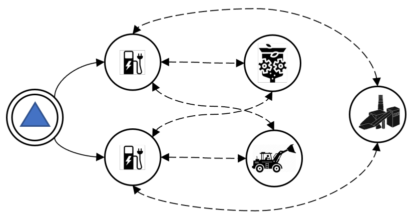
requirements. In this section, we show an example of a variant of our industrial case study: the autonomous quarry, which is slightly different from the problem definition (i.e., Definition 1).

We consider two special use cases, in which: i) new tasks appear after a mission plan is synthesized, and ii) the navigation area has a different topology and some tasks are periodic. Both use cases have trucks as the agents, wheel loaders, and primary crushers, and secondary crushers as the milestones to visit. Table 2 shows the parameters of the machines in the quarry. Trucks can carry 15 tons of stones, and the primary crusher can load 0.25 tons of stones per second, therefore the primary crusher takes 60 seconds to fill in one truck, while the wheel loader can do that in 10 seconds. The trucks can unload 1.5 tons of stones per second, so trucks unloading a full bucket of stones into the secondary crusher takes 10 seconds. The mission goal is to transfer 90 tons of stones as fast as possible. However, in case I, the target amount of stones is increased when new tasks appear.

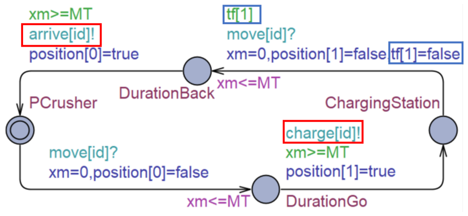
We use MALTA to create a mission plan for the trucks. The use cases do not specify distances in the quarry, therefore we assign them in a manner that ensures that the trucks finish the tasks without draining out. For path planning, the DALI* algorithm is applied. To download the models for the use cases, please see Footnote 5.

7.1 Case i: Additional Tasks

Case i) is an extension of the running example in Figure 2 where two agents have three consecutive tasks that already exist before the mission-plan synthesis starts and four additional tasks that appear after the three existing tasks are scheduled. Each additional task is bounded with a new milestone and randomly chooses a task from the existing tasks to be its preceding task. Hence, the additional tasks can be injected into or concatenated with the execution of the existing tasks. As the additional tasks do not influence the execution of the existing tasks, the new mission plan can be synthesized based on the existing one. As described in Section 4.3.2, the existing mission plan is encoded in a UTA model such that the agents' actions of executing the old tasks do not need to be scheduled again. MALTA automatically generates such a UTA model that also contains the components for the new tasks and milestones. We verify the model



(a) The topology of the autonomous quarry in Fig. 22



(b) A part of the adjusted movement TA

Fig. 23. Adjustments of the model for the industrial use case.

against Query (10) to obtain the fastest trace of accomplishing all seven tasks. In Section 7.1.1, we report the synthesizing time and compare it to the time of synthesis without an existing plan.

7.1.1 Results. The synthesis of a new mission plan that covers both the existing three tasks and the additional four tasks is conducted in two ways: i) based on the existing mission plan; ii) recomputing from the beginning. Both ways are automatically done by MALTA. In the first way, the synthesis costs 44.5 seconds, whereas the second way costs 623 seconds, 14 times more than the first way. The results demonstrate that, when additional tasks appear after a mission plan is synthesized, MALTA is able to adapt the mission plan in an efficient manner when the newly added tasks do not influence the execution of the existing tasks.

7.2 Case ii: Special Topology and Tasks

Case ii) is depicted in Fig. 22. The quarry has 3 identical autonomous trucks transferring stones from a primary crusher to a secondary crusher. Stones are gathered at the left side of the quarry and can be loaded into the trucks either by the primary crusher or by a wheel loader. This use case has two requirements that are not supported directly by the original model of MALTA. First, the primary crusher is required to minimize idle time, therefore the wheel loader can only be used if the primary crusher is already occupied by two trucks: one is being loaded and another is waiting in a queue. Second, on the way between crushers, there are two charging stations. The use case requires trucks to stop and charge every time they pass the charging stations, no matter how much battery they have left. Each charging stop takes 30 seconds. Besides, the topology of the map is also changed to match the special geographic arrangement of machines in the quarry. Therefore, we need to adjust the already introduced UTA models and queries for this use case.

7.2.1 Adjustments of the Models. The original movement UTA assumes a direct connection between every pair of milestones. However, the geographic arrangement of the use case is different. As the charging stations occupy the center of the quarry, trucks must pass them when traveling from the left to the right of the quarry, and vice versa. Hence, the topology of the quarry for this use case is adjusted. As depicted in Fig. 23(a), the primary crusher, wheel loader, and secondary crusher are connected via the charging stations. The generated movement UTA enforces the topology, thus only accepting the traveling between the charging stations and other milestones. From a truck's point of view, the wheel loader and primary crusher are both for loading stones, so there is no need to connect the wheel loader and primary crusher in the topology. The new requirement of the charging task also induces other adjustments of the movement UTA. Fig. 23(b) shows a part of the adjusted movement UTA, where changes are highlighted by the blue and red squares. When a truck, which is identified by variable `id`, leaves a charging station, its charging task, which is

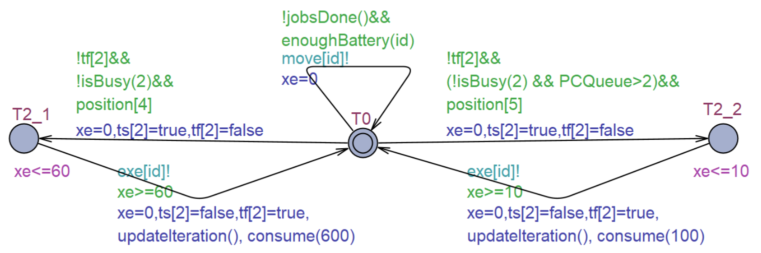

!jobsDone()&&
enoughBattery(id)
move[id]!
xe=0
!tf[2]&&
!isBusy(2)&&
position[4]
!tf[2]&&
(!isBusy(2) && PCQueue>2)&&
position[5]
T2_1
T0
T2_2
xe=0,ts[2]=true,tf[2]=false
xe=0,ts[2]=true,tf[2]=false
xe<=60
xe<=10
exe[id]!
xe>=60
xe=0,ts[2]=false,tf[2]=true,
updateIteration(), consume(600)
exe[id]!
xe>=10
xe=0,ts[2]=false,tf[2]=true,
updateIteration(), consume(100)

Fig. 24. A part of the adjusted task-execution UTA

represented by `tf[1]`, must be executed. After the truck leaves the charging station, the variable `tf[1]` flips to *false* so that the next time it reaches a charging station, the charging task can be carried out again.

The second additional requirement of this use case is the priority between the primary crusher and the wheel loader. To fulfill such a requirement, an adaptation of the task execution UTA is necessary. As depicted in Fig. 24, we add an additional constraint $PCQueue > 2$ to the guard of the *edge* going to *location* `T2_2` (representing task "Loading at the wheel loader), where *PCQueue* is a global variable counting the number of vehicles at the primary crusher. Therefore, the adapted task execution UTA models that when the length of the waiting queue at the primary crusher is less than two, trucks must go to the crusher; otherwise, the trucks can choose to wait in the queue or go to the wheel loader for loading stones. The synthesized mission plan is supposed to make a wise choice in this case for optimal productivity. In addition, in the movement UTA, *edges* going into and leaving from the location representing the primary crusher updates the *PCQueue* variable.

The mission of this use case is defined to carry all the stones to the secondary crusher rather than complete all the tasks a desired number of times. Therefore, we add the auxiliary variables *stone* and *load*, which represent the total volume of stones remaining to be transferred and the vehicle's capacity, respectively.

7.2.2 *Additional Adaptation of Queries and Models.*

The requirements formalised by Queries (7) - (9) are not changed for the use case, however, Query (10) is replaced, due to the different mission formulation, by:

$$E <> stone == 0 \tag{11}$$

The use case has two additional requirements:

(1) Prioritizing the primary crusher before the wheel loader: a truck can choose the wheel loader only in case when there are two other vehicles at the primary crusher (one being served and one in a queue).
(2) Battery charging: whenever a truck passes by a charging station, it must stop there and charge for 30 seconds. The trucks' batteries must never be consumed before they finish the global mission.

The former requirement has a straightforward encoding into the following UPPAAL query:

$$\texttt{A[] PCQueue < 2 imply !(task}_0\texttt{.T2\_2 || ... || task}_n\texttt{.T2\_2),} \tag{12}$$

This query checks that at any moment in case of the queue at the primary crusher being not full, the task execution UTA of any truck is not at the *location* `T2_2` that represents being loaded at the wheel loader.

The latter requirement consists of two parts. First, it requires the trucks to always charge themselves right after they arrive at a charging station. Second, it requires the trucks to charge themselves timely so that their batteries are not consumed. A logic formalization of the first part is called "*always next*", i.e., the *next* action of moving to a charging station is *always* charging. Unfortunately, the "*always next*" property cannot be formalized in the query language supported by UPPAAL (a subset of TCTL [HYP+06]). To overcome this difficulty, we design an auxiliary UTA, to help us verify this requirement. Fig. 25 shows the auxiliary UTA, namely *monitor*, where *channels* `arrive` and `charge`

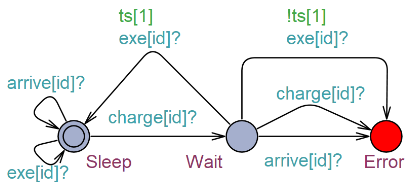


Fig. 25. The auxiliary UTA *monitor* for verifying the repetitive charging requirement.

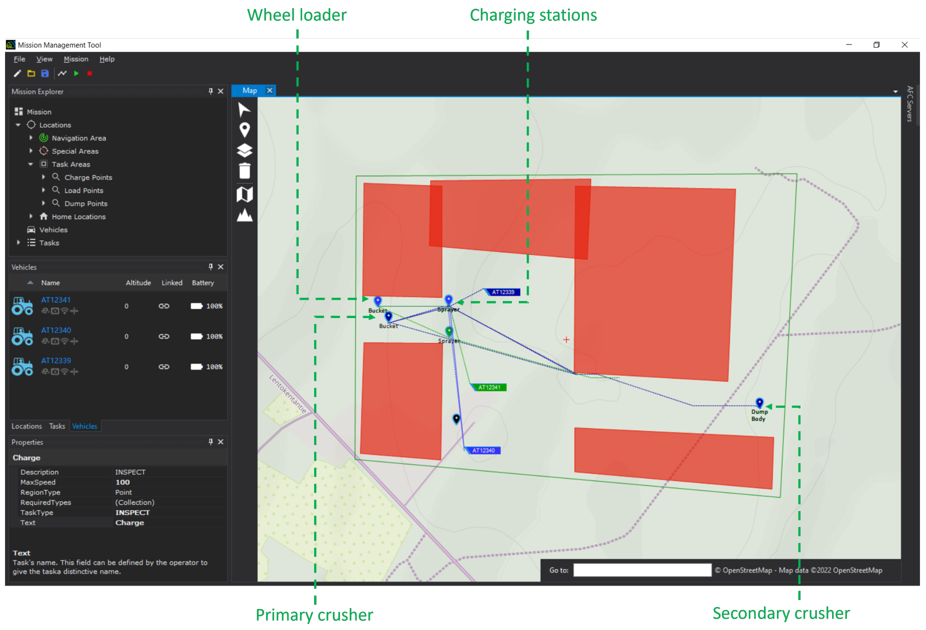
synchronize the movement UTA and the monitor UTA (see Fig. 23(b) too). The *channel* `exe` is for synchronizing the task execution UTA and the monitor UTA when the truck is going to execute a task (see Fig. 24 too). Therefore, the monitor UTA initially stays at *location* `Sleep` when the truck moves and executes tasks (i.e., two self-loops at *location* `Sleep` in Fig. 25). If the truck is moving to a charging station, the monitor UTA transfers to *location* `Wait`, and synchronizes with the movement UTA via *channel* `charge`. Next, the monitor UTA has multiple choices of the next transition: charging or executing other tasks (i.e., synchronization via *channel* `exe`), or moving to other milestones (i.e., synchronization via *channel* `charge` or `arrive`). A Boolean variable `ts[1]` is used to indicate whether the current truck is charging or not. The *edge* from *location* `Wait` to *location* `Sleep` is guarded by this variable, meaning that only charging can make the monitor UTA go back to its initial *location*, whereas other transitions will end up to a *location* representing errors. In summary, the monitor UTA regulates the correct order of a truck's task execution, i.e., moving to a charging station must be always succeeded by charging. If the trucks violate this regulation, they will be stuck at the `Error` *location*. The contraposition of this statement is if the truck never visits the `Error` *location*, the next action of moving to a charging station is always charging. Since the satisfaction of Query (11) guarantees the progress of task execution, the contraposition forms the "*always next*" constraint in the battery-charging requirement. Now, we encode an invariance query to verify this property:

$$\texttt{A[] !monitor}_0\texttt{.Error \&\& ... \&\& !monitor}_n\texttt{.Error} \tag{13}$$

Query (13) requires that *monitors of trucks* never reach the `Error` *location*. Satisfying this query indicates that the trucks always charge themselves after arriving at a charging station.

To verify the second part of the battery-charging requirement, we need to add an array of integers to store the battery levels of trucks. Since we only care about whether the battery level is always above zero, it is unnecessary to track the consumption curve of batteries. Hence, we only verify if the vehicle's battery level is always above zero in Query (14), where `N` is the index of the last truck. In the model, a variable for calculating the remaining battery of a vehicle is deducted every time the vehicle moves or executes a task. The deduction is proportional to the time consumption and is done in function `consume` in Figure 24. For instance, when the vehicle moves for 50 seconds, the battery is deducted by $k \times 50$, where $k \in \mathbb{R}$ is a coefficient representing a consumption rate.

$$\texttt{A[] forall(i:int[0,N]) battery[i]>0} \tag{14}$$



Vehicles

Name	Altitude	Linked	Battery
AT12341	0		100%
AT12340	0		100%
AT12339	0		100%

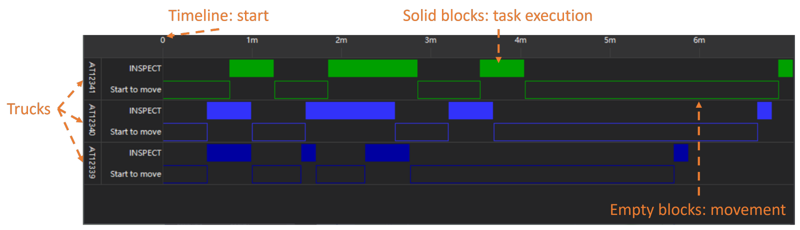
Properties

Charge

Description	INSPECT
MaxSpeed	100
RegionType	Point
RequiredTypes	(Collection)
TaskType	INSPECT
Text	Charge

Text
Task's name. This field can be defined by the operator to give the taska distinctive name.

(a) The path plans of trucks



(b) A part of the Gantt chat presenting the task schedules of trucks

Fig. 26. A mission plan of trucks working in the autonomous quarry of Fig. 22

7.2.3 Results. Given the machine parameters shown in Table 2, we use *MALTA* to synthesize a mission plan that controls the three trucks to transport 90 tons of stones to the secondary crusher while satisfying all the requirements of the use case and finding the fastest way to finish the global mission. After running *MALTA* to generate the fastest trace that satisfies Query (11), a synthesized result of the mission plan is illustrated in *MMT* (Fig. 26). Fig. 26(a) shows the paths of avoiding static obstacles and visiting different milestones. The task schedule (Fig. 26(b)) shows the interleaving sequence of movement (empty rectangles) and task execution (solid rectangles). One can check the details of path plans by clicking on the empty rectangles, and then the corresponding path plans will be highlighted in the GUI of path plans. The mission plan shows that the fastest time for transporting all the stones is 6.9 minutes. The fact that a mission plan is depicted in *MMT* demonstrates that Queries (12) - (14) are satisfied.

8 DISCUSSION

Experiments in Section 6 show the performance and scalability of our methods with respect to different parameters, such as the presence of temporary obstacles, numbers of milestones, heat areas, and agents. Based on the results of experiments and case study, we can see the strengths and weaknesses of our method. However, we first analyze the threats to validity of the experiments.

8.1 Threats to Validity

Internal validity. We have designed the experiments to measure the performance and scalability of the proposed methodology. To avoid the threat of the performance being affected by a particular combination of parameters, we measure results for all possible combinations. The comparison results of 1 or 2 parameters are valid for any combination of the remaining parameters. Performance has been measured by comparing the runtime, which is known to be imprecise and depends on other processes running in parallel during the experiment. To mitigate this threat, we run all experiments multiple times (50 times for groups 1 and 2, respectively, and 5 times for group 3), and report the mean value. The relative standard deviation between runs is below 0.1 for 90% of measurements, yet in a few cases, some of the runs were significantly slower than the other ones and affected the mean value. All runs have been independent, therefore we used statistical methods, in particular Welch's t-test [Wel47], to ensure the significance of the results. For group 3, the growth of time for multiple vehicles is more significant than any potential measurement noise, therefore we conclude the scalability effect with 5 runs only.
External validity. To mitigate the threat of non-generalizability, we evaluate the approach under different mission settings, such as the various number of agents and the types and numbers of obstacles and heat areas. The experiments covered all the representative and valid settings. They are designed in a way to have a significant impact on the resulting mission and its computation. For example, the addition of (temporal) obstacles affect paths among several milestones, the corresponding travelling times and, time constraints. Additionally, we set up the experiments based on a real-world use case, i.e., an autonomous quarry, thus making the evaluation results relevant to practical applications of MALTA.

8.2 Strengths and Weaknesses of MALTA

The computation time of path plans increases linearly when the number of agents increases because the agents run the path-planning algorithms independently. However, as task scheduling needs to maintain a global view of the entire mission, our algorithm must use a composed model that contains all the possible combinations of actions among the agents. Therefore, the computation time of task schedules increases exponentially with the linearly increasing number of agents. However, the performance of MALTA fulfills the industrial requirements, as the planning problem in this paper targets high-level missions, which means the frequency of planning is low (e.g., once per day) and safety has the highest priority. In this aspect, mission planning in MALTA comes with a correctness guarantee, that is, the result is guaranteed to be safe and traveling time is the shortest if users select the fastest trace, despite the complex and various environmental constraints, such as the existence of temporary obstacles and crowded areas. This correctness guarantee is based on formal verification, which is lacking in AI-based mission-planning algorithms. We compare our method with such algorithms in Section 9.

MALTA provides an open platform for mission planning and the fundamental tools that ease the work of model construction and trace parsing, and can be employed by engineers who design the mission. Based on this platform, we have also developed MCRL (model checking + reinforcement learning) [GJP$^+$22], which alleviates the scalability problem, a method for probabilistic mission planning that considers stochastic behaviors in the environment [GESL20a], and a method for scalable mission planning and mission plan compression [GJS+22]. The learning-based methods (e.g., MCRL) perform better than the search-based methods (e.g., TAMAA) regarding the number of agents. However, the latter is better when the number of agents is low (that is in fact the case in most construction sites, for instance), but the mission goal needs a long sequence of actions to achieve, i.e., the goal state is hidden deeply in the state space [GJP+22]. As MALTA provides both kinds of methods, users can choose between them according to the characteristics of their applications.

Case studies in Section 7 show the adaptability of our methods in special cases that do not perfectly match our problem definition. Self-adaptive systems (SAS) are capable of changing their behavior, whenever the environment shows that the systems are not accomplishing their mission [MEHDTH13]. One may wonder if the problems of SAS are solvable by using MALTA. We notice that formal methods have been used in SAS for decades [WIDLIA12], however safety, security, and scalability still lack enough consideration in the intersection of these two fields [LFD+19]. One of the reasons behind this issue is that the hybrid nature of SAS and its working environment is very difficult to model and verify. We emphasize that MALTA focuses on the planning phase of agents, which is designed to cope with the known factors in the planning problem, such as the locations of obstacles and the order of task execution. Although our methods present an extent of adaptability, we claim that the adaptation of agents to a dynamic environment is outside the scope of this paper. In our previous work [GMSL19], we propose a two-layer framework to separate the concerns of static planning and dynamic adaptation and keep a communication channel for sharing information between two layers. We believe this framework is a potential solution for utilizing MALTA in designing SAS.

9 RELATED WORK

Path planning, a.k.a., motion planning in the Artificial Intelligent (AI) community, has been an interest of research since the early days of robotics [N+84]. Sampling-based methods like Rapidly-exploring Random Tree (RRT) [LaV98] and a method based on probabilistic roadmaps for path planning [KSLO96], and graph-search-based methods like A* [Rab00] and Theta* [DNKF10] are two typical branches of path-planning algorithms. The main contribution of these algorithms is to find collision-free paths in a static and continuous world, in which the topology of the moving space does not change. Moreover, when a robot starts to interact with the world, e.g., picking an object and carrying it to another position, the robot's and object's dynamics and kinematics are changed, which can cause the initial motion plan to be unsuitable. Alami *et al.* [ASL90] and Hauser *et al.* [HL10] propose a modal structure of the robots and their working environments. Since the switch of modes is discrete, the problem is about identifying the modes of the systems, defining the transitions among the modes, and traversing the state spaces in order to find a trace that satisfies certain constraints. This is the so-called task planning in the AI community [GNT16]. These approaches do not guarantee correctness unless coupled with a formal verification technique.

Integrating task and motion planning (TAMP) provides us a good understanding of our problem: hybrid discrete-continuous search problem [GCH+21]. Research in this area often combines AI and robotics and seeks to provide a separation of concerns by designing hierarchical frameworks, in which high-level task planning and low-level motion planning are separated into different layers, and connected via an intermediate layer [GMSL19, STWZ10]. Downward refinement in the methods proposed by Bacchus *et al.* [BY94] and Nilsson *et al.* [N+84] first plans at the high level and then refines the high-level plans to low-level ones. The authors assume that their problems fulfill the *downward refinement property* [BY94], which is often not the case in reality. Our method, on the contrary, starts from the low level to calculate path plans that are collision-free and then integrates the path-planning results into the model for task planning. Therefore, our task-planning results are naturally collision-free.

There is an important line of work in task planning that uses temporal logic to specify the high-level requirements of tasks [KGFP09, BYG17]. Linear Temporal Logic (LTL) is the most widely used logic for requirement specification [FJKG10, CPLK20, BKV10], because of its expressive power that is able to capture relatively complex requirements, such as repetitively filling the water tank if the water level is lower than a certain level. Different from these studies, we adopt Timed Computation Tree Logic (TCTL). TCTL and LTL are members of a temporal logic family named CTL* [BK08]. Each of them has its own expressive power and thus is used in different problems. TCTL enables one to express timed requirements such as digging 1000 m^3 of stones per 24 hours, which is of a high industrial concern, in an attempt to ensure productivity when using autonomous vehicles. Most importantly, our task planning is fully integrated with path planning. Therefore, the results of our method comprehensively consider both the traveling time, as well as the task execution time and order. Bride et al., also adopt model checking in motion planning for autonomous systems. However, the modeling in this study is manual and does not mention the timing requirement that is important in our solution.

In the formal methods community, task planning is being challenged by various formalisms and methods. When the formalisms only have stochastic models, the problems fall into a category called $\frac{1}{2}$-player games [Jen18]. In $\frac{1}{2}$-player games, neither agents nor environments get control of their behaviors and the corresponding outcome, e.g., flipping a coin. By replacing the stochastic behaviors of agents with non-deterministic choice of actions, $\frac{1}{2}$-player games are changed to 1-player games, which is the problem that we are solving in this paper. Note that, 1-player games assume that the environment is fully controlled by the agents so that the winning strategies are totally dependent on the behaviors of the agents [Jen18]. Besides UPPAAL, there are many other tools that aim to solve this kind of problem, e.g., Kronos [BDM+98], LTSim [BvdPW10], and SpaceEx [FLGD+11]. The major difference between our tool and these mentioned ones is that our MALTA tool integrates path-planning algorithms and task-scheduling algorithms, and has a dedicated GUI for mission planning, which provides interfaces for an extension. Adding stochastic behaviors to environments makes the formalism represented as a $1\frac{1}{2}$-player game, and changing the stochastic behaviors of environments into non-deterministic ones that are independent of agents makes the formalism to be a 2-player game [Jen18], both of which are out of the scope of this paper. There are studies that investigate synthesizing controllers from various temporal logic specifications. Alur *et al.* [AMT16, AMT18] propose a compositional method for synthesizing reactive controllers satisfying Linear Temporal Logic specifications for multi-agent systems. Tumova et al. [BLDT19, NBTD18] present their method for motion planning of multiple-agent systems using Metric Interval Temporal Logic (MITL). Inspired by these works, our study aims to bring up a methodology that is dedicated to collectively solving multi-agent mission planning that includes two components: pathfinding and task scheduling, and dealing with complex environmental constraints and timing requirements of tasks.

In the field of robotics, the design and development of GUI for planning, execution, and supervision of missions involving several autonomous vehicles is getting increasingly much attention [ED06]. Such a GUI allows the operator of autonomous vehicles to plan and supervise several vehicles at the same time, which has been a research topic for different use cases including delivery services [SMCC18], military applications [KJK+15] and others [PMC+13, LKHM16, S+18]. Woodrow et al. [WPMG05] proposes a tool-supported method for mission planning and replanning of autonomous underwater vehicles (AUV). Their tool has a GUI and enables AUV to adpat its mission based on updates its situational awareness. MahmoudZadeh et al. [MPSY16] advances the planning for AUV by prosposing a reliable and robust method that can deal with uncertainties. However, the environmental constraints that their methods consider are not as rich as

MALTA and the AUV do not need to collaborate for the global mission. Additioanlly, most of these GUI however, are designed for specific use cases and cannot be used as a generic graphical user interface for other domains. In this work, we employ MMT which is a GUI that can be set up to communicate with different planners and autonomous vehicles. MMT has been used for planning and supervising underwater autonomous vehicles previously [ACME20].

10 CONCLUSIONS AND FUTURE WORK

In this article, we have presented a new methodology and a toolset to solve the mission planning problem of multiple autonomous agents. Our methodology includes an improved version of DALı for path planning, a timed-automata-based method for task scheduling, namely TAMAA, and an integration of these two methods to provide a complete solution of synthesis and verification of mission plans for multiple agents. As the improved version of DALı considers special road conditions, such as temporary obstacles, our method can deal with complex environments. TAMAA is based on formal modeling and model checking, so the synthesized task schedules are guaranteed to be both correct and the fastest to finish all tasks. The integration of DALı and TAMAA requires an iterative computation between path planning and task scheduling, so that the result mission plans consider both the traveling time and task execution time and are guaranteed to be the optimal solution. The methods have been implemented as a toolset named *MALTA*, which is made of three components. The front end of *MALTA* is a GUI for configuring the mission requirements and showing the results of mission planning. The back end of *MALTA*, which is responsible for running computationally expensive functions, can be deployed locally or remotely. The middleware of *MALTA* bridges the front end and back end, so the users can focus on designing the map and tasks for the agents, and benefit from the algorithms of path planning and task scheduling without knowing the technical details. We have employed the toolset to solve a mission-planning problem of an industrial use case of an autonomous quarry. We have observed the computation time w.r.t. the numbers of obstacles, agents, heat areas, milestones, and the granularity of the map. The experimental results demonstrate the capability and limit of our method, that is, the computation time of path-planning algorithms increases linearly with the increased size of the maps and the number of agents, whereas the task scheduling suffers from the state-space explosion problem when the number of agents becomes large. An instantiated quarry is introduced and solved to show the flexibility of our method to fit various applications of mission planning.

There are two potential directions to extend our work in the future. One is to enrich the path-planning and task-scheduling algorithms supported by *MALTA*, so that the toolset can cope with more complex problems such as more agents or larger environments. Integrating the toolset with machine learning techniques is another direction. As the current task scheduling assumes the environment to be collaborative, it can be interesting to investigate how the method can be adapted when the environment contains some competitive agents.

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