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Explaining AI Decisions in Autonomous Satellite Scheduling via Computational Argumentation

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The task of scheduling satellite operations is inherently complex and highly sensitive to alterations, a challenge compounded by the increasing number of satellites in orbit. The escalating risks and complexities have prompted organizations to explore automated solutions to replace traditional manual processes. However, concerns about the trustworthiness and transparency of automated systems prevent their widespread adoption.

eXplainable Artificial Intelligence (XAI) is an emerging field that aims to address these reservations by enabling Artificial Intelligence (AI) systems to provide explanations for their decisions, thereby eliminating opaqueness in understanding their reasoning. Within XAI, the use of computational argumentation frameworks has seen increasing utilisation. This approach quantifies the supportability of decisions, offering system operators enhanced understanding and justification for utilizing automated services.

This paper expands on previous research by detailing a method for generating a tripolar argumentation approach for assessing actions based on an Earth Observation (EO) satellite schedule. The method involves calculating and presenting the weights of arguments that support or attack the scheduled actions. The results illustrate the effectiveness of the approach in producing meaningful insights into scheduling decisions, highlighting its potential for practical applications in real-world satellite operations.

1 Introduction

The capability and utility of autonomous systems have grown exponentially in recent years and inevitably the applications for the space industry have been investigated. Studies into the function of AI for such areas as space exploration, earth observation, satellite telemetry, robotics, and space medicine have shown potential for meaningful enhancements to space mission design and operation [1–4]. However, research into autonomous satellite scheduling is still being explored with only a small handful of papers considering the possibilities and applications in recent years [5–8].

One of the limiting factors in broad adoption is the lack of trust teams and organisations have in the decisions AI systems make, especially where there is no means of understanding the reasoning behind a decision, often seen as an inherent challenge of designing AI systems [9].

XAI aims to eliminate this problem by allowing interaction between the user and systems to gain explanations for the decisions being made and thereby providing insight into system operations [10]. The gained knowledge will enable the growth of trust in the system, either through validating the correct logic judgement leading to decisions or by facilitating targeted training and reconfiguration of a system to achieve the desired outcome. XAI techniques presently include such approaches as Machine Learning (ML), Linear Regression, and Local Interpretable Model-agnostic Explanations (LIME), each of which has the intent of explaining the key factors that influenced the system into making one decision over another [11, 12].

The process of analysing the selection of a decision is known as argumentation [13], which has seen a marked increase in association with XAI as the approach offers a highly detailed assessment of all available options in an argument [14]. Argumentation considers all conditions that support, attack, or have a neutral stance in an argument, known as conflicts. Here a support is a condition that promotes the reasoning for a decision, an attack is a condition that counters the reasoning for a decision, and a neutral stance (sometimes referred to as a challenge or confusion) does not add to or detract from any decision. It is possible for the same condition to support or attack an argument, depending on the specific circumstances at the time of the assessment. The approach of determining these three argument conditions is known as Tripolar Argumentation, which allows for more com-

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plex and relatable argument structures and is the argumentation used in this paper [15]. Argumentation facilitates both a graphical and quantifiable representation of the decision-making process, allowing for the examination of reasoning logic and is naturally effective as a means of explaining the reasoning for one choosing one activity over another [16].

This paper explores the application of Tripolar Argumentation to XAI for an EO satellite schedule derived from a Reinforcement Learning (RL) approach [17], building on previously published work, to assess the capability and potential for real-world challenges for the operation of space missions. An outline of the underlying satellite scheduling problem is provided in Section 2, with the methodology detailed in Section 3, which is followed by an examination of the results in Section 4 and a discussion of the outcome in Section 5.

2 The satellite schedule problem

The satellite schedule derived by an RL technique considers a predefined set of locations (N) on Earth where a set of observations needs to be taken, processed and downlinked. The number of observations depends on the predefined goals for the mission [17].

Each scheduled action was influenced by two voice agents within the ML architecture. In this context, "voice" refers to distinct decision-making entities that guide the scheduling process. Each voice agent is focused on fulfilling independently the mission goals of the overall predefined subsets of target observations. Every action was subject to a combination of environmental and internal constraints, all of which were determined based on the satellite's coordinates and operational circumstances. The actions are:

- Image-taking (a_{ti}) - can only take place when the satellite is within light range (LR), has visibility of the target (T), and has enough onboard memory (M).
- Analyse (a_{an}) - can only take place when there is an unprocessed image in memory (I_{mem}).
- Downlinking (a_{dn}) - occurs when access to the ground station (GS) is possible and there is an analysed image (An_{mem}) in memory.
- Idle (a_i) - has no constraints, and only occurs when no other action can be scheduled.

These actions utilise onboard power (P) and require time to complete with the exception of the idle action, which allows for power to be restored. These schedule principles were used to develop an argumentation layer to assist in explaining the supportive and restrictive conditions experienced by each action throughout the schedule.

3 Methodology

In developing an argumentation layer for this problem, all factors must be considered, to develop the support $'+'$ and attack $'-'$ conditions for each action scheduled at each time interval. This is known as a binary attack as defined by [18]. For this specific problem, an additional consideration, such as power consumption, is included with the constraints of the availability of onboard memory and the satellite's coordinates.

The argumentation layer is derived from considering the possibility of every action (a), of all targets, to be scheduled at every time instance throughout the schedule. Still, as only one action can be scheduled per time interval, an argument is formulated by considering the weights that have been assigned between each action. Therefore, to assess what other action can replace the scheduled action at any time t, only the conditions at time t are analysed.

For example, if an image-taking action for a specified observation target (T) is scheduled at time t, it is necessary to assess all the attack conditions to the target T and of the actions related to the all the other observation targets, to discern why the decision maker has assigned the action of observing T. This involves evaluating attacks from $N-1$ other image-taking actions (one for each target that is not T), all other N actions (processing, downlinking, and idle), along with their environmental conditions and the environmental condition of T.

An overview of the structure of supports and attacks is represented in Figure 1, illustrating the interconnected nature of the actions and the associated conditions. Each action shares a goal (G) relationship that details how many images are requested for the n-th observation target T_n. Additionally, PR represents the probability of any action determined by the decision makers' output, reflecting the influence of the voices for the specific actions and targets impacting the scheduled action.

In calculating the weighted values for any image-taking action a_{ti}, the following calculations are used:

$$W_M = 1 - \left(\frac{M}{Tot_a}\right) \tag{1}$$

$$W_{T\_n} \in \{-5, 1\}^t \tag{2}$$

$$W_{LR} \in \{-5, 1\}^t \tag{3}$$

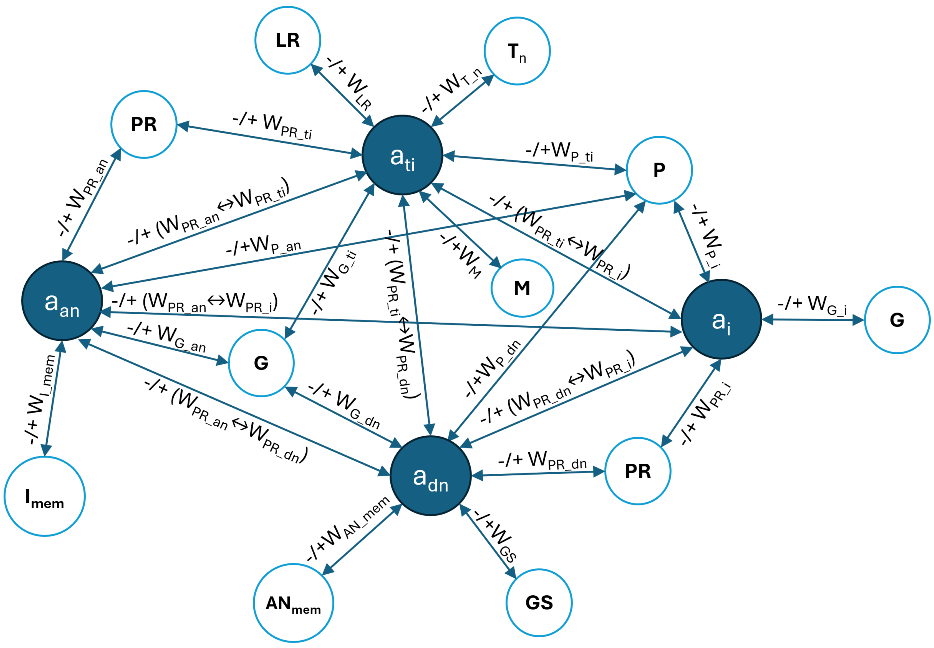

Figure 1: An overview of the argumentation structure for supports and attacks for all actions within the schedule.

Equation 1 represents the weight W_M of the argument between a_{ti} and the available memory onboard (M) where Tot_a represents the total number of actions. The weights, W_{T_n} in Expression 2, and W_{LR} in Expression 3, define whether the n-th target is visible, or light is within range for any instance of time t. Note that -5 is used to negate all positive supports as the action cannot execute without these conditions, and 1 is applied where the conditions have been met.

The weight between a_{an} and I_{mem} is calculated by:

$$W_{I\_mem} \in \{-1, 1\}^t \tag{4}$$

While the weights between a_{dn} and it's specific conditions An_{mem} and GS are as follows:

$$W_{An\_mem} \in \{-1, 1\}^t \tag{5}$$

$$W_{GS} \in \{-5, 1\}^t \tag{6}$$

W_{I_mem} in Expression 4 represents the presence of the specified target image in memory which can either support or prevent the action from being scheduled at any time t. Meaning, if the image of one target is in memory, and the processing of the image related to another target is being considered to be scheduled, this won't be possible, thus *-1* is applied.

Furthermore, W_{An_mem} in Expression 5, relies on whether there is an analysed image of the target in memory that is ready to be downloaded, while W_{GS} in Expression 6 represents if the ground station at any time t is accessible for downlinking. The value of -5 is used to negate all the positive supports if there is no ground station (as this would make the action impossible, similar to Expressions 2 and 3).

For idle, there are two weights to be calculated:

$$W_{G\_i} = -\left(\frac{1}{Tot_a}\right) \tag{7}$$

$$W_{P\_i} = 1 - \left(\frac{P-1}{100}\right) \tag{8}$$

W_{G_i} and W_{P_i} in Equations 7 and 8 represent the weights between the idle action, the mission goal G, and power (P), respectively, where the weight for idle increases with the decrease in P.

The common weight calculations across all actions a (namely a_{ti}, a_{an}, and a_{dn}), excluding idle, are:

$$W_{P\_a} = P - \left(\frac{P_C * t_{ad}}{100}\right) \tag{9}$$

$$W_{G\_a} \in \{-1, 1\} \tag{10}$$

W_{P_a} in Equation 9 represents the weight of the argument between P and any a, where P_C is the power consumption with respect to the duration required to complete the action t_{ad}. Additionally, Expression 10 represents the weight between the goal and any action W_{G_a} based on the specified goal requirement of images to be retrieved.

These weight values are summed to generate a total weight value representing an action's overall state within the schedule at time t. Table 1 shows an overview of the combined attack variations of actions and their environmental conditions.

Action	Action and Condition Attacks									
a_{dn}	P_a	G_a	PR	AN_{mem}	GS		$a_{dn}{}^{\text{1-N}}$	$a_{ti}{}^{\text{1-N}}$	$a_{an}{}^{\text{1-N}}$	a_{ai}
a_{an}	P_a	G_a	PR	I_{mem}			$a_{an}{}^{\text{1-N}}$	$a_{ti}{}^{\text{1-N}}$	$a_{dn}{}^{\text{1-N}}$	a_{ai}
a_{ti}	P_a	G_a	PR	M	T_i	LR	$a_{ti}{}^{\text{1-N}}$	$a_{an}{}^{\text{1-N}}$	$a_{dn}{}^{\text{1-N}}$	a_{ai}
a_i	P_i	G_i	PR				$a_{an}{}^{\text{1-N}}$	$a_{ti}{}^{\text{1-N}}$	$a_{dn}{}^{\text{1-N}}$	

Table 1: An overview of each action and condition attack required for every action type

The PR values from the decision maker were used for calculating attacks from the other actions a including idle. The direction of attacks and representative weight value W_{PR_a}, was determined by the action being attacked at time t. With respect to the unscheduled actions attacking each other, the larger weight value determines the direction of attack. Noting that without the PR values, computing the total argument value of every alternative action would cause exponential growth in the required calculations. Hence, the calculated PR reduced the use of computational resources to generate the results for this study.

4 Results

Exploring the results following the procedure in Section 3, each action for each time interval was calculated and assessed to determine the accuracy of the derived schedule representation. As the full schedule totals 9000 scheduled actions and time intervals, a sample of 3 scheduled actions, one of each type (excluding Idle), was selected to represent the results generated, with their resulting calculations shown in Table 2. Here, the closest alternative action, based on probability and total argument weight, has been added to provide context. The table highlights the time of the scheduled action and the action scheduled that were assessed with the weight values for each argument condition, using the outline in Table 1. As each action has 10 targets (except Idle), for the simplicity of displaying the data, only the total attack value for each action type was used as over 3500 calculations are required for each time interval of this problem.

At time 208, a_{dn4} (downlink action of observation target 4) was scheduled, with a total argument weight value of 4.0126, influenced by the high probability and the support of An_{mem} and GS conditions. The closest alternative action was a_{dn7}, which has a significantly smaller PR score, resulting in a total argument weight of 2.1247, which is much less than the scheduled action, meaning the decision maker made a justifiable decision to schedule a_{dn4}.

For time 480, a_{an1} (the analyse action of observation target 1) was scheduled, having a total argument weight value of 3.9029, chosen due to the high PR score returned by the decision maker. The next best option was a_{an2} which also had a target image in memory, but had a significantly lower PR score and, therefore, total weight value (1.9901), the decision maker again made a justified selection for scheduling action a_{an1}.

Looking at time 696, action a_{ti7} (the take image action of observation target 7) was scheduled to execute, shown with a total argument weight value of 5.4893. This was again due to the high PR score, coupled with the environmental conditions supporting the scheduling of the action (LR and T_7). By comparison, the next best alternative action would have been a_{ti10}, which only accumulated a total argument weight value of 1.4927, as the target was not available for this image at the time.

In Figure 2, the complete support (single arrow), attack (double-headed arrow), and neutral (bidirectional arrow) node map, with the relevant calculated values, was displayed for the action scheduled at time 208 (a_{dn4}). Each action's highest total argument weight value was 4.0126 for a_{dn4}, -4.0636 for a_{ti1}, 0.4025 for a_{an10}, and -1.4734 for a_{ai}. This again highlights that the decision maker made the correct choice, while also providing insight to the contributing supports that make this the right decision. Notably, for the unscheduled actions (a_{ti1}, a_{an10}, and a_{ai}), a_{ti1} was impacted due to the unavailability of light and observation target T_1 that are critical requirements needed for the action to execute despite the memory, goal and power being available. For a_{an10}, an image of observation target 10 was not available in memory, therefore negatively influences the decision to schedule the action when compared to a_{dn4} despite having enough power, goal and a supporting probability. This concept applies to a_{ai} and across all other actions at this time, representing the reasons why they have not been scheduled instead of a_{dn4}.

5 Discussion

The results prove that argumentation can help calculate, visualise, explain and validate autonomous systems' decisions by assessing all the conditions that contribute to determining the outcome. The satellite scheduling problem contained a broad number of variables that required calculating to evaluate the decisions made by the decision maker, and the approach performed very well at capturing the relevant information and completing the necessary calculations, making it clear how and why the scheduled action was correctly chosen and why others were not selected.

This can benefit users by understanding what fac-

Time (s)	Action	Action and Condition Attacks										Total
	a_{dn}	P	G	PR	An_{mem}	GS		a_{dn}*	a_{ti}*	a_{an}*	a_{ai}	
208	a_{dn4}	0.7300	1.0000	0.9715	1.0000	1.0000		-0.0273	-0.0000	-0.6614	-6.5974e^{-05}	4.0126
208	a_{dn7}	0.7300	1.0000	0.0276	1.0000	1.0000		-0.9715	-0.0000	-0.6614	-6.5974e^{-05}	2.1247
	a_{an}	P	G	PR	I_{mem}			a_{an}	a_{ti}*	a_{dn}*	a_{ai}	
480	a_{an1}	0.9500	1.0000	0.9764	1.0000			-0.0235	-0.0000	-0.0000	-5.2090e^{-08}	3.9029
480	a_{an2}	0.9500	1.0000	0.0200	1.0000			-0.9799	-0.0000	-0.0000	-5.2090e^{-08}	1.9901
	a_{ti}	P	G	PR	M	T	LR	a_{ti}	a_{an}*	a_{dn}*	a_{ai}	
696	a_{ti7}	0.7250	1.0000	0.9983	0.7667	1.0000	1.0000	-0.0000	-0.0001	-0.0000	-0.0006	5.4893
696	a_{ti10}	0.7250	1.0000	0.0000	0.7667	-1.0000	1.0000	-0.9983	-0.0001	-0.0000	-0.0006	1.4927

Table 2: Example calculations of argumentation weights for each action type and the closest probable alternative, except Idle. *Please note, the total of all attacking actions are presented here

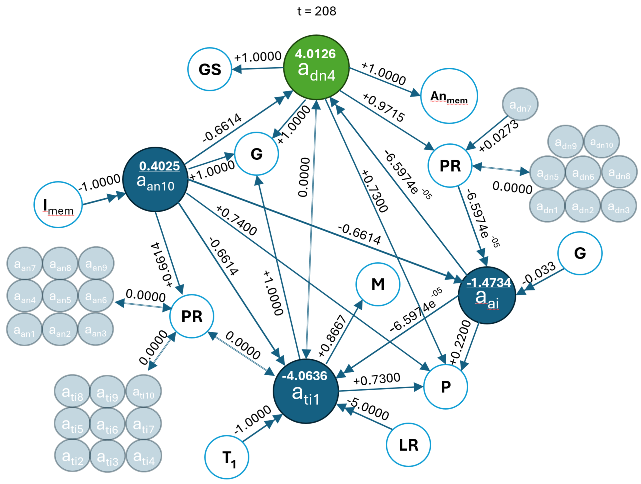

Figure 2: A Tripolar argumentation representation of arguments between 4 main actions (a_{an10}, a_{dn4}, a_{ai}, a_{ti1}) and environmental conditions at time $t = 208s$.

tors influence decisions, allowing for informed responses to modify system behaviour to generate the desired outcome, and validating the system's effectiveness. Care must be taken when designing and implementing argumentation, however, as datasets with a large number of variable conditions can require a very high number of calculations to generate results, as well as considering the appropriate values for each condition, which could be a limiting factor in some cases for the time needed to perform the calculations, as well as the computing resource necessary.

Further work and research should be conducted to assess the scalability of the approach outlined here. This would involve utilising more computing resources and allowing for more time to generate results. In addition, the opportunities for integrating argumentation into other decision-making systems, such as autonomous navigation guidance systems or robotics, should be explored.

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