An AI Manager System to Mitigate Coordination Challenges for Distributed Human-Machine Teaming in Space

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ABSTRACT

In 2021 and 2022, supported by an AFOSR grant (USAF FA9550-21-1-0104), our team demonstrated that we could collect and analyze sensor data from a complex simulated scenario that included NASA Mission Control, the Jet Propulsion Laboratory, a lunar Human-Machine Team (HMT), a lunar orbiter, the International Space Station with two astronauts, a Mars Orbiter, and a Mars Rover. Sensor data in the form of communication flow, heart rate variability, and vehicle positioning were collected as eight individuals enacted a scripted scenario. Data analytics were applied to test the ability of the analytic techniques to identify the timing, location, and cascading effects of those perturbations across system layers and the system as a whole. Machine learning approaches were applied to identify features of the anomalies. Results provide proof of concept that system state can be captured by applying the dynamic data analytic techniques to the sensor data.

1.0 THE VISION

Geographically and temporally distributed coordination is a challenge for space-based missions, Joint All Domain Operations (JADO), and, more generally, heterogenous, multi-domain teaming. This challenge is exacerbated by the complexity of teaming in a heterogeneous multi-team system composed of humans, robots, and Artificial Intelligence (AI) agents that can be confronted with unexpected/novel challenges ("perturbations") and communication bottlenecks/delays. One solution is to harness artificial intelligence to monitor and manage these complex systems. An AI Manager System (AIMS) could potentially assess the dynamic effects of changes in the state of Distributed Teaming Systems (DTS) and in cases of anomalous states, provide a suitable intervention to stabilize the DTS.

More specifically, AIMS could help to manage Joint All Domain Operations (JADO). The future of defense command and control involves an interconnected web of sensors and shooters linked by a centralized command node. In this future network, air, ground, sea, and space-based sensors provide real-time intelligence of adversary activities. Sensors and shooters composed of AI-aided human operators, (semi) autonomous agents, and multiple disparate applications push and pull data from this network. Data is the lifeblood of this system, with multiple communications layers automatically moving massive amounts of information between sensors and users, often with little to no human intervention. A human cannot realistically monitor such a system, so AIMS could continuously monitor the flow of information throughout the network to: 1) ingest communication signals, multi-domain sensor data, Position, Navigation, and Timing (PNT) data, and human physiological signals; 2) flag and locate the source of unexpected coordination patterns throughout the network and; 3) classify the type of abnormal coordination pattern/perturbation and then automatically recommend mitigations that re-establish trust in the system. For instance, AIMS may detect jamming of the C2 network of a Manned-Unmanned Team (MUM-T) executing a Suppression of Enemy Air Defenses (SEAD) mission in hostile airspace and automatically recommend an alternate C2 network that provides sufficient bandwidth to continue the mission.

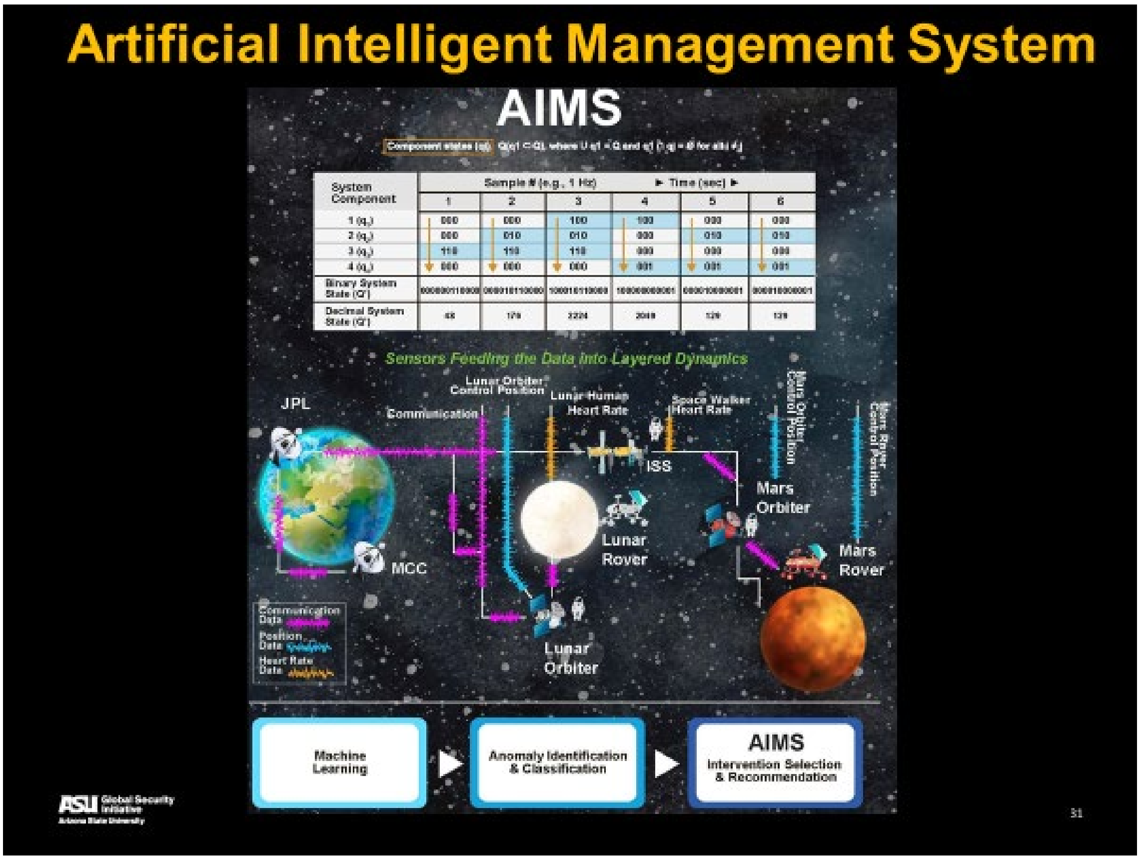

Figure 1: Artificial Intelligence Management System.

2.0 OVERVIEW OF APPROACH

To accomplish this vision, we leverage a non-linear dynamical systems approach (layered dynamics [1]; to assess intra-and-inter system dynamics and machine learning to classify the dynamic patterns as team states. Using dynamical systems metrics that have been validated in a variety of training domains and use cases (maritime, medical, air vehicle operations) as indicators of how and when teams should adapt, we seek to provide real-time unobtrusive tracking of anomalous system states and how/when teams should adapt using machine learning models.

Several steps were taken to test proof of concept of this approach: 1) Generation of a complex distributed space operation envisioned world scenario with scripted perturbations, 2) Scenario enactment and collection of sensor data, 3) Data analysis using the layered dynamics approach [1], and 4) Identify machine learning approaches for anomaly detection.

2.1 Scenario Generation

In 2021 and 2022, supported by an AFOSR grant (USAF FA9550-21-1-0104), our team demonstrated that we could collect and analyze sensor data from a complex simulated scenario that included NASA Mission Control, the Jet Propulsion Laboratory, a lunar Human-Machine Team (HMT), a lunar orbiter, the International Space Station with two astronauts, a Mars Orbiter, and a Mars Rover. To inform scenario development, nine interviews were conducted from three astronauts with 50-150 days experience in space, two astrogeologists, and four individuals with space robotics experience. Challenges in distributed space operations were identified around communications, training, distributed teaming, and system complexity [2].

Scenario perturbations aligned with the challenges identified in the interviews were integrated into the scenario to designate system anomalies. These included the sudden need to collect a substance called "Enerphoto" from the surface of the moon and Mars to replenish the earth's energy supply, an untrustworthy robot in the lunar colony, a lunar asteroid strike that creates a need to rebuild equipment to preserve oxygen supply, and a space walker at the International Space Station that becomes untethered. In addition, communication latency challenges between the earth and the Mars Rover were simulated. The untethered space walker's experience was made immersive through the use of a "Meta Quest Pro" Virtual Reality headset. A Husky unmanned ground vehicle with an integrated motion capture system was used to portray the Mars Rover. The human in the lunar colony rebuilt "equipment" by replicating a specified Legos structure. A human played the role of an untrustworthy robot on the moon. Individuals assigned to control the orbiters operated them through a Remotely Piloted Aircraft System (RPAS) simulator. Communications among the entities took place through a custom push-to-talk radio system that recorded time-stamped who talked to whom events. The scripted interactions among entities in the scenario are represented in Figure 2.

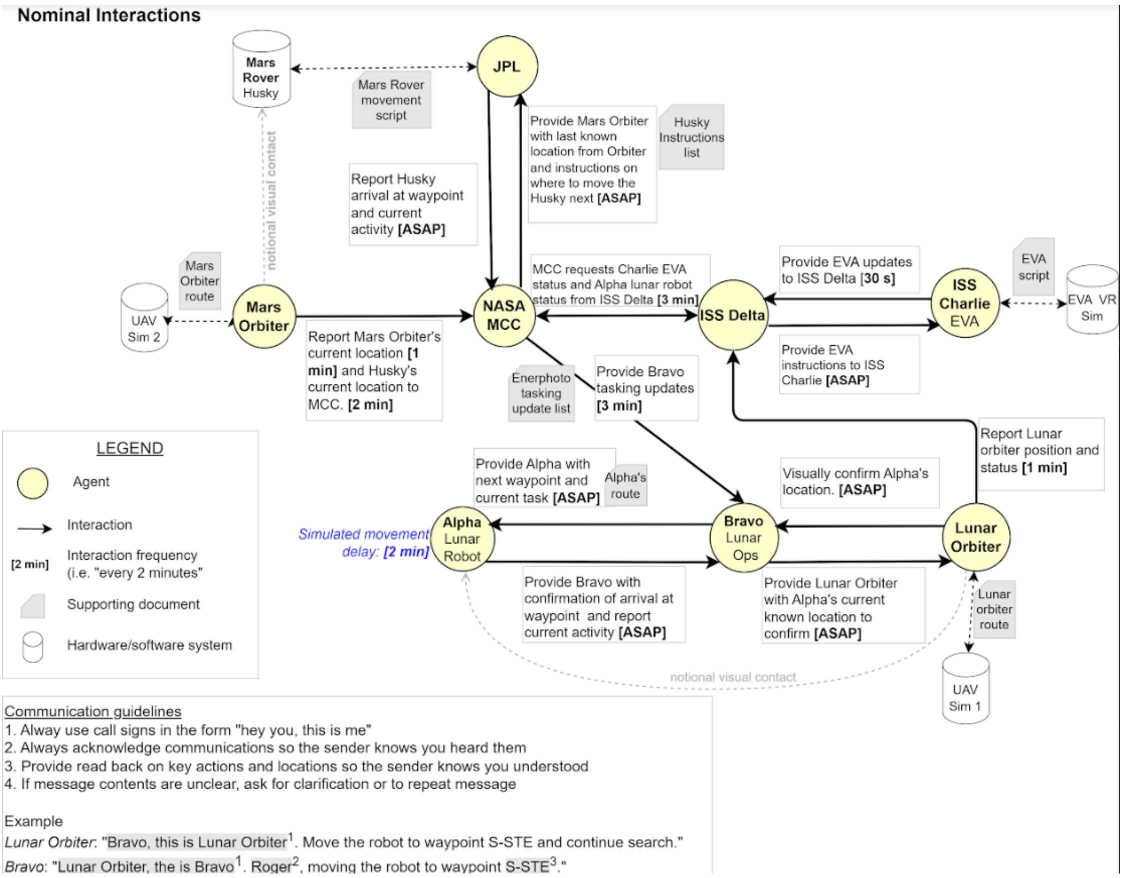

Figure 2: Communication flow among entities [2].

Sensors were included to generate data pertinent to the system state. These included communication flow, heart rate variability, and vehicle and robot activity. Communication flow was captured by the custom radio system (time-stamped who talked to whom). The spacewalker and human on the lunar surface were instrumented with iMotions sensors to collect heart rate variability. The Rover movements were captured by the motion capture system and the orbiters' positioning was captured by the RPAS simulator.

2.2 Data Collection

Eight individuals, each representing one of the agents depicted in Figure 2, enacted the scenario using a script. Individuals playing the roles of the space walker and human on the lunar colony were instrumented with iMotion sensors to detect heart rate variability. Depending on their role, individuals moved orbiters or the Rover, rebuilt equipment, or engaged in the VR spacewalk, all while communicating per the script over radios. Perturbations were inserted at designated times with the goal of testing the ability of the analytic techniques to identify the timing, location, and cascading effects of those perturbations across system layers and the system as a whole. Baseline runs were conducted per script. Other runs were conducted to compare resilient responses to non-resilient responses (written into the script) again to test the ability of the analytic techniques to discriminate responses.

2.3 Data Analysis

AIMS will ingest real-time data on system reorganization that quantifies components of resilience (enaction, adaptation, and recovery; [3]) in response to space challenge perturbations, which layers are reorganizing (communications, vehicles, physiological variables), and the amount of influence individual system components have on system reorganization. The reorganization and influence metrics that feed into AIMS are derived from a layered dynamics model [1] built for the space teaming scenario that captures the changing state of system organization across time.

A layered dynamics model is defined across the set of sensors available for monitoring a system. In the space teaming scenario, the model includes all communication channels, physiological monitoring, and vehicle/robot movements and actions [4]. Streaming data from each sensor are discretized into symbolic time series including on/off for communication channel and vehicle control states and number of embedding dimensions [5] for continuous variables (e.g., heart rate variability), and these symbolic time series are time aligned at 1Hz. Importantly, the symbols used to track each sensor's state are defined to be mutually exclusive and exhaustive over the symbol set, which means that 1) every possible combination across sensor states specifies a unique system state and 2) subsets of sensors (e.g., all communication channels; just the vehicle states) can be grouped together to measure their influence on overall system reorganization [6]. Symbolic time series from the layered dynamics model are then analyzed to quantify system reorganization in response to space challenge perturbations.

For a symbolic timeseries of length 1,800 (1Hz), continuous reorganization was computed by calculating information entropy using a moving window of size 60s. In the moving window approach, entropy is calculated for the distribution of the 60 data points currently in the window, and then updated each second by discarding the oldest value and ingesting a new value at a 1Hz update speed. The result is a reorganization timeseries wherein positive spikes indicate moments of increased system reorganization, during which the system is not any fixed pattern (e.g., repeating a routine), but is in a mix of states, akin to a phase transition in dynamical systems [7]. We observe resilience during a space challenge by measuring time to reach 1) a statistically extreme (> 99% confidence interval cutoff) entropy value ("initial" or enaction), 2) time to reach peak reorganization ("peak" or adaptation), and 3) time to recover a nominal level of reorganization ("end" or recovery) that comprise a resilience curve [3]. Figure 3 shows the response of the communication system reorganization time series for resilient vs. non-resilient runs of the space challenge scenario. This engineering test demonstrates tracking of system reorganization spikes in response to perturbations and that the resilient run resulted in shorter times to move through the resilience curve compared to a non-resilient run (Figure 3), which conforms with prior results in other teaming domains [3],[6],[7].

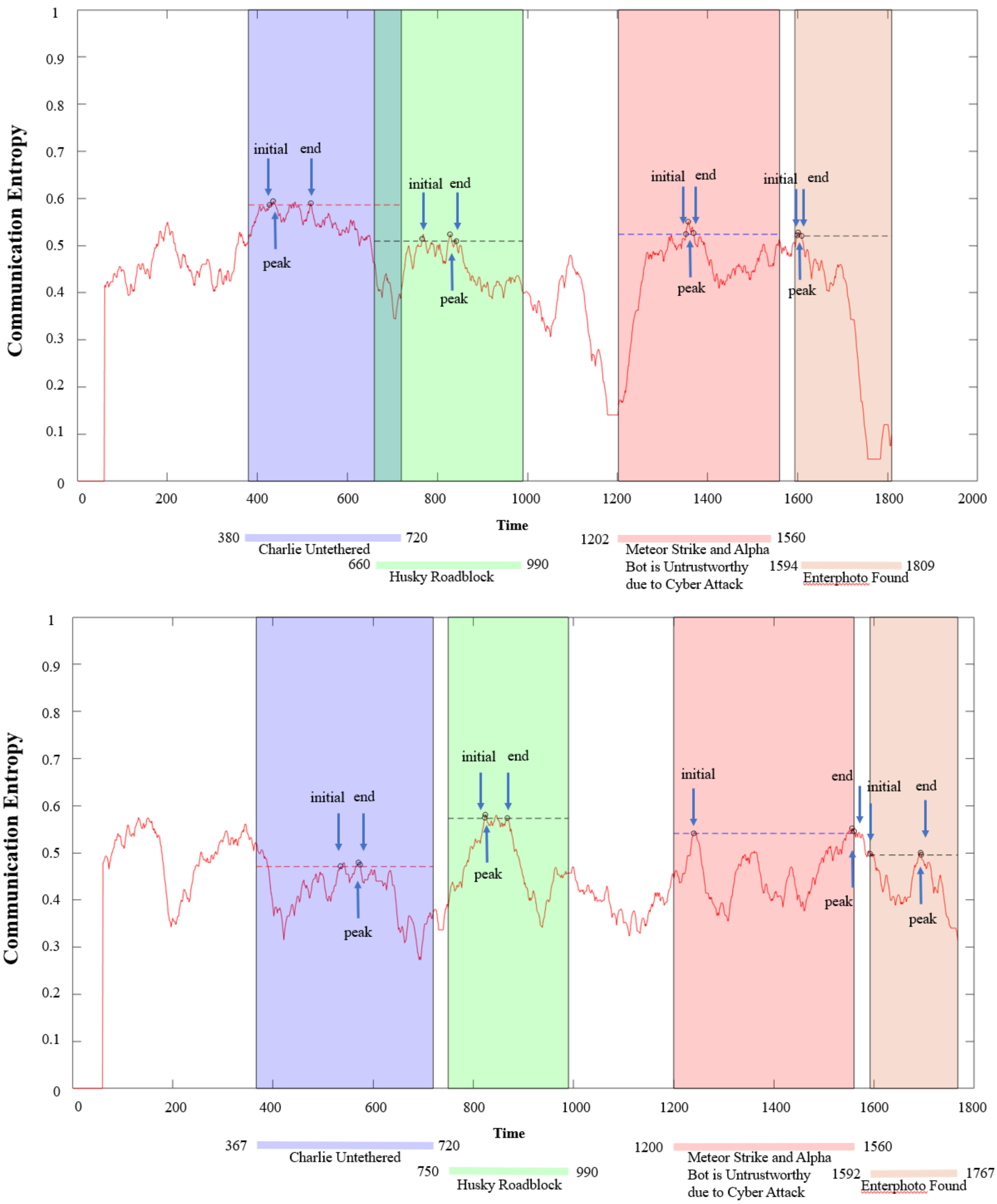

Figure 3: Top: A run of the space challenge scenario in which the researchers enacted timely responses that overcame the perturbations in addition to their routine, scripted interactions; Bottom: A run in which the researchers delayed and or temporarily ignored the perturbation while focusing on their routine, scripted interactions. Both figures show the system response in terms of communication reorganization, indicating visually detectable shifts in the stabilization of the communication system (reorganization peaks indicate stabilizing into a new system pattern). However, the resilience curve ("initial", "peak", "end") closes faster in the resilient (top) run. (Adapted from [4]).

Influence is defined as the capacity for the actions of a system element (e.g., an individual team member or piece of equipment/vehicle) or collection of system elements (e.g., a subset of team members or equipment) to change patterns in the systems [8]. For the space project, we quantified influence as the average mutual information (AMI; [9]) between subsets of states and overall system state from the layered dynamics model using the same moving window approach described earlier [4]. The result is a moving window influence time series that can be computed for any subset of system elements on system state from available sensor data. Table 1 shows the aggregate influence results for the communication layer for the resilient and non-resilient runs from Figure 3. Some of the most frequently used channels are the most influential up to Ranking 4; however, frequently used channels are not necessarily the most influential, as indicated by the inconsistencies between communication channel frequency and influence beyond Ranking 4. This inconsistency may be more evident when looking at just the perturbation sections of a space challenge run, in which infrequently used channels may be highly influential [10].

Table 1: Communication frequency and influence for resilient and non-resilient space challenge runs. (Adapted from [4]).

Resilient Run

Ranking	Most Frequent Channel Using Communication Frequency	Communication Frequency	Percent	Most Influential Channel Using AMI	AMI Percent
1	ISS Delta->NASA MCC	16	4.692	ISS Delta->NASA MCC	0.069
2	Lunar Bravo->Lunar Orbiter	14	4.106	Lunar Bravo->Lunar Orbiter	0.047
3	ISS Delta->ISS Charlie	10	2.933	ISS Delta->ISS Charlie	0.042
4	ISS Delta->Lunar Orbiter	10	2.933	Lunar Bravo->Lunar Alpha & Mars Orbiter->NASA MCC	0.040
5	NASA MCC->Mars Orbiter	10	2.933	ISS Delta->Lunar Orbiter	0.040
6	Lunar Alpha->Lunar Bravo & Mars Orbiter->NASA MCC	9	2.639	ISS Delta->NASA MCC & Lunar Orbiter->Lunar Bravo	0.031
7	Lunar Bravo->Lunar Alpha & Mars Orbiter->NASA MCC	9	2.639	ISS Charlie->ISS Delta & ISS Delta->ISS Charlie	0.031
8	Mars Orbiter->JPL & NASA MCC->Lunar Bravo	8	2.346	JPL->Mars Orbiter	0.030
9	ISS Charlie->ISS Delta & ISS Delta->ISS Charlie	7	2.053	ISS Delta->ISS Charlie & Lunar Bravo->Lunar Orbiter & Mars Orbiter->NASA MCC	0.026
10	ISS Delta->NASA MCC & Lunar Orbiter->Lunar Bravo	7	2.053	ISS Delta->NASA MCC & Lunar Alpha->Lunar Bravo	0.026

Non-Resilient Run

Ranking	Most Frequent Channel Using Communication Frequency	Communication Frequency	Percent	Most Influential Channel Using AMI	AMI Percent
1	Mars Orbiter->NASA MCC	34	9.605	Mars Orbiter->NASA MCC	0.081
2	ISS Delta->ISS Charlie	22	6.215	ISS Delta->ISS Charlie	0.073
3	Lunar Bravo->Lunar Alpha	13	3.672	Lunar Bravo->Lunar Alpha	0.038
4	Lunar Orbiter->Lunar Bravo	12	3.390	NASA MCC->ISS Delta	0.030
5	Lunar Alpha->Lunar Bravo	10	2.825	Lunar Orbiter->ISS Delta & Mars Orbiter->NASA MCC	0.030
6	Lunar Bravo->ISS Charlie & Mars Orbiter->NASA MCC	10	2.825	Lunar Alpha->Lunar Bravo	0.029
7	NASA MCC->ISS Delta	10	2.825	ISS Delta->NASA MCC	0.028
8	Lunar Bravo->Lunar Orbiter	9	2.542	ISS Delta->ISS Charlie & Lunar Bravo->Lunar Orbiter	0.028
9	Lunar Orbiter->ISS Delta & Mars Orbiter->NASA MCC	9	2.542	Lunar Orbiter->Lunar Bravo & NASA MCC->ISS Delta	0.025
10	NASA MCC->Mars Orbiter	9	2.542	ISS Charlie->ISS Delta	0.024

2.4 Machine Learning of Anomalous Patterns

We envision that AIMS will enable real-time autonomous monitoring of system and subsystem level states across spatiotemporal layered dynamics time series to detect anomalies and their sources. Anomalies can take the form of significant reorganization shifts within the system, which can be characterized in terms of the source(s) of reorganization and influence within the system. AIMS will utilize ML techniques such as anomaly detection, classification, and reinforcement learning to probabilistically classify anomalies compared to previously observed patterns of system reorganization, allowing AIMS to provide the user with a list of probable situations underlying the anomaly and suggest corrective action(s). We note, however, that as the pace of operations and complexity of the monitored system grows, uncertainty will grow beyond the bounds of traditional ML control policies, which often assume fixed sets. Therefore, AIMS incorporates human-autonomy teaming to allow for novel solutions to previously unimagined anomalies. To this purpose, AIMS can use an LLM interface to communicate the nature of the anomaly in terms of the underlying source(s) of sources of reorganization and distribution of influence across the monitored system elements. The human can use the LLM interface to communicate features of the situation based on their knowledge of situation-specific idiosyncrasies that may not match the situation identified by AIMS. In the human-autonomy teaming mode, AIMS will enable the user and machine to work together to find a path for stabilizing the anomaly (e.g., rerouting communications through an unused channel; increasing influence levels of currently unused but available system components such as vehicles). The capacity to introduce an unlimited number of system states by bringing in or culling out system components, as suggested by the human, is enabled by the inherent expansibility of the AIMS layered dynamics model, which is key to our vision of human-autonomy teaming in AIMS. Table 2 summarizes these envisioned capabilities of AIMS and associated key technologies and/or theories underlying them.

Table 2: List of Envisioned AIMS Capabilities and Associated Key Technologies and Theories.

AIMS Capability	Key Technology/Theory
1) Identify Anomalies Using Traditional ML Approaches	ML for Sparse Data Sets
2) Continuously Monitor Influence and Reorganization Across the System	Layered Dynamics
3) Communicate Nature of the Anomaly to the Human (Explainability, Trust)	LLM Interface
4) Match Anomaly with Known Anomalies to Provide a List of Probable Situations and Corrective Actions	ML, LLM Interface
5) Communicate with the User to Find Novel Paths for Stabilizing Unimagined Anomalies (Explainability, Trust)	Human-Autonomy Teaming

3.0 FUTURE DIRECTIONS

Work thus far has generated proof that the AIMs vision is tenable. However, there are additional issues to be addressed. 1) Future directions include inserting different perturbations and types of system responses into the scenario in order to test the ability of the analytics to capture a variety of system states. 2) In addition, a challenge for dynamic system measurement is converting the real-time dynamics metrics, such as reorganization and influence, into actionable information suited to the situation. Although the metrics generally predict performance and user experience, we have found that this step is unique to each use case. In the future, we plan to investigate technologies that support human-autonomy teaming (e.g., LLM) and theories of team cognition to help determine the nature (e.g., verbal communication) and format (e.g., what information to display) of human-autonomy teaming information in AIMS. 3) Finally, the methodology proposed here relies on scripted enactment of scenarios with purposefully placed perturbations. It does not produce the amount of data amenable to machine learning techniques as will be available from actual systems. But still in the case of actual systems, critical perturbations are rare. Therefore, we are exploring machine learning with sparse data and possibilities such as synthetic data generation.

4.0 CONCLUSION

The dynamic measurement of system reorganization and influence offers a framework for continuously monitoring anomalies and adaptations in large, distributed team tasks and human-machine systems. AIMS can process, analyze, and characterize large amounts of data across complex teaming paradigms such as those envisioned for JADO. Artificial intelligence is uniquely suited to this task of ingesting and quickly interpreting vast amounts of data from complex distributed systems. Humans are inherently adaptable, and by leveraging the capabilities of AI, they can team with AIMS to provide uniquely adaptable solutions to stabilize system anomalies.

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