Autonomous Agents and Multiagent Systems Challenges in Earth Observation Satellite Constellations

Blue Sky Ideas Track

Gauthier Picard
ONERA DTIS, Université de Toulouse

Clément Caron
Airbus Defence and Space, Toulouse

Jean-Loup Farges
ONERA DTIS, Université de Toulouse

Jonathan Guerra
Airbus Defence and Space, Toulouse

Cédric Pralet
ONERA DTIS, Université de Toulouse

Stéphanie Roussel
ONERA DTIS, Université de Toulouse

ABSTRACT

We identify several challenges and opportunities opened to agent and multiagent systems, following the recent developments in the domain of Earth observation constellations. We focus on three challenge categories that manifest in this field: (i) configuration problems of constellations and ground stations used to operate them, potentially owned by different actors, as to provide better services and coordination; (ii) offline planning and scheduling problems, which consist in finding solution methods to schedule observation and upload/download tasks over the constellation; (iii) the design of efficient and reactive online operation methods as to adapt schedules in dynamic settings. Being naturally distributed and composed of multiple entities and users, these problems clearly fit the multiagent paradigm, and may challenge researchers for many years.

KEYWORDS

Satellite; Constellation; Earth observation; Multiagent systems

ACM Reference Format:

Gauthier Picard, Clément Caron, Jean-Loup Farges, Jonathan Guerra, Cédric Pralet, and Stéphanie Roussel. 2021. Autonomous Agents and Multiagent Systems Challenges in Earth Observation Satellite Constellations: Blue Sky Ideas Track. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 6 pages.

1 INTRODUCTION

Recent years have shown a large increase in the development of satellite constellations. Instead of considering individual satellites, the idea is to take advantage of a group of satellites, some of them often sharing the same orbital planes, to provide richer services like positioning, telecommunication or Earth observation [62]. With few satellites (*e.g.* two in PLEIADES [38]), and in low or medium Earth orbits (altitude inferior to 35,000km), any region on Earth is not covered at any time. So, the main motivation to increase the size of these constellations is to allow capturing any point on Earth at higher frequency, as the Planet company with more than 150 Earth observation satellites (EOS) [53]. But, operating numerous EOS requires improving cooperation between assets and on-board autonomy as to make the best use of the system, which is a highly combinatorial task. Besides their growing number, constellations' composition is evolving too. Recent technologies allow the production and deployment of agile EOS able to change their orientation, and to provide multiple type of image shooting with multiple sensors. While providing richer services, this adds many degrees of freedom and decision variables to schedule EOS activity, opening many challenges [4, 65].

Figure 1 shows an EOS system with its ground and space operations. It highlights the multiplicity and richness of actors and components having their own activities and goals. Since EOS have a limited on-board computation capacity, major part of the mission is built offline and transmitted to EOS using ground stations. Besides, mission centers and agencies need to collaborate to share orbits, to schedule plan uploads, image acquisitions and data downloads. If EOS are owned by different stakeholders, they may even negotiate to share some on-board resources. In-space operations also require cooperation, notably between EOS which have to perform multiple and often composite acquisitions. For optical applications, weather uncertainties have to be handled to avoid capturing cloudfull useless images. EOS also share tasks, so that unusable observations made by an EOS can be performed later by a following EOS overflying the region. As to cooperate, EOS may rely on indirect communication (via dedicated relay satellites) or direct in-range communication as to transfer tasks from one to another, instead of waiting minutes to interact with accessible ground stations.

This scenario illustrates the need to cooperate, collectively solve and schedule, self-adapt and interact, which are the overarching motivations for multiagent systems (MAS). While MAS have early been identified to model satellite systems [32, 52], this scenario opens new challenges to be addressed by the MAS community, regrouped into three categories. We stress areas of interest of AAMAS call [1] each challenge falls into, using the ➥ *<Area>* notation.

2 CONSTELLATION DESIGN CHALLENGES

Prior to deploying a constellation and operating it, several hard problems have to be solved, related to constellation sizing and composition, fair allocation of orbits and plans between stakeholders.

2.1 System Modeling and Simulation

The design phase consists in dimensioning the constellation, *i.e.* deciding the orbital pattern(s), the number of satellites on each orbital plane along with their orbital elements, the set of ground stations used to download images and upload mission plans. The composite nature, heterogeneity, dynamics and openness of EOS constellation shall be considered in that phase. Moreover, space

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

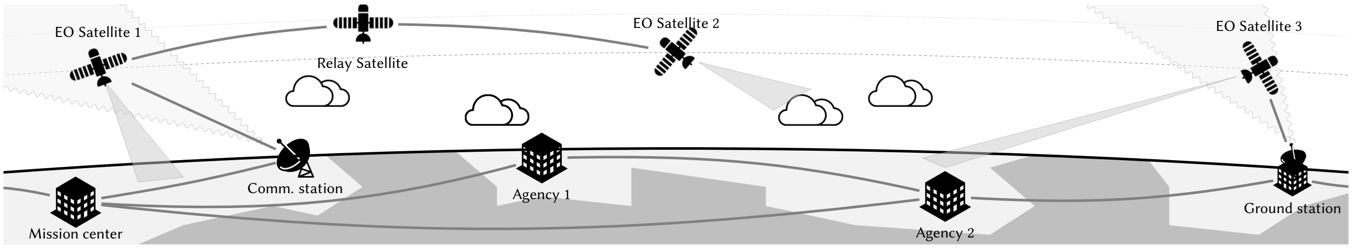

Figure 1: An Earth Observation system composed of a main mission center and distributed stations (with ranges), agencies emitting observation requests (to mission center), EOS (with image footprint), communication satellites (linking EOS)

systems are amongst the most demanding concerning functional guarantees and safety.

For instance, EOS clusters contain large numbers of satellites (from dozens to hundreds of satellites), that can be highly heterogeneous (platform, payload, orbit) and usually designed for a specific short-term goal (*e.g.* scientific mission) [19]. While all tasks can be performed by satellites, the catalog of requests is much larger than the actual observation capability of the constellation. The problem consists in selecting the subset of satellites in the cluster to perform the observation tasks. The cost of a team is an aggregation of the cost of the tasks to perform, which depends on the satellite that actually performs the tasks and the idle time of each satellite. This aims at finding the cheapest team for a set of tasks. Following such approach and MAS modelling concepts, it would be possible to consider a wider range of properties when designing teams (e.g. robustness or individual goals if satellites belong to different entities) [2]. *Multiagent modeling and programming* could be a great help by providing modeling concepts (e.g. roles, goals, organizations) and methodologies to develop platforms to manage multi-satellite and multi-operator systems [10, 68]. Plus, *Multiagent-based simulation* (MABS) appears as a relevant fine-grained approach to better grasp the operation of the system, or to make predictions about its performance [6, 16, 72]. In the space domain, existing simulators as Ptolemy [49] could benefit from MABS concepts and efforts, since more autonomy is predicted to be provided to space systems. However, such integration requires research efforts on simulator coupling and interoperability [18, 44]. Finally, since models used for assessing performance are different from models used for assessing requirements/safety [55], a challenging path for researchers in agent-oriented software engineering is opened.

EOS constellation design is a multi-objective problem to jointly optimize the number of satellite passes over target regions, the delay of revisit of a satellite over those same regions and also the cost of the constellation while complying with safety constraints. For simple models, analytical methods can be used for optimizing the EOS design [35, 51]. For complex models and simulations, architecture design can be handled through different numerical approaches, like Multi-Disciplinary Optimization [16], Genetic Algorithms [21] or Particle Swarm Optimization [66]. But, these *black box* techniques make difficult to understand the influence of parameters on the resulting configurations. Being able to explain to deciders the different components, their behavior and interactions is a major challenge while integrating MABS with optimization methods.

➥ *Modelling and Simulation of Societies*

➥ *Engineering Multiagent Systems*

➥ *Coordination, Organisations, Institutions, and Norms*

2.2 Resource Allocation and Fair Division

When an EOS constellation is used by several stakeholders, it can be required that its exploitation is equitable or fair, *e.g.* according to the financial investment of each user. This problem falls into the *MultiAgent Resource Allocation* (MARA) domain [20]. For EOS constellations, users or clients can share different types of goods, such as orbits, that can be seen as divisible goods, and get exclusivity on portions of orbit allocated to them. In that case, users have their own mission center and can operate EOS on portions allocated to them. Users can also share EOS by requesting some observation of a geographical zone. In that case, requests are seen as indivisible goods and the requests from a given user that are actually scheduled on the constellation can be seen as the bundle for this user.

Fair division case raises several challenges [14]. First, *fairness* is intricately linked to user preferences as it is required to compare bundles that can be allocated to each user. Representing preferences in a compact way while being able to reason efficiently on them is challenging (*e.g.* CP-net for ordinal preferences [13]). In the context of EOS, many features could be used to define request utility, *e.g.* priority, area of observation, and uncertainty about weather [61]. Most of preference formalisms assume that the utility of a bundle is the sum of the utilities of the elements in the bundle. In the space domain, utility of observation requests might not be independent from each other or could be quite complex (*e.g.* periodic requests), and require to go *beyond additivity* and consider more realistic hypotheses. Furthermore, there exist several concepts of fairness, and few works take fairness into account when scheduling EOS. In [37], fairness is defined as a proportionality with regards to the financial contribution in the constellation funding. Fairness can also be defined as *maxmin* fairness [33, 60]. Moreover, fairness is generally not the only criteria to be taken into account and a trade-off between several criteria is necessary (*e.g.* between efficiency and fairness). Several procedures characterizing efficient and fair allocations for EOS are studied [37], and alternatively fairness is part of a bi-objective criteria [60]. Finding procedures, centralized or decentralized, that return optimal or good quality allocation is a challenge by itself. In the case of EOS in which orbits are shared between several users, one could for instance consider auction mechanisms [9, 20]: users submit their bidding (*i.e.* report their preferences) publicly or privately, there can be one or several rounds and the allocation is made by the auctioneer.

➥ *Social Choice and Cooperative Game Theory*
➥ *Markets, Auctions, and Non-Cooperative Game Theory*

3 OFFLINE OPERATION CHALLENGES

In operation, mission centers compute offline plans for each EOS, given an order book. Beside acquisition scheduling, these plans should also specify when downloading the result of EOS activity to accessible ground stations as to save limited on-board memory, resulting in hard large-scale problems to solve.

3.1 Scheduling Observations

Such problems are distributed by nature, and thus partially or fully decomposable. This opens the door to MAS techniques for problem solving. For instance, the different components of the systems are considered being part of a market place to find agreements on scheduling tasks, using an extended *Contract Net Protocol* to solve a multi-satellite mission scheduling problem [48]. *Distributed constraint optimization* techniques (DCOP) [42] may also be efficient solution methods to address constellation task allocation problems, where decision variables and constraints are distributed amongst a set of agents. For instance, Distributed Large Neighborhood Search (DisLNS) [26] could be applied to multi-satellite scheduling, as done with its centralized counterpart [29]. Adding distribution will bring explainability (by identifying where hard conflicts appear), speedup (by splitting the search process into several concurrent subprocesses), and privacy (in case some tasks/slots are secret). Yet, scalability of DCOP solution methods, and the presence of mixed-integer decision variables, are open challenges to be addressed, as recently investigated in DCOPs with continuous variables [31].

Even more generally, constellation scheduling problems can be modelled as multi-objective (*e.g.* minimizing power consumption while maximizing successful observations) [8, 39, 40, 60, 69], asymmetric (*e.g.* users may not have the same reward if some observation is performed) problems, which are still challenging models concerning the efficiency of distributed solution methods [22, 28]. Finally, since these scheduling problems are very large-scale, *Distributed heuristics and self-organization* based on self-adapting time schedules could provide solutions in a fast, reactive and anytime manner [12]. However, such techniques don't provide quality guarantees, which are strong pre-requisites to be adopted by space agencies.
➥ *Knowledge Representation, Reasoning, and Planning*

3.2 Scheduling under Uncertainties

EOS systems are subject to two main types of uncertainties. First, some clouds can be present when making an observation. If the cloud cover fraction of the observation is larger than the maximal cloud cover fraction associated to the request then the observation is not valid. Moreover, since the plan is computed some time before the acquisition is actually made, this uncertainty is irreducible. For instance, the expectation of the absolute value of the difference between predicted and actual cloud cover fractions increase with the forecast horizon reaching 0.4 for a one hour horizon [71]. Considering that fractions are between 0 and 1, this value reflects a large uncertainty. Thus, there is a not neglectful uncertainty concerning the success of each planned observation. Second, observations are stored in the memory of satellites in a compressed form and the compression ratio is specific to each observation and not known beforehand. For instance, compression ratios varying from 3 to 6 are observed on a small set of images [70]. Thus, there is an uncertainty about the amount of memory that is taken by each observation before its download to a ground station and about the download time of each observation. Moreover, download times are also impacted by bit rate variability and recovery from transmission errors. The first type of uncertainty is directly related to the reward while the second one is a feature of the state transition.

Multiagent planning under uncertainties [56] and more specifically *decentralized partially observable Markov decision processes* (DEC-POMDP) [7] can be relevant in this context. Nevertheless algorithms providing DEC-POMDP solutions do not scale and the challenge is to design simpler solutions. Besides, Markov decision-based model approaches, distributed optimization techniques handling uncertainties recently led to the development of *Probabilistic DCOPs*. Those techniques extend classical DCOPs by augmenting the outcome of the cost functions with stochastic properties [5, 47, 57] or introduce random variables as input to the cost functions, to simulate exogenous uncontrollable traits of the environment, and thus optimize the expected outcome [36, 67]. However, it is also important to note that the prediction of uncertainty measures associated to observation success is a problem in terms of scope of the MAS under study, i.e. is the predictor agent inside or outside the MAS, and in terms of type of uncertainty measure, i.e. almost all satellite planning are based on probabilities but a better robustness could be obtained using imprecise probabilities or *Possibility Theory* [25]. Finally, the definition of a deterministic reward that considers requests of different types and priorities and that can easily be combined to the chosen uncertainty measure is an issue in itself.
➥ *Knowledge Representation, Reasoning, and Planning*

3.3 Deconflicting User Requests

Satellite constellations involve many actors, like satellite owners, satellite operators, service clients requesting observations, governmental agencies, or military operators. Sharing the constellation resources between agents having different objectives and agendas implies that some conflicts may arise, that cannot be solved in a centralized manner as to guarantee decision autonomy and privacy preservation. This last point is crucial: EOSs can be used for defence and security purposes and most of the actors do not want the others to be informed of the way they are using the satellites. For instance, one operator from a country may allow some client from another country to use its satellite to perform some observation, but may not allow to capture some image of its own country or to know what are the observations planned before and after the requested observation. This means that the different users have to solve a problem whose sub-components (decision variables, constraints, or parameters) are owned and private. *Distributed optimization techniques* like DCOP can be considered again, when users aim to a common objective (*e.g.* maximizing the number of scheduled observations) [54]. In case of diverging vision, one may also consider *Consensus optimization* where users build agreements on some shared decision variables [15, 45, 46]. Here again, the presence of discrete and continuous decision variables makes the application of such techniques even more challenging [59]. In more conflicting and non-cooperative settings, *Game Theory* may provide coordination schemes to solve this conflicting situations, as proposed in a recent work [58], or to design markets [23].

➡ *Knowledge Representation, Reasoning, and Planning*
➡ *Markets, Auctions, and Non-Cooperative Game Theory*

4 ONLINE OPERATION CHALLENGES

EOS constellations are dynamic systems deployed in dynamic environments. Offline planning is not sufficient to ensure a fully efficient operation, when weather may degrade the quality of images or when last-minute requests arrive. On-board autonomy has to be considered to equip satellites with some routines for on-the-fly adaptation in response to unpredicted events.

4.1 Dynamics and Rescheduling

Because image acquisition can fail due to the presence of clouds, or because last-minute request can occur, being capable of rescheduling some observations is of high importance. Rescheduling might be considered either on-ground or on-board. On-ground plan repair is triggered once EOSs have downloaded data, and that its bad quality is discovered by validation centers, that can then request rescheduling. Here classical centralized plan repair techniques can be considered to dynamically add tasks but requires to be fast enough so that the revised plan is pushed as soon as possible to the next EOS able to perform the task [64]. This repair should be provided as reactively as possible compared to full scheduling. Considering a partially or fully on-board decision-making, MAS techniques exist to cope with dynamic problems, like in *Dynamic Distributed Constraint Optimization* (DynDCOP), agents cooperate to optimize a series of problems instead of a single instance at a given point in time [30], or to be able to solve problems which are changing at runtime [50]. One may also consider, *Multiagent plan repair* techniques as those for on-board repair [34], which only consider changing some part of the plan for impacted agents instead of rescheduling from scratch. However, while providing good quality plans, such techniques still suffer limited scalability, and requires reliable communications. In our case, communication may not be persistent (*e.g.* ground stations are not accessible at any time or satellites may not be able to directly or indirectly interact) [33]. A distributed learning scheme to repair multi-satellite plans is proposed, noticing that the historical information of cooperative task planning will impact the latter planning results [63]. Another family of candidate techniques are those relying on *Consensus* [27, 41], where agents negotiate as to agree on some decision variables (*e.g.* the choice of the tasks to perform) while being *resilient* to environment disturbances and asynchronicity [24, 50]. Moreover, EOSs have limited computation capacity which limits the range of optimization techniques that can be performed on-board. Thus, self-organization techniques, only relying on limited communication and requiring limited computations, appears being be good candidates for providing plan adaptation at runtime [12, 33, 50], that might not provide optimal solutions, but could arbitrate between requests based on simple criteria (priority) and may transfer requests from EOS to EOS. However, pushing such autonomy and decision on-board remains a real challenge, that still requires strong research efforts in Artificial Intelligence and Robotics to be certified and then embedded in operational systems.

➡ *Knowledge Representation, Reasoning, and Planning* ➡ *Robotics*
➡ *Learning and Adaptation*

4.2 Interaction and Protocols

When dealing with multiagent online operations, considering communication opportunities is a key point for improving the performance of the system. For EOS, direct communications are obviously used between a mission center and the satellites, but many other kinds of communications can be used as well, such as direct communications between two satellites through an inter-satellite link, direct communication between two mission centers managing different parts of the constellation, indirect communications through geostationary relay satellites or drones, and more generally indirect communications through a network of communication links. Considering all such potential communication links for future constellations raises many challenges for online operations, such as "which communication protocol should be used?", "when to communicate?", "which data to communicate and to who?", or "what is the value of an information?", to name just a few. Some proposals have already been made to address such questions. For instance, *Delay Tolerant Network* (DTN) protocol can be used to build a system where a given satellite can warn other satellites about Earth points where a ground phenomenon has been detected [43]. Alternatively, each satellite maintains an estimation of the knowledge of the other satellites using an epidemic communication protocol between satellites [11]. Finally communication is used for negotiation and coordination between spacecraft agents [3, 52] and also to route observation data from one satellite to a ground reception station through inter-satellite links, so as to decrease the time at which users can get their images [17]. These few examples show that communications might be used both for epistemic reasons (to bring an information that can help in making better decisions or implementing some coordination protocol) and for outcome reasons (to communicate observation data and get an immediate reward from the users), one common goal being to get either better reactivity or better task sharing between the agents.

➡ *Coordination, Organisations, Institutions, and Norms* ➡ *Robotics*

5 CONCLUDING REMARKS

In this paper, we identified several open challenges with regards to Earth observation satellite constellations and related applications, addressed to the AAMAS community. Indeed, designing, deploying and operating such systems composed of several actors and resources are perfect fit for multiagent-based approaches. However, the hardness of these problems, and their novelty, are still challenging for the existing methods, which opens new research tracks for the years to come, especially in the identified AAMAS areas of interest, ranging from Engineering Multiagent System to Robotics by way of Knowledge Representation, Reasoning, and Planning.

ACKNOWLEDGMENTS

This work has been performed with the support of the French government in the context of the “Programme d’Invertissements d’Avenir”, namely by the BPI PSPC project “LiChIE”.

REFERENCES

[1] AAMAS'21. 2021. Call for Papers. https://aamas2021.soton.ac.uk/calls/papers/.
[2] E. Andrejczuk, J. A. Rodriguez-Aguilar, and C. Sierra. 2017. A Concise Review on Multiagent Teams: Contributions and Research Opportunities. In *Multi-Agent Systems and Agreement Technologies*, Natalia Criado Pacheco, Carlos Carrascosa, Nardine Osman, and Vicente Julián Inglada (Eds.). Springer International Publishing, Cham, 31–39.
[3] C. Araguz, A. Alvaro, I. del Portillo, K. Root, E. Alarcón, and E. Bou-Balust. 2015. On autonomous software architectures for distributed spacecraft: A Local-Global Policy. In *2015 IEEE Aerospace Conference*. 1–9.
[4] C. Araguz, E. Bou-Balust, and E. Alarcón. 2018. Applying autonomy to distributed satellite systems: Trends, challenges, and future prospects. *Systems Engineering* 21, 16 (03 2018), 401–416. https://doi.org/10.1002/sys.21428
[5] J. Atlas and K. Decker. 2010. Coordination for Uncertain Outcomes Using Distributed Neighbor Exchange. In *International Conference on Autonomous Agents and Multiagent Systems* (Toronto, Canada) *(AAMAS '10)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1047–1054.
[6] G. Bastianelli, D. Salamon, A. Schisano, and A. Iacobacci. 2012. Agent-based simulation of collaborative unmanned satellite vehicles. In *2012 IEEE First AESS European Conference on Satellite Telecommunications (ESTEL)*. IEEE, Rome, 1–6. https://doi.org/10.1109/ESTEL.2012.6400072
[7] D.S. Bernstein, R. Givan, N. Immerman, and S. Zilberstein. 2002. The complexity of decentralized control of Markov decision processes. *Mathematics of operations research* 27, 4 (2002), 819–840.
[8] N. Bianchessi, J.-F. Cordeau, J. Desrosiers, G. Laporte, and V. Raymond. 2007. A heuristic for the multi-satellite, multi-orbit and multi-user management of Earth observation satellites. *European Journal of Operational Research* 177, 2 (2007), 750 – 762. https://doi.org/10.1016/j.ejor.2005.12.026
[9] L. Blumrosen and N. Nisan. 2007. Combinatorial auctions. *Algorithmic game theory* 267 (2007), 300.
[10] O. Boissier, R.H. Bordini, J.F. Hübner, A. Ricci, and A. Santi. 2013. Multi-agent oriented programming with JaCaMo. *Science of Computer Programming* 78, 6 (2013), 747 – 761. https://doi.org/10.1016/j.scico.2011.10.004
[11] G. Bonnet and C. Tessier. 2007. Collaboration among a satellite swarm. In *International Joint Conference on Autonomous Agents and Multiagent Systems*.
[12] J. Bonnet, M.-P. Gleizes, E. Kaddoum, S. Rainjonneau, and G. Flandin. 2015. Multi-satellite Mission Planning Using a Self-Adaptive Multi-agent System. In *2015 IEEE 9th International Conference on Self-Adaptive and Self-Organizing Systems*. IEEE, Boston, 11–20. https://doi.org/10.1109/SASO.2015.9
[13] C. Boutilier, R. I. Brafman, C. Domshlak, H. H. Hoos, and D. Poole. 2004. CP-nets: A Tool for Representing and Reasoning withConditional Ceteris Paribus Preference Statements. *Journal of Artificial Intelligence Research* 21 (Feb 2004), 135–191. https://doi.org/10.1613/jair.1234
[14] S. Bouveret, Y. Chevaleyre, and N. Maudet. 2016. Fair Allocation of Indivisible Goods. In *Handbook of Computational Social Choice*. Cambridge University Press, Cambridge, UK, 284–310.
[15] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein. 2011. Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers. *Found. Trends Mach. Learn.* 3, 1 (Jan. 2011), 1–122. https://doi.org/10.1561/2200000016
[16] I. A. Budianto and J. R. Olds. 2004. Design and Deployment of a Satellite Constellation Using Collaborative Optimization. *Journal of Spacecraft and Rockets* 41, 6 (2004), 956–963. https://doi.org/10.2514/1.14254 arXiv:https://doi.org/10.2514/1.14254
[17] K.L. Cahoy and A.K. Kennedy. 2017. Initial Results from ACCESS: An Autonomous CubeSat Constellation Scheduling System for Earth Observation. In *31st Annual AIAA/USU Conference on Small Satellites*.
[18] B. Camus, T. Paris, J. Vaubourg, Y. Presse, C. Bourjot, L. Ciarletta, and V. Chevrier. 2018. Co-simulation of cyber-physical systems using a DEVS wrapping strategy in the MECSYCO middleware. *SIMULATION* 94, 12 (2018), 1099–1127. https://doi.org/10.1177/0037549717749014 arXiv:https://doi.org/10.1177/0037549717749014
[19] H. Chen, S. Yang, J. Li, and N. Jing. 2018. Exact and Heuristic Methods for Observing Task-Oriented Satellite Cluster Agent Team Formation. *Mathematical Problems in Engineering* 2018 (Aug. 2018), 1–23. https://doi.org/10.1155/2018/2103625
[20] Y. Chevaleyre, P.E. Dunne, U. Endriss, J. Lang, M. Lemaître, N. Maudet, J.A. Padget, S. Phelps, J.A. Rodríguez-Aguilar, and P. Sousa. 2006. Issues in Multiagent Resource Allocation. *Informatica (Slovenia)* 30, 1 (2006), 3–31. http://www.informatica.si/index.php/informatica/article/view/70
[21] C. Dai, G. Zheng, and Q. Chen. 2018. Satellite constellation design with multi-objective genetic algorithm for regional terrestrial satellite network. *China Communications* 15, 8 (2018), 1–10. https://doi.org/10.1109/CC.2018.8438269
[22] F. M. Delle Fave, R. Stranders, A. Rogers, and N. R. Jennings. 2011. Bounded Decentralised Coordination over Multiple Objectives. In *International Conference on Autonomous Agents and Multiagent Systems* (Taipei, Taiwan) *(AAMAS '11)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 371–378.
[23] G. Denis, A. Claverie, X. Pasco, J.-P. Darnis, B. de Maupeou, M. Lafaye, and E. Morel. 2017. Towards disruptions in Earth observation? New Earth Observation systems and markets evolution: Possible scenarios and impacts. *Acta Astronautica* 137 (2017), 415 – 433. https://doi.org/10.1016/j.actaastro.2017.04.034
[24] S.M. Dibaji and H. Ishii. 2015. Resilient Multi-Agent Consensus with Asynchrony and Delayed Information. *IFAC-PapersOnLine* 48, 22 (2015), 28 – 33. https://doi.org/10.1016/j.ifacol.2015.10.302 5th IFAC Workshop on Distributed Estimation and Control in Networked Systems NecSys 2015.
[25] D. Dubois and H. Prade. 2014. Possibilistic Logic — An Overview. In *Computational Logic*, Jörg H. Siekmann (Ed.). Handbook of the History of Logic, Vol. 9. North-Holland, Amsterdam, Holland, 283 – 342. https://doi.org/10.1016/B978-0-444-51624-4.50007-1
[26] F. Fioretto, F. Campeotto, A. Dovier, E. Pontelli, and W. Yeoh. 2015. Large Neighborhood Search with Quality Guarantees for Distributed Constraint Optimization Problems. In *International Conference on Autonomous Agents and Multiagent Systems* (Istanbul, Turkey) *(AAMAS '15)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1835–1836.
[27] P. Franceschelli and P. Frasca. 2018. Proportional Dynamic Consensus in Open Multi-Agent Systems. In *2018 IEEE Conference on Decision and Control (CDC)*. IEEE, Miami Beach, FL, USA, 900–905. https://doi.org/10.1109/CDC.2018.8619639
[28] T. Grinshpoun, A. Grubshtein, R. Zivan, A. Netzer, and A. Meisels. 2013. Asymmetric Distributed Constraint Optimization Problems. *J. Artif. Int. Res.* 47, 1 (May 2013), 613–647.
[29] L. He, L. Xiaolu, G. Laporte, Y.-W. Chen, and Y. Chen. 2018. An improved adaptive large neighborhood search algorithm for multiple agile satellites scheduling. *Computers and Operations Research* 100 (07 2018), 12–25. https://doi.org/10.1016/j.cor.2018.06.020
[30] K. D. Hoang, F. Fioretto, P. Hou, M. Yokoo, W. Yeoh, and R. Zivan. 2016. Proactive Dynamic Distributed Constraint Optimization. In *International Conference on Autonomous Agents and Multiagent Systems* (Singapore, Singapore) *(AAMAS '16)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 597–605.
[31] K. D. Hoang, W. Yeoh, M. Yokoo, and Z. Rabinovich. 2020. New Algorithms for Continuous Distributed Constraint Optimization Problems. In *International Conference on Autonomous Agents and MultiAgent Systems* (Auckland, New Zealand) *(AAMAS '20)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 502–510.
[32] Hongwei Xia, Guangcheng Ma, Weinan Xie, and Baomin Feng. 2006. Multiple satellite formation based on multi-agent. In *2006 1st International Symposium on Systems and Control in Aerospace and Astronautics*. IEEE, Harbin, China, 4 pp.–705. https://doi.org/10.1109/ISSCAA.2006.1627430
[33] M. Johnston. 2020. Scheduling NASA's Deep Space Network: Priorities, Preferences, and Optimization. (2020).
[34] A. Komenda, P. Novák, and M. Pěchouček. 2014. Domain-independent multi-agent plan repair. *Journal of Network and Computer Applications* 37 (2014), 76 – 88. https://doi.org/10.1016/j.jnca.2012.12.011
[35] C. L. Korb and A.R. Korb. 2020. Methods for optimizing the performance, cost and constellation design of satellites for full and partial earth coverage. US Patent 10,664,782.
[36] T. Léauté and B. Faltings. 2011. Distributed Constraint Optimization under Stochastic Uncertainty. In *Twenty-Fifth AAAI Conference on Artificial Intelligence* (San Francisco, California) *(AAAI'11)*. AAAI Press, 68–73.
[37] M. Lemaître, G. Verfaillie, H. Fargier, J. Lang, N. Bataille, and J.-M. Lachiver. 2003. Equitable allocation of earth observing satellites resources. In *5th ONERA-DLR Aerospace Symposium (ODAS'03)*.
[38] M. Lemaître, G. Verfaillie, F. Jouhaud, J.-M. Lachiver, and N. Bataille. 2002. Selecting and scheduling observations of agile satellites. *Aerospace Science and Technology* 6, 5 (2002), 367 – 381. https://doi.org/10.1016/S1270-9638(02)01173-2
[39] L. Li, H. Chen, J. Li, N. Jing, and M. Emmerich. 2018. Preference-Based Evolutionary Many-Objective Optimization for Agile Satellite Mission Planning. *IEEE Access* 6 (2018), 40963–40978. https://doi.org/10.1109/ACCESS.2018.2859028 Conference Name: IEEE Access.
[40] L. Li, F. Yao, N. Jing, and M. Emmerich. 2017. Preference incorporation to solve multi-objective mission planning of agile earth observation satellites. In *2017 IEEE Congress on Evolutionary Computation, CEC 2017*. IEEE, 1366–1373. https://doi.org/10.1109/CEC.2017.7969463
[41] Z. Li, Z. Duan, and F. L. Lewis. 2014. Distributed robust consensus control of multi-agent systems with heterogeneous matching uncertainties. *Automatica* 50, 3 (2014), 883 – 889. https://doi.org/10.1016/j.automatica.2013.12.008
[42] P.J. Modi, W.-M. Shen, M. Tambe, and M. Yokoo. 2005. Adopt: Asynchronous Distributed Constraint Optimization with Quality Guarantees. *Artif. Intell.* 161, 1–2 (Jan. 2005), 149–180.
[43] S. Nag, A. Li, V. Ravindra, M. Sanchez Net, K.-M. Cheung, R. Lammers, and B. Bledsoe. 2019. Autonomous Scheduling of Agile Spacecraft Constellations with Delay Tolerant Networking for Reactive Imaging. In *International Conference on Automated Planning and Scheduling SPARK Workshop*.
[44] K. Ndiaye, F. Balbo, J.-P. Jamont, and M. Occello. 2018. Simulation Coupling Limitations with Respect to Shared Entities Constraints. In *8th International Conference on Simulation and Modeling Methodologies, Technologies and Applications*.

INSTICC, SciTePress, 338–346. https://doi.org/10.5220/0006859603380346

[45] A. Nedić, A. Olshevsky, and Wei Shi. 2018. *Decentralized Consensus Optimization and Resource Allocation.* Springer International Publishing, Cham, 247–287. https://doi.org/10.1007/978-3-319-97478-1_10

[46] A. Nedić, A. Ozdaglar, and P. A. Parrilo. 2010. Constrained Consensus and Optimization in Multi-Agent Networks. *IEEE Trans. Automat. Control* 55, 4 (2010), 922–938. https://doi.org/10.1109/TAC.2010.2041686

[47] D. T. Nguyen, W. Yeoh, and H.C. Lau. 2012. Stochastic Dominance in Stochastic DCOPs for Risk-Sensitive Applications. In *International Conference on Autonomous Agents and Multiagent Systems* (Valencia, Spain) *(AAMAS '12)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 257–264.

[48] Peng Feng, Hao Chen, Shuang Peng, Luo Chen, and Longmei Li. 2015. A method of distributed multi-satellite mission scheduling based on improved contract net protocol. In *2015 11th International Conference on Natural Computation (ICNC)*. IEEE, Zhangjiajie, China, 1062–1068. https://doi.org/10.1109/ICNC.2015.7378139

[49] Claudius Ptolemaeus (Ed.). 2014. *System Design, Modeling, and Simulation using Ptolemy II.* Ptolemy.org, Berkeley, California, USA. http://ptolemy.org/books/Systems

[50] P. Rust, G. Picard, and F. Ramparany. 2020. Resilient Distributed Constraint Optimization in Physical Multi-Agent Systems. In *European Conference on Artificial Intelligence (ECAI)*. IOS Press, Amsterdam, Holland, 195 – 202. https://doi.org/10.3233/FAIA200093

[51] T. Savitri, Y. Kim, S. Jo, and H. Bang. 2017. Satellite Constellation Orbit Design Optimization with Combined Genetic Algorithm and Semianalytical Approach. *International Journal of Aerospace Engineering* 2017 (31 May 2017), 1235692. https://doi.org/10.1155/2017/1235692

[52] T. Schetter, M. Campbell, and D. Surka. 2003. Multiple agent-based autonomy for satellite constellations. *Artificial Intelligence* 145, 1 (2003), 147 – 180. https://doi.org/10.1016/S0004-3702(02)00382-X

[53] V. Shah, V. Vittaldev, L. Stepan, and C. Foster. 2019. Scheduling the World's Largest Earth-Observing Fleet of Medium-Resolution Imaging Satellites. *IWPSS* (2019).

[54] P. K. Sinha and A. Dutta. 2016. Multi-satellite task allocation algorithm for Earth observation. In *2016 IEEE Region 10 Conference (TENCON)*. IEEE, New York, New York, US, 403–408. https://doi.org/10.1109/TENCON.2016.7848030

[55] A.H. Sánchez, T. Soares, and A. Wolahan. 2017. Reliability aspects of mega-constellation satellites and their impact on the space debris environment. In *2017 Annual Reliability and Maintainability Symposium (RAMS)*. 1–5. https://doi.org/10.1109/RAM.2017.7889671

[56] M. T. J. Spaan and F. S. Melo. 2008. Interaction-Driven Markov Games for Decentralized Multiagent Planning under Uncertainty. In *International Joint Conference on Autonomous Agents and Multiagent Systems* (Estoril, Portugal) *(AAMAS '08)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 525–532.

[57] R. Stranders, F.M. Delle Fave, A. Rogers, and N.R. Jennings. 2011. *U-GDL: A decentralised algorithm for DCOPs with Uncertainty.* Project Report. https://eprints.soton.ac.uk/273037/

[58] C. Sun, X. Wang, and X. Liu. 2018. Distributed Satellite Mission Planning via Learning in Games. In *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, New York, New York, US, 4381–4386. https://doi.org/10.1109/SMC.2018.00740

[59] R. Takapoui, N. Moehle, S. Boyd, and A. Bemporad. 2020. A simple effective heuristic for embedded mixed-integer quadratic programming. *Internat. J. Control* 93, 1 (2020), 2–12. https://doi.org/10.1080/00207179.2017.1316016 arXiv:https://doi.org/10.1080/00207179.2017.1316016

[60] P. Tangpattanakul, N. Jozefowiez, and P. Lopez. 2015. A multi-objective local search heuristic for scheduling Earth observations taken by an agile satellite. *European Journal of Operational Research* 245, 2 (Sept. 2015), 542–554. https://doi.org/10.1016/j.ejor.2015.03.011

[61] A.E. Vasegaard, M. Picard, F. Hennart, P. Nielsen, and S. Saha. 2020. Multi Criteria Decision Making for the Multi-Satellite Image Acquisition Scheduling Problem. *Sensors* 20, 5 (2020), 1242. https://doi.org/10.3390/s20051242

[62] J.G. Walker. 1984. Satellite Constellations. *Journal of the British Interplanetary Society* 37 (Dec. 1984), 559.

[63] C. Wang, J. Li, N. Jing, J. Wang, and H. Chen. 2011. A Distributed Cooperative Dynamic Task Planning Algorithm for Multiple Satellites Based on Multi-agent Hybrid Learning. *Chinese Journal of Aeronautics* 24, 4 (2011), 493 – 505. https://doi.org/10.1016/S1000-9361(11)60057-5

[64] J. Wang, X. Zhu, L.T. Yang, J. Zhu, and M. Ma. 2015. Towards dynamic real-time scheduling for multiple earth observation satellites. *J. Comput. System Sci.* 81, 1 (2015), 110 – 124. https://doi.org/10.1016/j.jcss.2014.06.016

[65] X. Wang, G. Wu, L. Xing, and W. Pedrycz. 2020. Agile Earth observation satellite scheduling over 20 years: formulations, methods and future directions. *CoRR* abs/2003.06169 (2020), 36. arXiv:2003.06169 https://arxiv.org/abs/2003.06169

[66] X. Wang, H. Zhang, S. Bai, and Y. Yue. 2021. Design of agile satellite constellation based on hybrid-resampling particle swarm optimization method. *Acta Astronautica* 178 (2021), 595 – 605. https://doi.org/10.1016/j.actaastro.2020.09.040

[67] Y. Wang, K. Sycara, and P. Scerri. 2011. Towards an Understanding of the Value of Cooperation in Uncertain World. In *2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology (WI-IAT '11)*. IEEE Computer Society, USA, 212–215. https://doi.org/10.1109/WI-IAT.2011.244

[68] M. Winikoff and L. Padgham. 2013. *Agent Oriented Software Engineering.* MIT Press, Chapter 13, 695–757.

[69] W. Yang, Y. Chen, R. He, Z. Chang, and Y. Chen. 2018. The Bi-objective Active-Scan Agile Earth Observation Satellite Scheduling Problem: Modeling and Solution Approach. In *2018 IEEE Congress on Evolutionary Computation (CEC)*. 1–6. https://doi.org/10.1109/CEC.2018.8477851

[70] G. Yu, T. Vladimirova, and M.N. Sweeting. 2009. Image compression systems on board satellites. *Acta Astronautica* 64, 9-10 (2009), 988–1005.

[71] I. Yucel, J. W Shuttleworth, X Gao, and S Sorooshian. 2003. Short-term performance of MM5 with cloud-cover assimilation from satellite observations. *Monthly weather review* 131, 8 (2003), 1797–1810.

[72] C. Zhang, Y. Wang, and Y. Zhao. 2013. Agent-Based Distributed Simulation Technology of Satellite Formation Flying. In *Proceedings of the 2013 Fourth World Congress on Software Engineering (WCSE '13)*. IEEE Computer Society, USA, 13–16. https://doi.org/10.1109/WCSE.2013.7