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A Multi-Agent Planning Model for Airport Ground Handling Management

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Abstract— **Inefficiency airport ground handing operations is one of the main reasons for flight delays, as it comprises a series of processes and collaborations between various airport's services. Using multi-agent planning (MAP) method, this paper proposes a framework as a management system to improve the airport ground handling management (GHM). With the identification of the services and resources related to GHM, the forward MAP approach is applied to coordinates the tasks and planning in order to reduce both the delays and the operating cost. In this case, the key contribution includes MAP model for airport ground handling operations under a unified framework compatible with the airport collaborative decision making (A-CDM) strategy.**

Index Terms— **Multi-Agent Planning, Airport Collaborative Decision Making, Airport Ground Handling Management.**

I. INTRODUCTION

Air traffic flow management (ATFM) is a challenging area for the application of artificial intelligence, operation research and other techniques due to the continuous increase of air traffic flows and the amount of the involved data [1], [2], [3]. Today, delays and congestion have become a common situation resulting in high financial and social cost for airlines and passengers [4], [5]. For example, in 2014, approximately 23% of the flights in the United States were delayed by more than 15 minutes, while another 3% were canceled [6].

One way to reduce flight delays is to expand the airport infrastructure. However, this usually has a high financial cost. Furthermore it demands years to be successfully implemented. Indeed, there is a consensus among experts in the air transportation industry that infrastructure development alone will not be enough to satisfy the increasing in delay above current levels [7], [2]. If delays resulting from bad weather are mostly unavoidable, the advanced performance of traffic management at airport is needed by searching new operational approaches for improving the overall airport performance.

Ground handling management (GHM) comprises various services required by airplanes while they are on the ground, parked at a terminal gate or on a remote position in an airport. This includes the processing of boarding/de-boarding passengers, baggage and freight, as well as the maintenance of the aircraft itself (e.g., fueling, cleaning, sanitation, among others) [8].

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In most airports with intense traffic movement, there is a considerable number of airplanes landing and departing everyday. However, some ground operations related to airplanes have to be done before departure, including loading and unloading of luggage, refilling of fuel and water, safety check, among others.

Airport Collaborative Decision Making (A-CDM) is a wide accepted concept which creates a common ground management procedure for the different components of the Air Transportation System (ATS). This concept is based on an improved communication between the different stakeholders of the airport (e.g., Air Traffic Control, Airport Authority, and Airlines). CDM has already been applied to some major airports in Europe and in the United States; and it has helped to improve air traffic management performance. As a result, it has received the attention of different stakeholders. Nevertheless, within the turnaround process of aircraft at airports, GHM of aircraft has not been well developed specifically in the A-CDM procedure.

Multi-agent planning (MAP) is a method of Artificial Intelligence and refers to the problem solving by planning in domains where several independent stakeholders (agents) plan and act together. MAP is concerned with planning by multiple agents, i.e., distributed planning and planning for multiple agents. It can involve the planning of agents for a common goal, for which an agent coordinates the plans with others, or agents refine their own plans while negotiating over tasks or resources [9].

The main objective of this paper is to model the ground handling (GHM) operations under a unified framework, by using Multi-agent planning method to improve GHM performance. The new model is proposed to be compatible with the CDM procedure. It also seeks in particular to plan and allocate a number of different ground services to an flight in order to reduce its waiting time in an airport.

The reminder of this paper is organized as follows. Section II describes some related works in the domain of airport ground handling. Section III presents the environment followed by our MAP model in Section IV. Then, the experimental results are discussed in Section V. Finally, Section VI concludes this paper and presents envisioned future works.

II. RELATED WORKS

Du *et al.* [10] studied the fuel ramp operations and considered the scheduling problem of fueling vehicles and proposed a solution approach based on the Vehicle Routing Problem with Tight Time Windows (VRPTTW) with multiple objectives. Once merging some of these objectives into a single one and transforming the others in level constraints, this problem can be formulated as a large Integer Linear Optimization Problem. Then, they adopted a specialized Ant Colony Optimization (ACO) to try to solve efficiently this multi objective combinatorial optimization problem.

Clausen *et al.* [11] formulated the problem of managing the fleet of ground vehicles in charge of transporting baggage for connecting passengers between their arrival and departure flights in an airport as a cumbersome Integer Programming problem where N baggage must be transported using K identical vehicles of capacity Q. Considering the size of real life instances and the dynamic aspect of the problem, a greedy algorithm was proposed to solve approximately this problem.

A more sophisticated solution was proposed by Ho *et al.* [12] to tackle the airline catering operations including the staff workload. They considered the problem as a manpower allocation problem with time windows and job-skill constraints. The optimization objective consists in the maximization of the total number of assigned jobs. They presented a comparison between Tabu Search and Simulated Annealing approaches to solve the problem.

Dohn *et al.* [13] concentrated on the management of ground handling manpower by considering that ground handling is managed by a central entity responsible for dynamically building up the teams with the different skills, which will be in charge of each arriving or departing aircraft. This problem is close to the vehicle routing problem with time windows. So they adopted a Column Generation technique associated with a Branch and Bound technique, resulting in a Branch and Pricing approach. The formulated problem is NP-Hard.

The decentralized solution approach of the global ground handling assignment problem has been coped in two ways: *(a)* by considering that the global ground handling scheduling problem is an instance of a multi-project scheduling problem and *(b)* by considering that it is a distributed decision making problem. A representative work for this approach is the one of Mao *et al.* [14], which proposed a solution to solve the airport ground handling scheduling problem under uncertainty by considering that the global ground handling scheduling problem is an instance of a multi-project scheduling problem (MPSP), so, they considered the aircraft as a project agent which is composed by a set of activities, and the ground handling providers as resource agents, each one is responsible of a resource which performed a specific type of activity.

Following this approach, Ansola *et al.* [15] considered the ground handling processes as a distributed decision support system. To deal with this problem, they created a new theoretical and experimental Multi-Agent System called MAS-DUO. The architecture of this new MAS was based on a combinations of many existing methodologies. The MAS-DUO is a division of the organization model in two platforms: system of information model and physical model. The communication between the two platforms was assured by using of an interaction protocol based on sharing parameters of the Markov reward function. This new organization was tested to manage the ground handling operations on the Ciudad Real Central Airport.

Relating to the airport GHM, Fitouri-Trabelsi *et al.* [8] proposed a hierarchical structure to organize the ground handling management compatible with the A-CDM concept. The proposed structure introduces a ground handling coordinator (GHC) which is considered as an interface for communication between the partners of the A-CDM and the different ground handling managers (GHMs). This hierarchical structure allows sharing information with partners in the A -CDM on the one side and on the other side, interacting with GHMs. The global objective is to turn available the ground handling resources so that arriving and departing flight are serviced with as little delay as possible.

According to Fitouri-Trabelsi *et al.* [8], the considered applications of Operational Research to solve ground handling operations problems at the operations level, treat in general a nominal problem with no perturbation to the aircraft arrival schedule or to the operations of the different ground fleets. Even in this nominal case, the corresponding mathematical programming problems are of hard complexity class with big difficulties to get exact solutions for real size problems.

This research introduces the MAP method to manage the ground handling operations. The proposed framework uses a social collaborative approach to plan by multiple intelligent entities to work together for planning tasks that they are not able to solve by themselves, or to at least accomplish them better by cooperating [9]. MAP method places the focus on the collective effort of multiple agents to accomplish tasks by combining their knowledge and capabilities.

III. Working Scenario and Formal Modeling

A. Multi-Agent Planning Method

Multi-Agent Planning (MAP) method refers to multiple agents planning and acting collaboratively. More specifically, agents interact to design a plan that none of them could have generated individually in most cases. During the plan construction, the agents keep in mind that the devised plan will be jointly executed by themselves such that they collectively achieve their individual and common goals [16].

In MAP, a planning process is distributed to across several planning/executing agents that devise a joint, non-linear plan which will be later executed by the same agents. It is assumed that the agents are specifically designed to be cooperative, but they can also have their own private goals. Agents' decisions must not only be derivative from the collective goals but also from the other agents' strategy [16].

A MAP problem can be described as follows: given an initial state, a set of global goals, a set of (at least two) agents, each agent with a set of its capabilities (the actions they can perform) and (probably) its private goals, will find its action by a plan. These plans together are coordinated and the problem's global goals are met [9].

The complexity of a MAP task is often described by means of its *coupling level* [16], which is measured as the number of interactions that arises among agents during the resolution of a MAP task. According to this parameter, MAP tasks can be classified into loosely-coupled tasks (which present a few interactions among agents) and tightly-coupled tasks (which involve many interactions among agents). Therefore, agents in a MAP context want to minimize the information they share with each other, either for strategic reasons or simply because it is not relevant for the rest of the agents in order to address the planning task.

In the literature, there are two main approaches for solving MAP tasks. One is the centralized strategy and the other is the decentralized. On the one hand, the centralized relies on an intermediary agent that must have complete information about the tasks. The adoption of a centralized approach may help on improving the planner performance by taking advantage of the inherent structure of the MAP tasks [17], however, this may represent an issue when there are sensible data that must be kept private [18]. The distributed or decentralized approach, on the other hand, spreads the planning responsibility among different agents, which must coordinate their local solutions, if necessary [19].

In this paper, Forward MAP (FMAP) is used as the basic model, since it is a domain-independent MAP system that is designed to cope with a great variety of planning tasks of different complexity and coupling level.

B. Forward Multi-Agent Planning

FMAP is a fully distributed method that interleaves planning and coordination by following a cooperative refinement planning strategy. This search scheme allows us to efficiently coordinate agents' actions in any type of planning task (either loosely-coupled or tightly-coupled) as well as to handle cooperative goals, i.e., goals that cannot be solved individually by any agent since they require the cooperation of specialized agents [16].

The FMAP model is a multi-agent refinement planning model, which is a general method based on the refinement of the set of all possible plans. The internal reasoning of agents in FMAP model is configured as a Partial-Order Planning (POP) search procedure. Other local search strategies are applicable, as long as agents build *partial-order plans*. The following concepts and definitions are standard terms from the POP paradigm [20], which have been adapted to state variables. Additionally, definitions also account for the multi-agent nature of the planning task and the local views of the task by the agents.

A **partial-order plan** or partial plan is a tuple $\prod = <\Delta, OR, CL>$. $\Delta = \{\alpha | \alpha \in A\}$ is the set of actions in $\prod$. OR is a finite set of ordering constraints ($\prec$) on Δ. CL is a finite set of causal links of the form $\alpha \overset{<v,d>}{\rightarrow} \beta$ or $\alpha \overset{<v,\neg d>}{\rightarrow} \beta$, where α and β are actions in Δ. A causal link $\alpha \overset{<v,d>}{\rightarrow} \beta$ enforces preconditions $<v, d> \in PRE(\beta)$ through an effect $(v = d) \in EFF(\alpha)$. Similarly, another causal link $\alpha \overset{<v,\neg d>}{\rightarrow} \beta$ enforces preconditions $<v, \neg d> \in PRE(\beta)$ through an effect $(v \neq d) \in EFF(\alpha)$ or $(v = d') \in EFF(\alpha)$, $d' \neq d$.

An empty partial plan is defined as $\prod_0 = <\Delta_0, OR_0, CL_0>$, where OR_0 and CL_0 are empty sets, and Δ_0 contains only the fictitious initial action α_i. A partial plan $\prod$ for a task T_{MAP} will always contain α_i.

The introduction of new actions in a partial plan may trigger the appearance of *flaws*. There are two types of flaws in a partial plan: preconditions that are not yet solved (or supported) through a causal link, and threats. A *threat* over a causal link $\alpha \overset{<v,d>}{\rightarrow} \beta$ is caused by an action γ that is not ordered w.r.t. α or β and might potentially modify the value of v ($(v \neq d) \in EFF(\gamma)$ or $(v = d') \in EFF(\gamma), d' \neq d$), making the causal link unsafe. Threats are addressed by introducing either an ordering constraint $\gamma \prec \alpha$ (this is called *demotion* because the causal link is posted after the threatening action) or an ordering $\beta \prec \gamma$ (this is called *promotion* because the causal link is placed before the threatening action).

A *flaw-free* plan is a threat-free partial plan in which the preconditions of all the actions are supported through causal links.

Planning agents in FMAP model cooperate to solve MAP tasks by progressively refining an initially empty plan $\prod$ until a solution is reached. The definition of refinement plan is closely related to the internal forward-chaining partial-order planning search performed by the agents.

Refinement planning is a technique that is widely used by many planners, specifically in anytime planning, where a first initial solution is progressively refined until the deliberation time expires [18].

A **refinement plan** $\prod_r = <\Delta_r, OR_r, CL_r>$ over a partial plan $\prod = <\Delta, OR, CL>$ is a flaw-free partial plan that extends $\prod$, i.e., $\Delta \subset \Delta_r$, $OR \subset OR_r$ and $CL \subset CL_r$. $\prod_r$ introduces a new action $\alpha \in \Delta_r$ in $\prod$, resulting in $\Delta_r = \Delta \bigcup \alpha$. All the preconditions in $PRE(\alpha)$ are linked to existing actions in $\prod$ through causal links; i.e., all preconditions are supported: $\forall p \in PRE(\alpha), \exists\ \beta \overset{p}{\rightarrow} \alpha \in CL_r$, where $\beta \in \Delta$. Refinement plans in FMAP model include actions that can be executed in parallel by different agents.

Finally, a **solution plan** for T_{MAP} is a refinement plan $\prod = <\Delta, OR, CL>$ that addresses all the global goals G of T_{MAP}. A solution plan includes the fictitious final action α_f and ensures that all its preconditions (note that $PRE(\alpha_f) = G$) are satisfied; that is, $\forall g \in PRE(\alpha)$, $\exists \beta \overset{g}{\rightarrow} \alpha_f$, $\beta \in \Delta$, which is the necessary condition to guarantee that $\prod$ solves T_{MAP}. Every time agent i refines a partial plan by introducing a new action $\alpha \in A^i$, it communicates the resulting refinement plan to the rest of the agents in T_{MAP}. In order to preserve privacy, agent i will only communicate to agent j the fluents in action α whose variables are common to both agents.

FMAP is based on a cooperative refinement planning procedure in which agents jointly explore a multi-agent, plan-space search tree. A multi-agent search tree is one in which the partial plans of the nodes are build with the contributions of one or more agents [16]. Agents in FMAP keep a copy of the multi-agent search tree, storing the local view they have of each of the plans in the tree nodes. Given a node $\prod$ in the multi-agent search tree, an agent i maintains $view^i(\prod)$ in its copy of the tree. Likewise, FMAP relies on a theoretical model which defines a more sophisticated notion of privacy than most of the existing MAP systems and it is a complete and reliable planning system that has proven to be very competitive when compared to other state-of-the-art MAP systems. The experimental results show that FMAP is particularly effective for solving tightly-coupled MAP problems with cooperative goals [16].

C. Specification of MAP Tasks in GHM

A **MAP task** in FMAP is defined as a tuple T_{MAP} = $< AG, V, I, G, A >$, where:

- $AG = \{1, ..., n\}$ is a finite non-empty set of agents.
- V = $\bigcup_{i \in AG} V^i$. It means that V^i is the set of state variables known to an agent i.
- Each state variable v is associated to a finite domain D_v, of mutually exclusive values that refer to the objects in the world. $D_v^i \subseteq D_v$ is the set of values of the variable v that are known to agent i. I = $\bigcup_{i \in AG} I^i$ is a set of fluents[1] that defines the initial state of T_{MAP}.
- G is the set of goals of T_{MAP}, i.e., the values of the state variables that agents have to achieve in order to accomplish T_{MAP}.
- A = $\bigcup_{i \in AG} A^i$ is the set of planning actions of the agents. In this case, A includes two actions α_i and α_f that do not belong set of actions from the agent. In this case, α_i represents the initial state of T_{MAP}, i.e., $PRE(\alpha_i)$ = $\emptyset$ and $EFF(\alpha_i)$ = I, while α_f represents the global goals of T_{MAP}, i.e., $PRE(\alpha_f)$ = G, and $EFF(\alpha_f)$ = $\emptyset$. An $action$ is a tuple α = $< PRE(\alpha), EFF(\alpha) >$, where, $PRE(\alpha)$ is a finite set of fluents that represents the preconditions of α; and $EFF(\alpha)$ is a finite set of positive and negative variable assignments that model the effects of α.

Following the settings used in FMAP and applying it to GHM, we have more detailed descriptions:

- AG = $\{ag_1, ..., ag_n\}$ represents ground handling managers, which are defined as the *planning* agents. Each of these agents has vehicles resources to serve flights.
- Flights are variables $\in V$, assigned to vehicle resource $d \in D_v$, which describes the realization of the flight tasks by vehicles. The planning agents know all these flights.
- Each agent has two actions: $move - vehicle(from, to)$ and $perform - task(flight)$.
  The preconditions and the effects include:
  - *PRE(move-vehicle)* = $\{(be\ at\ location\ FROM)\}$;
  - *PRE(perform-task)* = $\{(at\ same\ location\ of\ flight),$ $(flight\ with\ task\ not\ performed)\}$;
  - *EFF(move-vehicle)* = $\{(not\ be\ at\ location\ FROM),$ $(be\ at\ location\ TO)\}$;
  - *EFF(perform-task)* = $\{(flight\ with\ task\ performed)\}$;

Agents in our model interact with each other by sharing information on their actions. So each agent will take a time t_1 to move vehicle resource to flight, a time t_2 to perform the task for a flight, and needs another Δt for communication. So the $t_1 + t_2 + \Delta t$ is the time of the agent i needing to complete a task for a flight j.

[1] variable assigned to some domain value, i.e, $v = d, v \in V, d \in D_v$

IV. PROPOSED MAP MODEL FOR GHM

In order to compute an optimal plan for the MAP task using tuple T_{MAP} at the airport ground handling management scenario, Airlines share flight plans between ground handling managers as presented in Figure 1.

Figure 1 shows the organization of the proposed MAP model, whose main components are listed as follows.

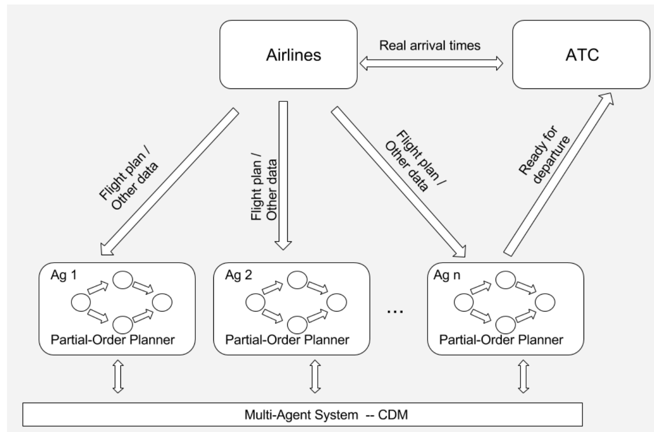

Fig. 1. Overview of the MAP model

The agents in the MAP model are classified into two categories according to the techniques employed in their decision making: (a) Airlines and ATC: are *reactive* agents. The Airlines send the data to the ground handling managers on scheduled arrival and departure times and (b) $Ag_1, Ag_2, ..., Ag_n$, represent ground handling managers, which are defined as the *planning* agents. They have a principal function in *Planning operations* for the ground handling manager agent to solve its *Planning problem* and to cover all planned demands for its services.

Then, each manager will knows all flights. However, this sharing, by itself, does not imply to optimal plans but takes each manager to build its optimal plan from their vehicle resources and the flight plan received.

Since the sharing process must be done aiming for the global solution, must have a process of coordination of the plans of managers to generate an optimal solution plan. Therefore, we propose a model to choose goals and delegate them to managers achieving a optimal multi-agent plan through distributed cooperative multi-agent planning.

The decision making considered is to solve the global planning of ground handling resources. The idea is to order arriving and departing aircraft according to their planned start time of the corresponding ground operations (either arrival ground handling tasks or departure grand handling tasks). Then each ground handling manager agent will process in this order each aircraft ground handling activity by linking each resource to aircraft to build a ground handling duty.

Starting from an empty base plan $\prod_0$, the following iteration composes the planning operations:

1) Each ground handling manager agent, through its embedded partial-order planner, expand $\prod_0$ and generate all its refinement plans over $\prod_0$, i.e., the agent, using its resources vehicles, performs actions *move-vehicle* or *perform-task* by linking each resources vehicles to flight. For example if r is a resource vehicle of the agent and f a flight, the agent has two actions: *move-vehicle (r, f)* and *perform-task (f)*. These refined plans are candidates to be chosen as the next base plan.
2) Each ground handling manager agent i evaluates its refinement plans $\prod_r$ by applying a classical A^* evaluation function $(f(\prod_r) = g(view^i(\prod_r)) + h(view^i(\prod_r)))$. The expression $g(view^i(\prod_r))$ stands for the number of actions of $\prod_r$ and $h(view^i(\prod_r))$ applies the Domain Transition Graph based (DTG-based) heuristic approach [16] to estimate the cost of reaching a solution plan from $\prod_r$.
3) Each ground handling manager agent communicates its refinement plans to the rest of the ground handling managers agents. The information that an ground handling manager agent i communicates about its plan $\prod_r$ to the rest of the ground handling managers agents depends on the level of privacy specified with each of them, i.e., more specifically, whereas $f \in V$ and r_i is a vehicle resource of ground handling manager agent i, the fluent (f, r_i) is partially private to ground handling manager agent i w.r.t. ground handling manager agent j. Instead of (f, r_i), ground handling manager agent i will send a fluent $(f, \perp)$ to ground handling manager agent j, where, $\perp$ indicates that f is not assigned any of the vehicles resources known to ground handling manager agent j. Along with the refinement plan $\prod_r$, ground handling manager agent i communicates the result of the evaluation of $\prod_r$, $f(\prod_r)$

Once the iteration is completed, the leadership is handed to an ground handling manager agent, which adopts the coordinator role, and a new iteration starts. The coordinator agent selects the open node $\prod$ that minimizes $f(\prod)$ as the new base plan $\prod_b$, and then, ground handling managers agents proceed to expand it. This iterative process carries on until $\prod_b$ becomes a solution plan to support the final action α_f. When all the open nodes have been visited, in this case, the ground handling managers agents will have explored the complete search space without finding a solution for the MAP task T_{MAP}

A refinement plan $\prod$ is evaluated only by the ground handling manager agent that generates it. The ground handling manager agent communicates $\prod$ along with $f(\prod)$ to the rest of the ground handling managers agents. Therefore, the decision on the next base plan is not affected by the ground handling manager agent that plays the coordinator role since all of the ground handling managers agents manage the same $f(\prod)$ value for every open node $\prod$.

V. Experimental Results

In this step, the research focuses on the optimization of vehicles planning for ground handling services. Therefore, it needs to filter out the unrelated activities about the use of vehicles and focus on optimizing the activities involving the services vehicles. The research also considers the deboarding/boarding vehicles, refueling vehicles and catering vehicles, which will be focused in the optimization model. Thus, our scenario comprises four agents: boarding agent, de-boarding agent, refueling agent, and catering agent.

Table I shows the time duration of the actions of each agent; and Figure 2 presents the structure assumed for the ground handling activities.

TABLE I
Time Duration in minutes of the actions of agents

Action	Boarding	De-boarding	Refueling	Catering
Move-vehicle	3	3	3	3
Perform-task	15	7	9	10

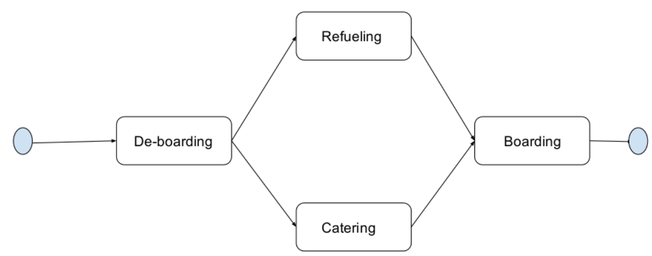

Fig. 2. Structure of the ground handling activities

The set of tests compares the quality of the solution plans obtained by the proposed MAP model with ones generated by a centralized approach. The testbed includes a different number of flights of increasing difficulty. MAP tasks have been tried out with the MAP model using DTG-based heuristic approach shown in [16] and an A* search strategy. As for centralized tasks, they have been solved by the MAP model which is configured as a single-agent POP, using again DTG-based heuristic approach and an A* search process.

TABLE II
Single-Agent vs. Multi-Agent Planning comparison

	Mult-Agent Planning		Single-Agent Planning	
# Flights	# Actions	Planning time	# Actions	Planning time
5	40	205	40	265
6	48	246	48	318
7	56	287	56	371
8	64	328	64	424
9	72	369	72	477
10	80	410	80	530
40	320	1640	320	2120

Table II shows the obtained results by the simulation. #Actions and Plan. times refer to the number of actions and planning times in minutes of the devised solution plan. task As it can be observed, both approaches obtain the same results in terms of the number of actions of the solution plans.

However, the biggest difference comes in terms of the planning time. The planning time takes into account the actions that can be performed simultaneously in order to measure the time necessary to execute the plan. The proposed MAP approach enforces the operation in parallelism, since the different planning entities devise different parts of the plan that can be executed at the same time. The centralized approach is not as effective at introducing parallel actions. In conclusion, the proposed MAP approach obtains better solution plans in terms of planning time.

VI. Conclusion

To improve the efficiency of airport ground handing operations, in this paper, we presented an approach by multi-agent planning (MAP) for re-organizing the airport ground handling management. The developed model follows a refinement planning strategy. In this case, the solutions rely on progressive refinement of partial-order plans.

The model uses tightly-coupled tasks domains, where the agents can interact each other in order to achieve the goal state. The amount of exchanged messages may become the biggest obstacle but agents in the proposed model want to minimize the information that they share with each other either for strategic reasons.

Preliminary results show that our model helps on dealing with the airport ground handling management planning. However, it still demands more case studies to improve the applicability in real scenarios and we leave this for future work.

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