Highly Responsive MPS for Dynamic EO scenarios

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Distributed missions have become of great interest in the last decade as they offer a number of potential benefits for Earth Observation, especially global monitoring and disaster management. the first examples of this increasing demand are the Global Monitoring for Environment and Security - GMES or the Disaster Monitoring constellation. The increasing trend in the use of multiple platforms is opening new challenges in terms of coordination and high responsiveness principally in critical scenarios. In particular, a new concept of mission planning has been identified in order to operate such constellations of spacecraft and provide a greater level of responsiveness.

In this paper, we describe an innovative ground-based automated planning & scheduling system for multiple platforms, specifically for the Disaster Monitoring Constellation. First, we show how the system can be applied to a single platform case study designed for a highly dynamic environment. The system will be required to respond appropriately to different priority levels and the needs of different user groups. Finally an outline will be given regarding the systems extension to the whole Disaster Monitoring constellation in order to show the coordination benefits of our solution.

The novelty of this project is applying a natural-inspired paradigm, such as stigmergy, to coordinate a platform and compute the solution. More specifically, a novel algorithm designed for dynamic planning is applied. It offers a high-level of adaptability and responsiveness allowing the system to find near-optimum solutions on a global level thanks to the collaboration of all the agents interacting and modifying the environment. This approach is based on ant colony algorithms and aims at extending mission planning applications to face real constellation scenarios.

I. Introduction

Mission Planning is an activity dealing with problems of high complexity which is usually faced with methods and techniques from the wide field of Automatic Planning & Scheduling. Due to the complexity and the computation power required, historically the ground segment has been responsible for the mission planning. Few major examples are: the SPIKE scheduling system,[16] designed for the NASA's Hubble Space Telescope and used since 1990; the autonomous planner ASPEN[3] developed by the AI group at the NASA's JPL and the ESA APSI.[27] Clear advantages, as reducing operational costs and increasing the efficiency, are pushing the planning & scheduling activity on board of the spacecraft. Promising results have been achieved by NASA DS-1,[22] NASA EO-1 with the re-planning system CASPER[17] or the more recent ESA demonstrator mission Proba-2.[21] However, this paradigm alone is not suitable for the new trend of distributed missions

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as the single spacecraft are not able to deal with the whole system. The coordination aspect of a multiple platform introduces a new level of complexity in the mission planning.

Multiple platforms offer a number of key scientific and engineering benefits over single monolithic spacecraft and are already largely adopted for communication, geo-location (GPS) and meteorology purposes. In these cases however the satellites are sparsely distributed and do not require coordination. The new challenges come from three main scenarios:

- Cluster or swarm satellites used for remote sensing or astronomy
- Swarm satellites used for space exploration
- Earth Observation constellations

For the first two cases, the main challenges regard formation-flying astrodynamics combined with precise attitude determination and control systems used in order to avoid spacecraft collisions and to maintain the configuration. In the space exploration scenario moreover, frequent and timing communications to the ground can be unfeasible. The coordination problem therefore needs to be handled onboard.

In the Earth Observation (EO) constellations scenario the main goal is to satisfy efficiently the user community. The plan can be produced on ground and uploaded to the whole constellation because the communication link is not a critical resource. The level on uncertainty is quite low and this approach does not exclude re-planning capability onboard in case of failure. In this scenario therefore, the need of autonomy is shifted from onboard to the ground segment. One of the few autonomous Operations examples that have been demonstrated in space, is the tandem mission TerraSAR/TanDEM-X,[19] where basic functionalities of automated scheduling have been implemented though without optimizing the resources. The real big challenge is coordination and optimization at the same time. A number of studies have recently shown interest on Earth Observation constellations,[4,11,24] in particular in case of disaster management.[25,30] Most of them tried to reduce the coordination aspect to an optimization problem and to solve it with classic techniques such as greedy,[24,30] backtracking[11] or simple heuristics.[4] In these cases either they did not achieve efficient solutions either they considered small problems (reduced number of spacecraft). Furthermore, these works did not consider the dynamics of the problem itself. This scenario needs to be faced as a dynamic environment. In case of the GMES or of the Charter system, the five ESA spacecraft devoted to Earth Observation (Sentinel-1 to Sentinel-5) need to cooperate with other existing and/or planned missions provided by ESA, EUMETSAT, other national agencies or private companies such as Surrey Satellite Technology Ltd (SSTL) with the Disaster Monitoring constellation or the RapidEye constellation. Moreover, the solution envisaged needs to be highly responsive to the requests coming from the user community. The demonstrator of the DAFA study[23] aims at addressing these issues with a multi agent architecture based on negotiation paradigm and deliberative agents. The main drawback however is still in the lack of scalability and flexibility.

The EO scenario presented above motivates the investigation of the multi agent paradigms in the context of distributed platforms, to model the coordination and control aspects of such missions. Moreover extending these systems with natural-inspired techniques can result in high reactivity and scalability. The following section II introduces the multi agent paradigm, a general framework for modelling distributed system, before focusing on the emergent properties which such systems can present using a natural-inspired communication paradigm called stigmergy. Section III presents the case study considered, the Disaster Monitoring Constellation operated by SSTL, specifically the mission UK-DMC2. Section IV is going to describe the solution developed whereas section V shows the results of such a solution applied to the case study. Finally, section VI draws the global picture of how the approach presented is going to be extended to a multiple platform case study while section VII discusses the main benefits and drawbacks of this solution. This work is based on a previous paper[15] where we introduced the planning problem of an EO constellation and we addressed a static single platform case study. This paper represents a step forward along the same roadmap, addressing now a dynamic single platform case study.

II. Technical Background

The majority of the work on planning for multiple spacecraft has adopted the multi agent paradigm to model the coordination and control aspects of such missions. Multi Agent Systems (MAS) is a relatively new field bringing together techniques and theories from multiple disciplines. When multiple agents coordinate together for a common purpose, there are a number of different mechanisms that can be used. These approaches are strictly connected with the capabilities of the agents which range across the spectrum from reactive to deliberative architecture. In essence, we can talk about performing a task in a highly planned manner (deliberative), or relying instead on an instantaneous spontaneous manner (reactive).The reactive approach is highly suited with problems with uncertainty. It is the most suitable for describing natural complex systems with high number of entities interacting with complex dynamics. Deliberative approaches are generally more efficient than reactive planning for more well understood problems. However, they require large quantities of processing power to resolve all the rules built into the plans and produce more rigid solutions not able to face dynamic problems. The majority of work on autonomous systems for spacecraft, mentioned in the previous paragraph, focus on deliberative techniques exemplified by methods for deliberative planning and re-planning.

Discussions on reactive behaviours naturally lead on to the concept of self-organization and emergence. In a swarm consisting of a large number of entities, the result of combining simple behaviours at local level can end in an emergent complex behaviour at the system level able to achieve significant results. Moreover, the structures or patterns exhibited at system level can be achieved in a self-organizing manner, without a central or external authority. As presented, self-organization and emergence are desirable characteristics which need to be imported in artificial systems that cope with high uncertainty and dynamic environments, such as in space applications. The challenge in designing a self-organizing system is that there is no systematic way to formulate required micro-level behaviours given desired top-level macro behaviours. Researchers have been experimenting with several mechanisms leading to self-organisation and to emergent phenomenon.[26] The most promising is the *stigmergy* mechanism as it has been showed achieving complex system behaviours.

A. Stigmergy

The term stigmergy has been introduced in the 1950's by the French biologist Grassé.[10] It indicates a communication mechanism based on traces left in the environment. This information stored in the environment forms a field which supports agent coordination stimulating their actions. Such techniques are common in biological distributed decentralized systems such as insect colonies where the information assumes usually the shape of pheromones. Several are the examples in nature of stigmergy: termites nest, ant brood sorting, ant and bee foraging, glow-worm clustering, etc. In all cases, the colonies are able to achieve remarkable results considering the capabilities of the single agents. From the engineering point of view, stigmergy presents a number of attractive benefits:

- **Simplicity**, the system is formed by simple reactive agents with limited cognition capabilities.
- **Scalability**, it allows coordination of large numbers of simple agents without direct communication.
- **Robustness**, the system's performance is robust against the loss of a few individuals.
- **Environmental integration**, the environmental dynamics is at the same time affected by and affecting the system due to the explicit use of the environment in agent interactions.

All the patterns presented above have been migrated form the biology to the computer science, specifically to the field called Swarm Intelligence which focus on applying these models to a number of tasks: optimization, clustering, task allocation, network routing and so on. The most popular is the ant foraging process which inspired the Ant Colony Optimization (ACO) meta-heuristic,[8] a family of stochastic techniques for solving combinatorial optimization problems reduced in finding good paths through graphs. The system presented in this paper is based on this technique. The following section is going to give some more theoretical detail of it before moving to the application level.

1. Ant Colony Optimization

Deneubourg[6] demonstrated how the Argentine ant was able to choose successfully the shortest between the two paths to a food source. From there, Dorigo already in the early '90s[7] developed a heuristic inspired on such a model, ACO. Nowadays there is a wide number of ACO heuristics. The inspiring idea is that the ants looking for food deposit pheromones along the path. These pheromones influence the following ants to get the same path. However only the shortest path will end having the strongest pheromone distribution because is the one that requires the minimum travelling time. This is an example of collective spontaneous problem solving strategy. The best path is expected to emerge with the strongest pheromone distribution.

The uniqueness of the ACO algorithms is their constructive nature, as opposed to local search; they generate solutions adding solution components iteratively until completion. Without going in details, ACO algorithms have been successfully applied to a wide spectrum of theoretical and real problems: routing such as the travelling salesman problem (TSP), assignment, subset such as the Knapsack problem and scheduling, the closest to the mission planning problems.[2,12,14,20]

III. Case study

The scenario considered is the Disaster Monitor Constellation (DMC). This platform is the first Earth observation constellation of low cost small satellites; it provides daily images for a wide range of applications, commercial or of public interest including disaster monitoring. The DMC satellites are designed and built by UK company (SSTL). The constellation is currently composed of 6 satellites (Beijing-1, NigeriaSat-1, UK-DMC-2, Deimos-1, Nigeriasat-NX, Nigeriasat-2) owned by different entities. DMC works within the International Charter "Space and Major Disasters" to provide free satellite imagery for humanitarian use in the event of major international disasters. The national civil protection authorities of Algeria, China, Nigeria, Turkey and UK are direct authorised users of the Charter. The problem of imaging campaign planning & scheduling for this constellation rises because the number of requests and the typology of customers that such platform has to satisfy is quite varied and exceeds the capabilities of the whole system. The challenge is in giving the ability for a satellite constellation to respond to a number of users, making asynchronous requests, and having to schedule their tasks to respond in reasonable time.

A. UK-DMC2

We decided to approach the problem considering one satellite of the DMC constellation: the UK-DMC2. This spacecraft is a mini-satellite of 120 kg flying at 686km of altitude in sun-synchronous orbit. It carries a multi-spectral imager with a resolution of 22 metres and 660 km of swath, operating in green, red and near infrared.

The mission has to satisfy a number of costumers which request images of specific targets within certain time windows. Because of the limited memory on-board, time constraints between requests and limited number of downlink passes, it is required to determine a subset of such requests which satisfy all the constraints and maximize certain performance metrics.

Given this context, the requirements for the mission planning system (MPS) goes along three different dimensions:

- **Optimization**, it needs to produce efficient solutions that maximize the performance.
- **Responsiveness**, it needs to respond and adjust the solution when changes occur (new user requests, disaster management).
- **Scalability**, it needs to be scalable on the number of satellites considered.

Such a system aims at generating imaging schedules that account for different priority levels and the needs of different user groups. The planning & scheduling problem considered is therefore on the ground segment and the system is foreseen to run centrally abstracting from on-board processing and communication aspects among the satellites. Differently from the standard operational workflow, our approach is going to run continuously offering the update plan at any time. Traditionally the plan is generated only for a specific uplink opportunity and when all the input are available. In our approach instead the operator is called to evaluate a number of equivalent plans proposed by the system during a specific time-frame. Our system act as an interface abstracting the decisional work of the operators from the actual variability of the problem. The benefits of this setup are an higher flexibility for the operators and a high-responsiveness to asynchronous events. However, those advantages need to match the actual resources available in terms of uplink opportunities and man-power dedicated to the plans revision.

IV. Proposed approach

The solution we considered in inspired by self-organizing reactive multi agent architectures, as defined in section II. Inside this field, we focused on the stigmergy mechanism giving high level of scalability and in particular on the ant colony algorithms which achieved high-level of performance in optimization problems.

Our approach proposes to model the whole problem in a graph-like environment which ant-like agents could explore. Thanks to the stigmergy mechanism, the ants will be able to optimize and coordinate. Broadly speaking, we propose to implement a MPS that behaves as an ant colony, continuously exploring and exploiting its environment, adapting to its changes. The problem representation is a quite critical phase in the system design because it defines the environment and as consequence, how the entities interact. The environment is not a passive element; it supports a number of functions relative to the pheromones. It reflects the dynamics of the problem itself increasing drastically the reactivity of the system. The following sections describe first the problem modelling and then the ant algorithm.

A. Problem modelling

A natural way of building a solution responsive to the user requests is to use such requests as the main environment components. Moreover, the goal is to maximize the efficiency of one spacecraft which can be expressed in term of the images acquired. They become therefore the nodes of the graph, called tasks. The edges instead represent the time constraints between them. The result is a directed graph where the direction of the edges reflects the real time direction and the order between the requests reflects their position on the globe. Lastly, the ground station passes need to be included in the graph complying with their temporal constraints. The tasks are characterized by the memory needed and the *quality* which indicates the importance of the specific task, whereas the ground station pass is indicated only with the memory downloaded. The environment supports a pheromone field (scalar field) with the aggregation and evaporation effects.

The problem domain can be modelled as a binary reusable resource, the camera, strictly dependent on a depletable resource, the memory. The task is an activity that consumes memory while locking on the camera. The ground station pass instead is an activity that produces memory. The constraints considered then are the memory available which is a limited resource and the access to the camera which is exclusive. The environment is a one-dimensional space representing the time dimension of the spacecraft activity. Incorporating all the temporal constraints in the environment, the graph becomes the feasibility space and directly represents the timeline of the camera which, being exclusive, identifies the spacecraft timeline itself. That being defined, the problem can be represented as a knapsack problem with scheduling constraints. It can be formulated as:

$$\max f(s) = \sum_{i=1}^{n} b_i x_i \tag{1}$$

subject to

$$\sum_{i=1}^{n} r_i x_i \leq a, \tag{2}$$

$$x_i \in \{0,1\}, \quad i = 1 \ldots n. \tag{3}$$

where x_i is an assignment variable that indicates if the request i has been performed. The equation 1 defines the objective function as a sum of the activities performed multiplied by the relative quality. This function tell us how good is a plan. Lastly, equation 2 expresses the memory constrains.

The most natural way to translate a knapsack problem in a graph is to use a binary representation inspired by the assignment variables itself which characterize the knapsack problem.[9,18,31] In this problem the variables are binary and the two possible states can be represented as distinct edges. In this way, the solution is just the path connecting these edges. Figure 1 shows the binary representation of the environment where the squares represent the task whereas the triangle the ground station passes. Considering the dynamic scenario presented, the representation chosen offers the possibility to express any events with minor changes in the graph reducing the overall impact.

B. Ant colony algorithm

The algorithm that is behind the behaviour of the ant agents can be seen as a proper ACO algorithm. The ant behaviour needs to be designed in a way that collectively optimizes the objective function and complies with the environment representation. The ant during its exploration is driven by the pheromones found along each edge of the graph; they represent the recent history of the decisions of the previous ants. The

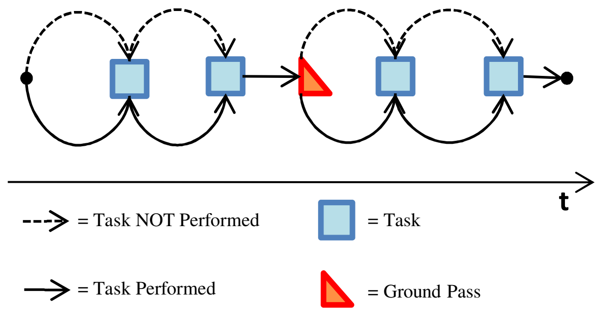

Figure 1. Schematic binary representation of the environment.

objective function influences the quantity of pheromone which the ant deposits on its path. In our approach, the ants start the exploration always from the beginning of the planning windows and have to respect the time direction which reflects the order of the tasks positioned in the ground track. Inconsistencies on the memory utilization must be separately checked by the ants.

The fundamental steps of the algorithm are the followings:

- 1. Pheromone trail initialization.
- 2. Exploration phase, each ant decides its path using a probabilistic rule function of the pheromone trail.
- 3. Evaporation phase, a fraction of the pheromone of each path evaporates.
- 4. Depositing phase, each ant deposits on its path an amount of pheromone, which is proportional to the quality of its path, the solution.

Our solution sees a novel ACO algorithm developed specific for dynamic problems exploiting the system dynamics occurring in this type of graphs. We have defined a new theoretical model that can describe and foresee the long-term dynamics of the system. Thanks to it, we are able to evaluate the impact of parameters on the global dynamics and to influence them changing the stability of the long-term behaviours. We are therefore able to adjust dynamically the trade-off reactivity/reliability. The algorithm alternates exploration phase with exploitation phase. During each exploitation phase, the system converges on a specific path which represents the current plan. This theoretical model gives us confidence in the reliability of the algorithm. A strong model a priority for a system applied to critical scenarios such as mission planning. Further details of the theoretical model and of the algorithm are outside the scope of this paper. The following section describes the problems used to evaluate empirically the performance of our approach.

V. Empirical evaluation

It is necessary to validate the approach presented in IV with real-instance problems presenting complexity similar to the operational case. No theoretical model has able so far to describe all the aspects of a real problem. Theory and simulations are always complementary tools. The setup of the experiment sees the system running for a long time frame on a dynamic problem. The time is measured in number of ants, because the graph is explored and modified only by one ant at a time. New events, i.e. changes in the problem are translated in changes in the environment, i.e. in the graph. We consider two experiments with two typologies of events which define different type of changes:

- **Weather updates**, the weather information is a key factor for the quality of the final image acquired. Depending on the season, some regions can present high weather instability. Update weather information need to be considered to realize an efficient plan. On the graph level, this information affects the *quality* of the single task, which affects the amount of pheromone deposited on the relative path. The system is going to be responsive to these events because a task that decreases the pheromone level of its path will be less favourable for the following ants which will most likely consider new paths.

- **Disaster management**, new images at high priority can be requested at any time. In this case, the images are translated in new tasks which need to be inserted in the graph. It is important to note that the connectivity of the graph is not affected. However, in this case the system will have to converge quickly to new solutions.

The following paragraphs show one problem instance for each of the two scenarios considered above. The problems considered are formed by 20 possible tasks with 5 ground station passes. These numbers represent a typical planning horizon of one day. Of note is the download capacity for each ground station pass is inferior to the whole memory onboard. Representing the tasks as binary variables where "1" means "acquired" whereas "0" means "not acquired", the solution can be written as binary string. The digits order reflects the graph order (chronological). The solution space is therefore made of 2^{20} solutions, a million of possible plans. It is clear that an exhaustive search is not possible. Given a dynamic problem, we are interested in observing how the system responds to such changes. Moreover as explained in section IV, independently from any change, the system continuously searches for new solution and updates the current plan. Rather than showing batch performances, we believe is more meaningful to give an intuitive understanding of what the system does during a single run.

A. Weather updates scenario

The charts in Fig. 2 and Fig. 3 show one single run of 40k time steps on a specific problem instance where we introduce weather updates during the run.

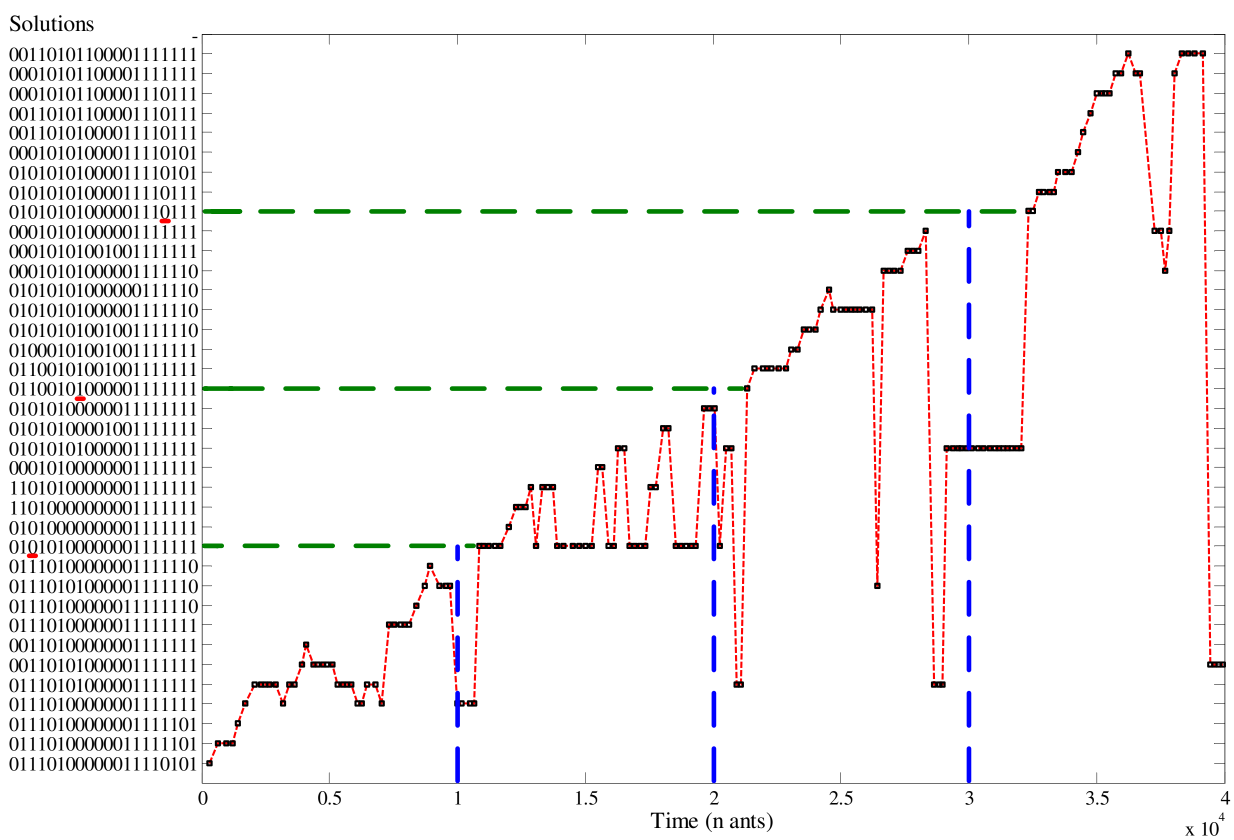

Figure 2. Solution dynamics for a problem instance of the weather updates scenario.

The time axis is a computational time; the real time will depend on the computational capabilities of the ground segment. At this stage, the computational power required is negligible as the whole simulation takes about 5 minutes in a desktop pc dual-core. Each point of these charts represents the current plan, it is the solution proposed by the system. Figure 2 shows the solutions proposed by the system along the run. The order of the solutions on the y axis is purely temporal and does not represent their quality. Fig. 2 needs to be read together with Fig. 3, showing the quality of each solution. Looking at the period [0 - 10k], the system does not experience any change but it is quite evident that it keeps changing solution. However, it moves between close solutions where all the high quality tasks (3-4-6-14-15-16-17-18-19) are selected for acquisition. This behaviour is more evident in Fig. 3 that shows the value of the objective function for each of these solutions. The fluctuation of the objective function is quite limited, around 10% of the current optimum. The weather updates introduced in this run are the following 3 events, one every 10k time steps:

1. Time step 10k, the task 3 drops its quality to low level (drop of magnitude 2).
2. Time step 20k, the task 8 increases its quality to high level (increase of magnitude 2).
3. Time step 30k, the task 17 drops its quality to low level (drop of magnitude 2).

Figure 2 shows that whereas before event 1 the task 3 was always selected in the solution, after the event it looses its priority respect other tasks and it is almost always discharged. Similarly, as the task 8 increases its quality after the second event, it is always selected in the solution, as it is a high quality task. The third event shows the same effect of the first, this time on the task 17. We can observe the effect of these changes as well in Fig. 3 where after each change the overall objective function shows a drop or an increase.

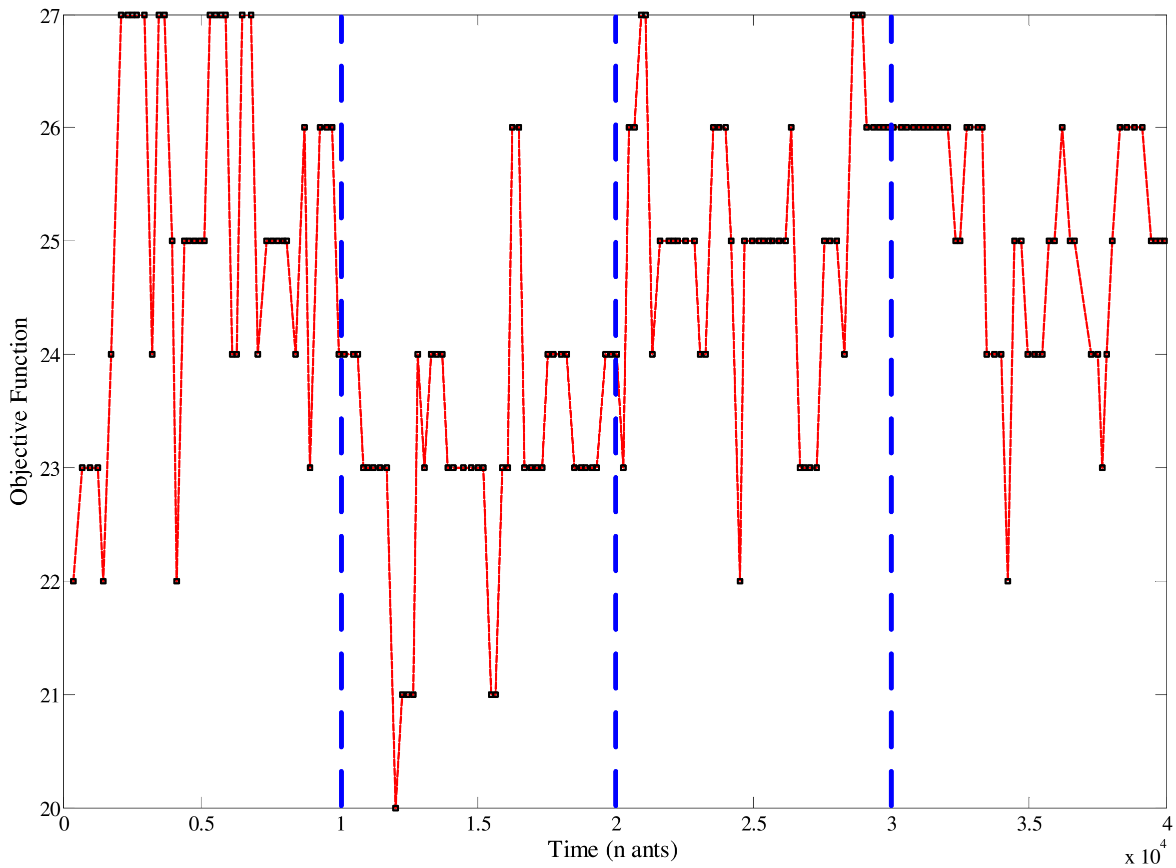

Figure 3. Objective Function dynamics for a problem instance of the weather updates scenario.

B. Disaster management scenario

Figure 4 shows one single run of 30k time steps on a specific problem instance where we remove and introduce new tasks during the run. Specifically 2 updates are introduced:

1. Time step 10k, the task 17 is removed.

2. Time step 20k, a new task is introduced after the task 8.

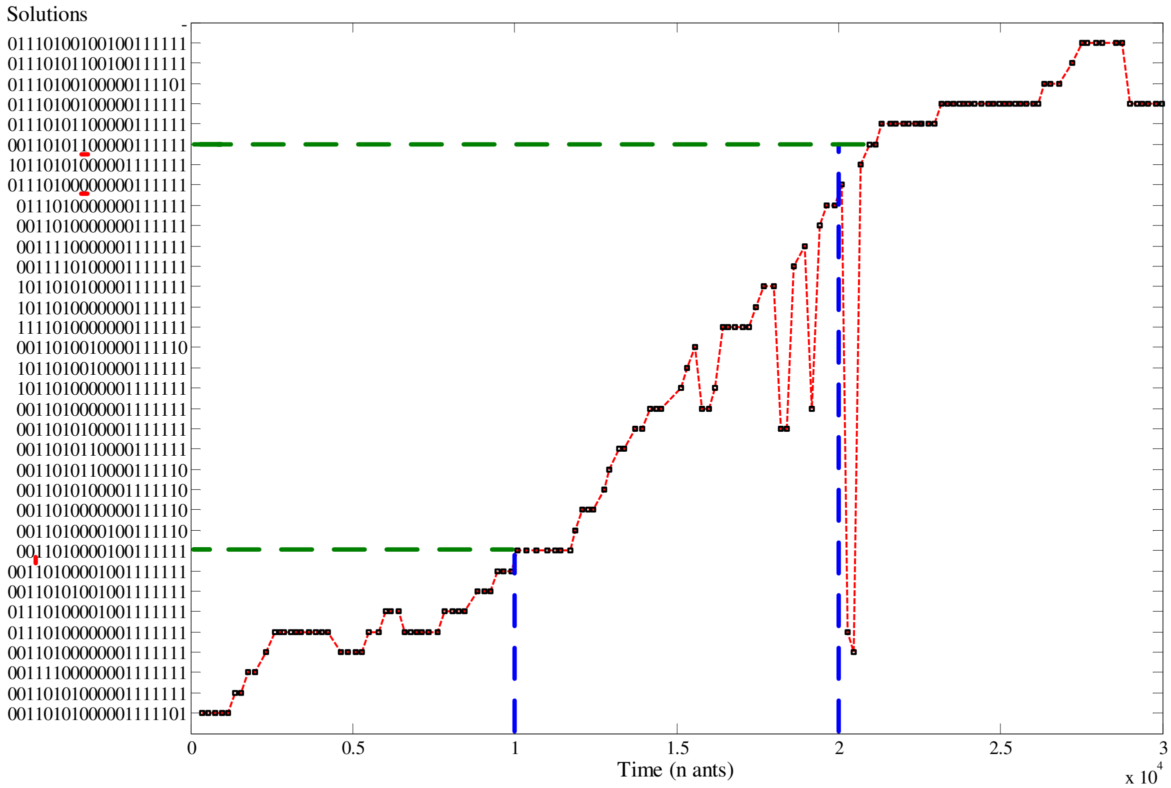

Figure 4. Solution dynamics for a problem instance of the disaster management scenario.

As in the previous scenario, the system shows to react efficiently to the events. The first event demonstrates how the system adapts when resources, in this case memory, become available. Figure 4 shows that after the first event the plan contains one task less and however after few iterations the system is able to find new solutions with a higher value of objective function. The second event demonstrates how the system reacts when a new high quality/priority task is introduced. It is evident from Fig. 4 that all the solutions proposed after the event select the task 9, the one just introduced.

Though the scenarios presented above show promising results, the evaluation proposed in this paper is only qualitative and it need to be extended to include a wider class of problems. The experiments require a quantitative analysis evaluating the reaction time as well as the robustness of the system, key element to understand the impact of the events on the overall dynamics.

VI. Multiple Platform scenario

In the previous sections, we presented our approach and how it can be applied to a dynamic single platform case study. In this section, we aim at drawing the general picture of our solution. There are many possible extensions to our paradigm, going from ground to onboard applications but here we are mainly interested in the multiple platform scenarios. The use case considered in section V was able to show the level of responsiveness and of optimization of our solution. However a further step is necessary to demonstrate its highly scalability. As introduced in section III, the multiple platforms scenario is provided by the Disaster Monitoring Constellation. Depending on the service level agreements, the users of the DMC community are allocated to one specific satellite or more. The goal now is to avoid duplications in the image acquired and at the same time to optimize the performance of each spacecraft. To extend our solution to this problem we need to extend the concept of stigmergy to the entire multi agent system. In the ACO algorithms, stigmergy is applied only at the ant-agent level whereas it can be effectively used to coordinate complex agents, in our case the spacecraft. This idea is behind the multi agent systems called synthetic ecosystems.[1] Their aim is to provide practical engineering solutions of industrial strength, exploiting the underlying logic of the biological systems. Brückner showed how to develop a manufacturing system based on pheromone field. He represented the industrial machines and workpieces as single agents which propagate their intentions downstream while resource agents propagate load forecasts upstream. Several other works[5,13,29] showed self-organizing manufacturing system using artificial ants which navigate through a number of pheromone layers. Similar idea is used in the on-board coordination system for cluster of satellites developed by Tripp and Palmer[28] where stigmergy was able to reduce the computational and communication overhead and the task duplication.

Taking inspiration by the synthetic ecosystems, the spacecraft can be modelled as agents communicating using stigmergy. More specifically, each spacecraft will have an ant colony in charge of exploring the environment and finding a solution for the planning problem.The graph-like environment presented in section IV can be extended building a graph for each spacecraft and letting them intersecting on the tasks shared. To achieve coordination on the shared tasks we can use different pheromone flavours for the ant colonies of different spacecraft. The pheromone of one spacecraft will be able to inhibit the actions of the others spacecraft avoiding conflicts on the shared tasks. Figure 5 represents this concept.

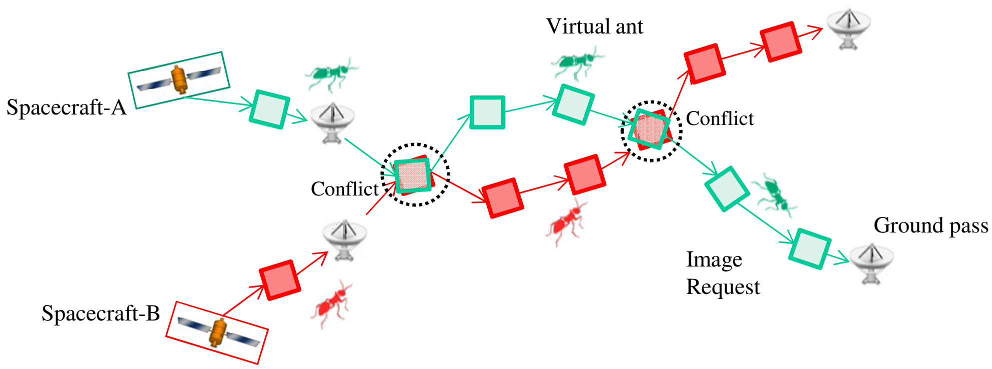

Figure 5. Schematic representation of the environment in case of multiple spacecraft.

We envisage ant agents exploring continuously the environment, keeping enforcing the pheromone distribution of a particular trail which represents the current plan. The ground segment is going to update at any time the environment with new information coming from the users, the spacecraft or from the real environment (weather forecast). At every ground station pass, the spacecraft can receive the current plan corresponding to the tasks trail with the higher level of pheromone for its specific sub-graph.

VII. Conclusions

The distributed mission scenario presents new challenges for the autonomy solutions. They need to be highly responsive, adaptable to face dynamic environments and scalable to a various number of spacecraft. Today a number of advanced technologies are available for meeting these requirements such as self-organizing agent architectures and natural-inspired collective algorithms. In this paper we presented a solution that takes advantage of these technologies to face dynamic scenarios. In this paragraph we want to summarize the main benefits and limitations of our approach. The main benefits are:

- **Responsiveness**, reactive multi agent architectures are by definition more flexible and adaptable then monolithic solutions. As shown in V, the ant algorithm in particular guarantees adaptability and responsiveness thanks to the integration of the environmental dynamics in the solution construction.
- **Scalability**, classic multi agent architectures suffer of scalability due to the strong responsibility schema. A self-organizing approach theoretically solves this problem at a reasonable price in terms of efficiency.

- **Optimization**, the solution exploits the optimization capabilities of the ant colony algorithms which have been showed to achieve high performance in a number of contexts, in particular for assignment and scheduling problems. Many other techniques and heuristics are available in literature achieving similar performance but it is difficult to find at the same time the same level of reactivity and scalability.

Despite these benefits, a number of limitations need to be taken in account.

- **Problem modelling**, a clear difficulty lies in translating the problem with the relative constraints in a graph-like structure though most of the planning & scheduling problems offer a natural representation in decision networks.
- **Black box**, all the *soft-computing* techniques such as neural networks and ant colony algorithms offer solutions without showing the reasoning chains that give those solutions. This is a critical issue considering the human side. Autonomy and specifically goal-oriented operations reduces the low-level control of the human operators giving a higher view of the spacecraft status. The challenge is making this transition acceptable. This can be achieved offering a number of tools able to display goals, plans and plan execution status. They must indicate deviations from the plan and any corrective actions the system takes. The human operator needs to become a supervisor and needs powerful tools for this task. The solution proposed looks at this direction giving the possibility to the operator of choosing among a number of equivalent solutions.
- **Cost & Operational feasibility**, the solution presented in this paper is proposing a different Operational workflow. As explained in section III the system generates continuously plans of equivalent quality which the operator is called to evaluate. Such a solution offers more flexibility and responsiveness but it requires resources such as man-power and frequent uplinks which need to be assessed carefully. The adoption of such technology is subjected by this trade-off, benefits-costs. However, as all the enabling technologies, it has the aim of fostering new concepts for the future ground segments and enabling the design of more reactive missions.
- **Stochastic nature**, a further challenge is the mindset shift. The space sector and in particular the Operations is quite resilient to new approaches because is strongly adverse to the risk of failure. In this case, the issue is to shift from a deterministic to a nondeterministic stochastic solution. If distributed missions are the future, it must be accepted and embraced. Of course, it may take some time for the collective mindset to shift from the current rigid and inflexible guaranteed approach towards a more reactive and probabilistic system and one of the challenges is the creation of a roadmap to make this process feasible.

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