Simulating an AI Approach to DSS Formation Maintenance

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Summary

The space environment is becoming heavily congested due to the increasing number of smaller 'cube' satellites, larger 'monolithic' satellites, and plans for launching distributed satellite systems. The current management of earth satellites relies heavily on human intervention and decision-making, resulting in a lack of a coordinated system that creates legal, administrative, and capability problems. To address this, the proposed solution is to automate the operations and allow inter satellite communication to remove the risk of human error and enable quicker responses. This work could constitute a steppingstone to full autonomy. Researchers have proposed the concept of trusted autonomous operations (TAO) for distributed satellite systems, which involves the use of advanced algorithms and AI to enable autonomous decision-making and coordination among satellites and ground stations. A protocol for sharing information between members of the system is required for total autonomy in distributed systems.

Statement of problem

With the proliferation of smaller ‘cube’ satellites, the increasing deployment of larger ‘monolithic’ satellites and plans to launch distributed satellite systems containing thousands of spacecrafts, the space environment is quickly becoming heavily congested. The management of earth satellites currently relies heavily on human intervention and decision making. Several teams and organisations operate under various standards and are beholden to the whims of their governments. This lack of a coordinated system has created a spaghetti of legal, administration and capability problems. Using these systems, the organisations are tasked with manually performing predictive calculations and issuing corrective or emergency avoidance manoeuvres – some of which are highly critical and dependant on the shared information.

The importance of implementing space operations correctly is paramount, as a single failure could result in damage to multi-billion-dollar infrastructure and start a cascade of runaway collisions. The current system is inherently risky for several reasons. First, there are limitations to what information is available from the ground, due to visibility and resolution issues. Secondly, where the problem is time sensitive and solutions rely on the sharing of accurate data, a large amount of overhead is inherently part of the system as teams need to contact each other while accounting for relevant geo-political issues. Thirdly, organisations are under no obligation to share data or wont due to security concerns. The culmination of these problems is a system where different organisations or teams are making decisions that affect each other but are not considering the same data. With the number of resident space objects rising rapidly and tracking capability's being dramatically different between organisations the rate of collisions is rising. To mitigate these issues organisation have implemented safeguards balanced with the need for timely decision making, but these policies are also inconsistent between participating parties.

With proposals to add thousands of extra satellites some of which act as distributed systems into orbit it is obvious that a rigorous, standardised and responsive system for managing these satellites is needed as the current system does not scale well.

The proposed solution is to automate the operations and allow the satellites to communicate with each other. This would largely remove the risk of human error and allow for quicker responses. These quick responses are also a requirement for the implementation of close range DSS formations as in some cases they need to maintain strict positions where centimetres and picometers can be significant.

Our focus is on the coordination between individual DSS formations as that is a significant step towards implementing a global system and can be readily implemented into existing space infrastructure while relieving the pressure on manual operators. It is notable that full autonomy is not necessarily the focus, but an AI based system that can take high-level commands and coordinate the whole formation at a low level autonomously. This work however could constitute a steppingstone to full autonomy.

Background and literature review

Distributed satellite systems (DSS) are becoming increasingly popular in space exploration due to their ability to provide global coverage with high agility and redundancy. However, DSS operations require the coordination of multiple satellites and ground stations, leading to increased complexity and potential vulnerabilities in the system. To address these challenges, researchers have proposed the concept of trusted autonomous operations (TAO) for DSS, which involves the use of advanced algorithms and artificial intelligence (AI) to enable autonomous decision-making and coordination among satellites and ground stations while ensuring the integrity and security of the system.

Historically autonomy has been required and implemented primarily for deep-space missions. This was required as these missions cannot rely on control from ground-based stations due to communication delays over these distances [1]. Partial autonomy on a low level however has been included in all space missions. Total autonomy however is still an area of active research and its applications in Low Earth Orbit (LEO) are still being evaluated. Whether or not a mission should incorporate autonomy and to what extent is dependent on the mission requirements and architecture. Cramer et al in [4] outline when it is prudent to apply autonomous systems. They clarify that: response time, performance improvement and risk awareness are significant considerations when choosing to implement autonomy. Araguz et al in [5] outline the key issues that autonomy can solve. They list mission robustness and tolerance against failures, improvement of science return, reduced visibility and communication delays. All of these are significant considerations in the deployment of DSS formations and as such the application of robust autonomy in DSS systems is of paramount importance if they are to succeed at scale.

Given the need for total autonomy in distributed systems a protocol for sharing information between members of the system is required. Lagona et al in [1] discuss the use of an ad-hoc communication network, a principle taken directly from existing computer networks. They point out that a lead spacecraft would coordinate the calculations passing the data periodically to the members of the network so that a new lead could be appointed if the former lead loses visibility, the communication link fails, or it can’t perform the function appropriately. The hardware solutions to transmit the data vary depending on the configuration and data requirements. Rupp in [6] and Bauer et al in [7] discuss the viable solutions to both communication and navigational challenges in this regard. They point out that low to medium performance formations (km - cm level control) can use Radio frequency (RF) based techniques while high performance formations (sub-cm to picometer level control) would require optical methods. They also outline the need for GPS-like systems to coordinate positioning, the Starling project employed the use of star tracking optical devices for a similar purpose. Other data sources that are periodically updated sourced from ground-based systems or other formations could also be incorporated into the network. This could allow for the tracking of RSOs or to supplement the network's existing information to fill in blanks or verify data.

Several models and approaches have been proposed for managing DSS systems. The most studied architecture is the Leader/Follower type. Under this architecture the problem is modelled as a relative motion control problem [3]. The AI approaches vary, several approaches have been tested and implemented in space missions. Others have been proven to have merit but are yet to be applied in the field of DSS [1]. AI models are metaheuristic; this is due to the lack of determinism in their approaches. There is no guarantee that subsequent evaluations from the model will yield the same result given the same starting conditions. However, AI methods can be made to run a lot faster than strictly numerical approaches [1]. Several nature inspired models were proposed by Oche et al in [2] they list several insect swarm-based approaches to optimisations. Lagona et al in [1] discuss Particle Swarm Optimisation (PSO), Genetic algorithms (GA) and neural networks as approaches to issues of trajectory calculation and formation optimisation. The general approach is to allow for high level commands to be sent to the formation as a whole and to then have the formation apply AI models to determine the low-level procedures each satellite in the formation would have to perform.

In conclusion, the use of autonomy in space missions is not a new concept, and partial autonomy has been included in all space missions. However, total autonomy is still an area of active research, and its application in Low Earth Orbit is still being evaluated. The decision to incorporate autonomy in a mission depends on various factors such as response time, performance improvement, and risk awareness. Autonomy can solve many issues in space missions such as mission robustness, tolerance against failures, improvement of science return, reduced visibility, and communication delays. To enable total autonomy in DSS, a protocol for sharing information between members of the system is required, which can be achieved through an ad-hoc communication network. Several AI approaches have been tested and implemented in space missions, and nature-inspired models such as insect swarm-based approaches, Particle Swarm Optimization, Genetic algorithms, and neural networks have been proposed for managing Distributed Space Systems. Overall, the application of robust autonomy in Distributed Space Systems is crucial for their success at scale.

Research questions

Question 1: How effective are AI methods when compared with to conventional techniques?

Question 2: What components of satellite missions are improved by AI techniques?

Question 3: How robust are AI techniques factoring in the lack of determinism?

Question 4: How do AI techniques interface with physics-based trajectory methods?

Materials

Material	Justification
STK	Basis simulation environment that will be used to model the satellite configurations and test the models.
PC	Personal Laptops or Computers, needed to store data, run simulations, evaluate models, write up documents.
University Server Time for training	Training models and running simulations could take a long time on a conventional PC or Laptop. So, access to more computing power would be ideal.

Methodology

Our procedure will be entirely computational, first we will construct an existing satellite formation - a constellation. This will be modelled in STK. The first formation will be of the US GPS network which consists of 31 satellites. This will allow for an analytically viable base for the testing of models. The data for these satellites will be pulled from Celestrak using the Simplified General Perturbations 4 (SGP4) format. Other relevant astronomical bodies such as the earth and moon will be pulled from JPL Horizons.

Once this simplified model is implemented, we will assess our propagation methods (built into STK) and verify them with historical data for a given epoch. Concurrent with this process we will implement AI models, specifically metaheuristic methods. These methods include Deep Reinforcement Learning (DRL), Particle Swarm Optimisation, Genetic Algorithms (Neural Network Basis) and a set of insect swarm algorithms. As DRL is a data driven approach it will require training before being implemented and assessed. This data will consist of historical manoeuvres which will be extracted from Celestrak by running propagations on the orbits and comparing them to the historical outcome. If the two vary then a manoeuvre occurred, we can then extract this data, determine the manoeuvre performed and use it for training. This extraction approach can be automated with Python. As the DRL is a reinforcement learning model a large part of the approach will be training it in the STK simulated environment. The other methods will be trained and improved in situ during simulation.

The AI models are primarily used for decision making. This means that physics-based trajectory models will need to be implemented to process the AI model output. This will be a large part of the propagation testing and as such these models will be assessed during our initial assessment of the test GPS formation. Most simulation software including STK models the earth as a set of harmonics to account for perturbations. Frequently used is the J2 perturbation model with includes a set of two harmonics but this can be made more precise if we also assess to a J6 perturbation model, but this might prove irrelevant. We will determine this in the original propagation testing phase.

All the models will have to be verified in comparison to some expected output. We propose selecting a set of past manoeuvres again from Celestrak and ranking them in terms of complexity. The trained models will then be tasked with responding to the initial situation that resulted in these manoeuvres. The outcomes will be compared to each other and how it was approached at the time. Metrics considered will be fuel usage, how reliably the formation maintains required parameters (distance, viewing area, viewing angle, altitude, attitude, etc) and the chance of collision during the manoeuvre(s). It is notable that we intend to find test situations that depict the scenario of launching a constellation and how the satellites progress to their final stable orbits.

The actual satellites themselves will be modelled as a type of network node for communication purposes and will incorporate a leader-follower decision making protocol. This will require the determination of a communication strategy. We will assume that any satellite with visibility of another satellite can communicate. From a modelling perspective this will allow us to build a graph between the nodes and use this to evaluate whether a given member is connected to any other member. Regarding external data, it will be assumed that the satellites have perfect positioning data and periodic access to RSO trajectory data as if from ground stations.

We can take the output data from the simulations and process it in excel or with Python. This will allow for the creation of graphs depicting the model, situation and relevant comparison metrics (as outlined above). Using this data, we can compare the overall performance of each model as well as the situational performance. This will allow us to outline the best model overall and for a given situation.

Project Planning

Planning of time and resources is straight forward for this project. As most tasks rely on personal computer access and the methodology follows a software engineering approach, many tasks are concurrent and iterative. As such for most of the project learning the simulation software, training the models, implementation and running simulations will be continuously done with skills being refined. The first task is to dive deeper into the relevant literature and theory underpinning DSS, orbital mechanics and AI followed by learning the software. Most tasks are not interdepended but testing of propagation methods must be done before implementation of models and gathering comparison scenarios before running simulations. Processing of data and documentation of findings and results will be continuous for most of the project, culminating in a final report and presentation in November. This project is also marked by assessment tasks and holidays to consider. A progress report is due on the 28th of May and a presentation on the 2nd of June before mid-year break over June and July. Work is planned to be completed over the holidays but at a slower rate.

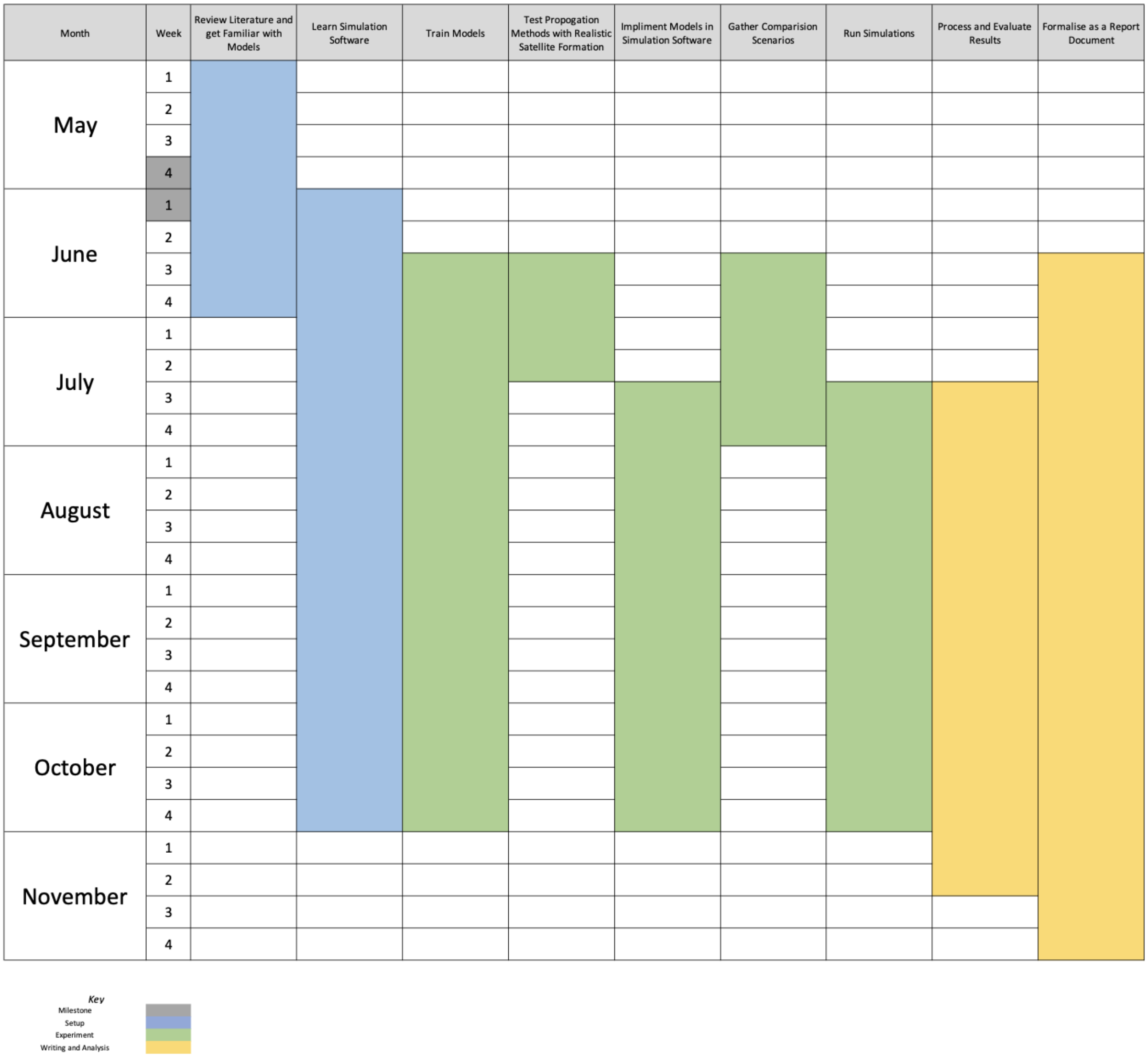

Figure 1 - Gantt Chart outlining the project timeline and major milestones.

Risk Assessment and Ethical Considerations

No ethical considerations are required for this project as no human data or tissue will be used. However, these techniques need to be considered for a human interface as future ground crews will have to make decisions based on the information calculated.

Due to the software and mathematical nature of the proposed project, it includes low grade hazards and some but notable risks for completion. Majority of the risk hangs on the ability of the group to coordinate and implement AI techniques in a MATLAB or STK environment. Included with this, STK may not be available to students and so a more mathematical environment of MATLAB and Simulink will be relied on. Furthermore the AI programs trained using MATLAB or Python may not interact with the STK environment properly further limiting the simulation and requiring a work around to be used. File sharing is critical to both members working on this project and so an adequate and functional file organisational system must be decided upon. Furthermore, if no examples of previous programs exist then AI algorithms will have to be created from scratch with the understanding available making development longer. Developing feasible and working techniques could be complicated and beyond our understanding. Progress maybe limited if a solution or knowledgeable person cannot be consulted. Lastly data to train models and test algorithms on will need to be sourced from online or through our supervisors. Real world hieratical data might be classified or proprietary and so hidden from our use. Failure to find real world hieratical data will limit the applicability of the programs created as it will reply on synthetic and assumed data.

Below is a SWOT and Risk Scenario table to quickly summarise the above information.

Table 1: SWOT Analysis

Strengths	**Weaknesses**
• Quicker satellite response. • Reduced likely hood of space collisions • Reduced groundcrew maintenance required.	• Limited time to develop and understand. • No previous experience with AI or deep software programs.
Opportunities	**Threats**
• Future Application. • Cutting edge of space systems development. • Reduced groundcrew overhead.	• Stuck not understanding principles. • No access to real, historical data. • No STK access. • STK doesn’t interact with AI models generated in Python or MATLAB. • AI Training time is extensive.

Table 2: Scenarios and Solutions

Risk Scenario	**Proposed Solution**
STK not available for students	Use MATLAB and Simulink, or Python instead
File sharing is available to allow simultaneous work	Upload latest version and blend features while completing integration acceptance testing
AI examples are unable to be sourced or implemented	AI created from scratch
Historical data for training cant be accessed	Synthetic data created based of papers and with some assumptions
Limited understanding of theory needed to implement AI model	Simplify model to allow for ideal case removing complicated areas
STK doesn’t work with Python or MATLAB AI models	Create models in language that works with STK
AI Training time is extensive to tarin or refine	Use University computers with more processing power
Other university commitments reduce useable time due to assignments and deadlines	Simplify goals to allow for other commitments

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Contribution

Section	**Person(s) responsible and percentage**
Summary	All ground members contributed equally
Background	All ground members contributed equally
Methodology	All ground members contributed equally
Research Questions	All ground members contributed equally
Planning	All ground members contributed equally
Risk and Ethics	All ground members contributed equally