

Advancing Satellite Network Consensus through Optimal Orbital Configurations**Robert Cowlshaw^{a*}, Annalisa Riccardi^b, Ashwin Arulselvan^c**^a *Mechanical and Aerospace Engineering Department, University of Strathclyde, UK, robert.cowlshaw.2017@uni.strath.ac.uk*^b *Mechanical and Aerospace Engineering Department, University of Strathclyde, UK, annalisa.riccardi@strath.ac.uk*^c *Management Science Department, University of Strathclyde, UK, ashwin.arulselvan@strath.ac.uk** *Corresponding author***Abstract**

As the number of Earth-orbiting satellites continues to grow, ensuring consensus among them becomes increasingly crucial for autonomous, unbiased decision-making. With greater autonomy moving onboard satellites, the ability for them to make collective decisions on critical tasks such as space environment monitoring or disaster detection becomes essential. Consensus algorithms are key in enabling this cooperation, but fault-tolerant algorithms, like Practical Byzantine Fault Tolerance (PBFT), require significant communication between network members, leading to frequent satellite interactions. While some satellite constellations have improved communication within their own networks, inter-constellation and individual satellite communication remain limited. To support universal inter-satellite communication, close proximity between satellites is vital. This makes optimal orbital strategies essential for maximizing interactions and facilitating seamless communication across constellations. This paper explores improving consensus protocol efficiency by identifying optimal orbit strategies for PBFT. By simulating both theoretical and existing satellites, we compute the time required to reach consensus for various network sizes. This analysis helps pinpoint optimal orbital configurations that minimize consensus time. Additionally, simulated satellites are arranged into constellations - similar to space relays - further reducing consensus time. However, each simulated satellite acts as a single node in the network, avoiding centralization and maintaining the decentralized nature of the system. Real and simulated satellite orbits are propagated, allowing us to analyze potential interactions, distances, and timings between satellites. These interactions are then evaluated through multi-objective optimization, minimizing consensus time while maximizing the diversity of satellites involved. Pareto fronts from this optimization provide insights into the most efficient simulated orbits for consensus. A genetic algorithm is also employed to optimize the Keplerian elements of these orbits for further refinement. The study finds that simulated satellite orbits resembling space relays significantly reduce consensus time, although they require a large number of satellites to establish such a network. Alternatively, to optimize satellite interactions in terms of both quantity and diversity, orbits with a mean motion deviating from the norm (approximately 15 revolutions per day) are needed. Additionally, orbital inclination and eccentricity are shown to play a major role in enhancing satellite interactions. This research sets the theoretical basis for developing future decentralized orbital networks, designed for trustless decision-making in orbit, setting the stage for future autonomous on-board satellite operations.

1. Introduction

With an increasing number of Earth-orbiting satellites, and more crucial decision moved on-board the satellites, reaching consensus on orbit is becoming a progressively critical goal. These decisions range from space environment monitoring, such as collision avoidance, to automatic disaster detection from Earth Observation (EO) data. Group decisions across constellations, satellite operators, and various types of satellites must remain impartial and neutral to encourage broader participation, which in turn enhances decision accuracy by incorporating greater diversity. Consensus mechanisms' are a method to complete adversary proof collective decision making. They are typically used in trustless distributed networks where there

is no way of determining the trust ability of another individual. This allows satellites from various sources to collaboratively reach consensus without needing to rely on pre-established trust or centralized authority. This ensures decisions are made impartially, despite the diverse ownership and interests involved, fostering broader cooperation in space.

Different types of consensus mechanism include Byzantine Fault Tolerant (BFT) algorithms [1], Paxos/Raft [2]/[3] and Directed Acyclic Graphs (DAG) [4]. The most commonly used mechanism in trustless distributed networks is BFT algorithms due to the lack of requirement of a trusted party. Practical Byzantine Fault Tolerance (PBFT) [1] is an implementation of BFT that

is simple and well tested and is the consensus mechanism that is adopted in this work.

Since most satellites, excluding constellations, are not currently designed for decentralized communication, their orbits are not optimized for inter-satellite interactions, making it challenging to complete a consensus round. However, by introducing new satellites with trajectories designed specifically to improve inter-satellite communications, the number of diverse satellites capable of participating in a consensus round can be significantly increased, improving overall network collaboration.

Consensus mechanisms are increasingly essential for improving coordination, scheduling, and decision-making in multi-satellite systems, especially as space missions become more autonomous and decentralized. Several studies explore how these mechanisms can address challenges like task allocation, orbital control, and real-time adaptability in satellite constellations. One prominent application is in data fusion for weather forecasting. [5] illustrates how consensus mechanisms can combine data from various sensors on different satellites to produce more accurate estimates of cyclone intensity. This consensus method reduces uncertainty and improves decision-making, making it valuable for real-time weather forecasting and post-event assessments, especially when other data sources like reconnaissance aircraft are unavailable.

Beyond data fusion, consensus mechanisms are also critical for coordinating tasks and maintaining stable satellite formations. [6] propose a system where satellites can share information and coordinate task execution using improved communication methods. This reduces the communication load between satellites and ensures the system remains robust even when some satellites fail. Similarly, [7] investigates a decentralized task allocation approach, allowing satellites in low-Earth orbit to autonomously divide tasks among themselves, further supporting the trend toward reducing reliance on ground control. This kind of decentralization is becoming more necessary as satellite constellations grow larger and more complex.

In terms of orbital management, [8] uses consensus theory to ensure stable orbital adjustments. The satellites coordinate their positions to maintain a specific formation, which is vital for missions requiring long-term stability. In Earth observation, where rapid response to environmental events is key, [9] introduces a system where satellites independently evaluate their ability to complete a task based on real-time contextual data. This enables quicker reaction times to short-lived phenomena, such as natural disasters, without waiting for ground control. Additionally, [10] tackles the problem of task allocation when multiple authorities control satellites. Using a consensus-based algorithm, this approach ensures that the most capable satellite,

based on its current situation, takes on each task, thereby maximizing the overall system's performance.

Although these studies look into consensus mechanisms for current and future missions, they do not however design a mission or satellite position around the application of a consensus mechanism. This is where this paper sets itself apart from the previously discussed work.

To determine which trajectory/orbit is more strategic for improving inter-satellites communications, a way of propagating the orbits of existing satellites and measuring how many of these satellites can complete PBFT consensus in a given time period is needed. A Genetic Algorithm (GA) that defines 6 Keplerian orbital parameters is then used to generate theoretical satellite orbits which are then propagated together with the current fleet of satellites to increase the number of satellites participants that can complete PBFT consensus in the given time period.

To make the problem computationally tractable and easier to visualise a subset of satellites is chosen to refine the number of possible satellite participants in PBFT. A group of satellites that could require making a decision in a timely manner on-orbit, is the satellites used in the International Charter: Space and Major Disasters (ICSMD) [11]. These satellites provide EO data to early responders of natural disasters and has satellites from 17 different nations participating. This case study provides a realistic scenario for group decisions in an international scenario where geopolitics could potentially affect the neutrality of its decisions outcomes.

This paper addresses key aspects of satellite consensus by examining several important factors. First, it determines the number of satellites capable of completing consensus without the introduction of a new theoretical satellite. This is done through modelling consensus within a subset of satellites, measuring the number of satellites that can participate in a consensus round. After understanding how many satellites can participate in consensus rounds from this ICSMD subset, a new theoretical satellite is added. The orbital parameters of this satellite are the inputs into the optimisation algorithm to determine the optimal trajectory that maximises the number of participants in consensus rounds.

2. Method

2.1 PBFT Protocol

PBFT [1] is fault tolerant up to $\frac{n-1}{3}$ nodes. Where n is the total number of nodes participating in the consensus round. As the total number of nodes participating in consensus increases, the number of communications required increases at a rate of $2n^2 - n - 1$ [1]. Therefore, in a high latency scenario such as inter-satellite communication, the time taken to achieve consensus approaches millennia if

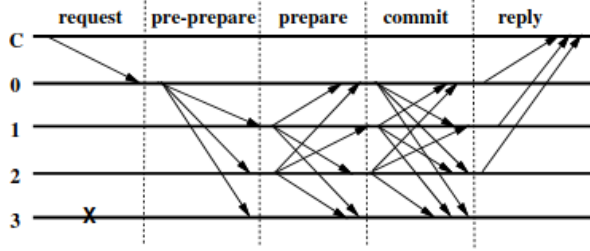


Fig. 1. Practical Byzantine Fault Tolerance (PBFT) works through communicating rounds of messages between participants as seen below [1].

all satellites are participating. Therefore for a given round of consensus, a subset of satellites from the ICSMD charter is chosen to take part in the process. In this example case study, a value of $n = 4$ is used to keep the problem computationally tractable, however analysis of $n = 5$ and $n = 6$ is also undertaken. $n \geq 4$ to maintain that at least 1 node can be faulty. This protocol can be seen in Figure 1.

2.2 Consensus Participation

In this section we define a fitness function. This is a function that, given a certain start date and the complete pool of ICSMD satellites, computes the size of the subnetwork that can be used for running the consensus algorithm. The goal of the optimisation will be to maximise the size of this subnetwork.

For each satellite evaluated as potential participant of the ICSMD subset, the following quantities are calculated:

- $comm_{i,j,k}$ is the satellite id in a subset of p consensus participating satellites in the 3 dimensional matrix **comm**. Equation 1 shows an example where the primary has $id = 0$ and $p = 4$. Where i is the consensus stage given by the columns in equation 1, j is the communication number in that stage given by the rows in equation 1 and k defines whether the satellite is the sender ($k = 0$) or the receiver ($k = 1$). This is built from [1] where the primary satellite is $id = 0$. Swapping a given id with $id = 0$ will change the primary satellite used in consensus. In this case study all combinations of primary are calculated.
- Possible combinations (**poss**) is a 2 dimensional matrix of dimension $\binom{N}{p}, 4$ where N is the number of ICSMD satellites in the subset and p is the number participants required in the given consensus round. It represents the satellites in ICSMD participating in each possible arrangement participants in a consensus round.

- Interaction grid (**grid**) is a 3 dimensional matrix of dimension (N, N, t_{max}) where N is again the number of satellites in the ICSMD subset, and t_{max} is the maximum allowable time to reach consensus. It is the time step t_{step} in which satellites can interact with other satellites because they are within a minimum distance, in this case 500km. The method of generating this matrix is defined in Algorithm 1. Satellite positions are calculated using Two Line Element data up to date as of 11/09/2024 produced by [12] with PyEphem [13]. Perturbations such as J2 are not considered due to the small time period this problem is computed across.

$$comm_{:,0} = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 3 \\ 2 & 1 & & \\ 2 & 1 & & \\ 2 & 1 & & \\ 3 & 2 & & \\ 3 & 2 & & \\ 3 & 2 & & \\ 3 & & & \\ 3 & & & \\ 3 & & & \end{bmatrix} \quad comm_{:,1} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 2 & 2 & 2 & 0 \\ 3 & 3 & 3 & 0 \\ 0 & 0 & & \\ 1 & 2 & & \\ 3 & 3 & & \\ 0 & 0 & & \\ 1 & 1 & & \\ 2 & 3 & & \\ 0 & & & \\ 1 & & & \\ 2 & & & \end{bmatrix} \quad [1]$$

After these values are computed the satellites that are able to participate in a successful consensus round can be determined from Algorithm 2. This returns a list of subnetworks of the ICSMD charter that can be used to run consensus protocols (using 4 satellites in the subnetwork) to establish the verification of a natural disaster on-board the satellites.

2.3 Optimisation of Orbital Elements

In Section 2.2 the fitness function has been defined given the subnetwork of ICSMD satellites that can participate in a consensus round and a start date. If we consider now adding a theoretical satellite to this subnetwork, we need to define a function that reevaluates the original fitness function and estimates the time needed to reach consensus taking into account an additional participant.

The six orbital parameters, that is also the vector of optimisation variables for the problem are

$$x = [\omega, e, i, \Omega, M, \nu]$$

namely: argument of periapsis, eccentricity, inclination, right ascension of the ascending node, mean anomaly and mean motion.

The exploration space for all orbital parameters is given as all possible values except for eccentricity being

Algorithm 1 Generating Interaction Grid (*grid*)

```

satellites =satellites in subset
N =length of satellites
grid = matrix of entirely -1 of shape (N, N, tmax)
for i in {0, N} do
  for j in {0, N} do
    temp = []
    for t in {0, tmax} increment by tstep do
      if distance between satellitesi and satellitesj <= 500km at time t then
        Append t to temp
      end if
    end for
    templength =length of temp
    gridi,j,0:templength = temp
    gridj,i,0:templength = temp
  end for
end for

```

$e \in [0, 0.14]$ and mean motion being $\nu \in [11.1, 18]$. These values are calculated from 3 standard deviations (99.7%) from the mean of orbital parameters of all satellites currently on orbit (eccentricity is capped at zero as minimum). This is done to limit the exploration space to realistic orbits.

As seen in Figure 2, the search space is complex, therefore a global optimisation strategy needs to be used to determine the optimal values of the 6 orbital parameters. The genetic algorithm implementation from the library PyMoo [14] is used in this study. The mutation probability and crossover probability are set to 0.9 and 0.5 respectively. A basic hyper-parameter study was implemented to acquire these values however further hyper-parameter optimisation is outwith this work. The population is set to be 200 and the algorithm runs over 50 generations. These values for population and number of generations were selected to provide adequate learning rate while continuing learning until learning started to plateau while maintaining computational tractability. Increasing these values could improve final satellite configurations however it is predicted that little improvement would be made due to the plateau in learning rate already visible from the results. This optimisation process is run 10 times with different starting days (10 consecutive days from 11/09/2024) and repeated with different values for t_{max} , these being 0.1 days, 0.5 days and 1 day to complete consensus. 10 starting days is selected as this covers approximately 10 orbits of the slowest and 150 orbits of the fastest orbiting satellites in the ICSMD subset. This value is considered to generalise to other time frames and therefore make the choice of starting date independent of the investigation. Table 1 shows the baseline number of satellites that could complete a round

of consensus with 3 other satellites out of the 79 satellites within the ICSMD charter without adding the new theoretical satellite.

The genetic algorithm optimisation solves two different scenarios. All dates and times are in Coordinated Universal Time (UTC).

- **Scenario 1** - The first scenario is maximising the size of the subnetwork of satellites among the set $X_{ICSMD} \cup x$, where X_{ICSMD} represents the orbital elements of the 79 satellites in the ICSMD charter. Considering a fix starting date t_0 and maximum time to reach consensus t_{max} the problem we want to solve is defined as

$$\max_x J(x \cup X_{ICSMD}, t_0, t_{max})$$

where J is the function defined in Section 2.2. This problem is solved for 10 different values of t_0 : midnight UTC before 11/09/2024 and each day following; and 3 different values of $t_{max} = 0.1, 0.5, 1$. Therefore 30 different optimal values for x are found, representing 30 theoretical optimal orbits to place a newly launched satellite to maximises the ICSMD subnetwork size.

- **Scenario 2** - In the second scenario formulation, the maximum time to reach consensus is fixed to $t_{max} = 0.1$ and the following problem is solved

$$\max_x \frac{\sum_{i=0}^9 J(x \cup X_{ICSMD}, t_0 + i \cdot \text{day}, 0.1)}{10}$$

where $t_0 + i \cdot \text{day}$ with $i = 0, \dots, 9$ represent the series of 10 starting dates, starting from midnight UTC

Algorithm 2 Measuring Number of Satellites with Successful Consensus Participation

```

poss = possible combinations
comm = communication rounds
grid = interaction grid
success = []
for p in poss do
  timer = [0, 0, 0, 0]
  for comm_round in comm do
    timer_next = timer
    for c in comm_round do
      found = False
      i = c_sender
      j = c_receiver
      for t in {0, t_max} do
        if gridpi,pj,t ≥ timeri then
          found = True
          if gridpi,pj,t > timer_nextj then
            timer_nextj = gridpi,pj,t
          end if
          Break
        else
          if gridpi,pj,t == -1 then
            Break
          end if
        end if
      end for
      if not found then
        Append False to Success
        Break
      end if
      timer = timer_next
    end for
  if not found then
    Append False to success
    Break
  end if
end for
Append True to success
end for

```

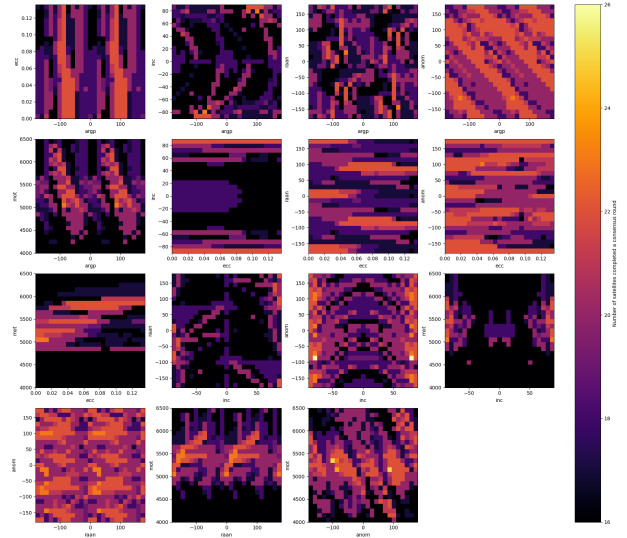


Fig. 2. A flat grid search analysis of the search space. 6 orbital parameters are compared against each other with linearly spaced inputs. Consensus is from 11/09/2024 for 0.1 days into the future. Computed with a resolution of 30 linear steps in each designated orbital element between 3 standard deviations from the mean. In all other orbital element dimensions 5 linear steps between 3 standard deviations from the mean are used and the maximum value is plotted. Eccentricity is plotted in the range $(0, \mu + 3\sigma)$ as negative eccentricity is meaningless. The mean and standard deviations are taken from all satellites currently in orbit [12]

before 11/09/2024. Only one optimisation problem is solved and the optimal values of orbital parameters for a newly launched satellites that maximised the average size of subnetwork across all the different starting dates is found.

The second scenario is introduced to determine if the GA is overfit to a specific starting day t_0 .

3. Results

Figure 3 shows 50 generations with a population of 200 satellites. This is evaluated against the fitness function which computes every possible consensus round out of the available satellites and checks if they can be completed within 1 day. Figure 4 shows how different numbers of required participants in the consensus round effects the maximum number of possible participants completing within 0.1 days.

Figures 5 6 and 7 illustrate how the population converges toward specific regions of the search space as the genetic algorithm optimizes. The darker areas indicate

Starting Day	0.1 Days	0.5 Days	1 Day
1	16	38	54
2	15	44	56
3	9	44	64
4	14	42	64
5	19	33	51
6	18	46	60
7	15	39	62
8	4	32	56
9	12	46	58
10	13	45	56

Table 1. Baseline number of satellites that could complete a round of consensus with 3 other satellites out of the 79 satellites within the ICSMD charter without the new theoretical satellite, where starting days are sequential with day 1 being 11/09/2024.

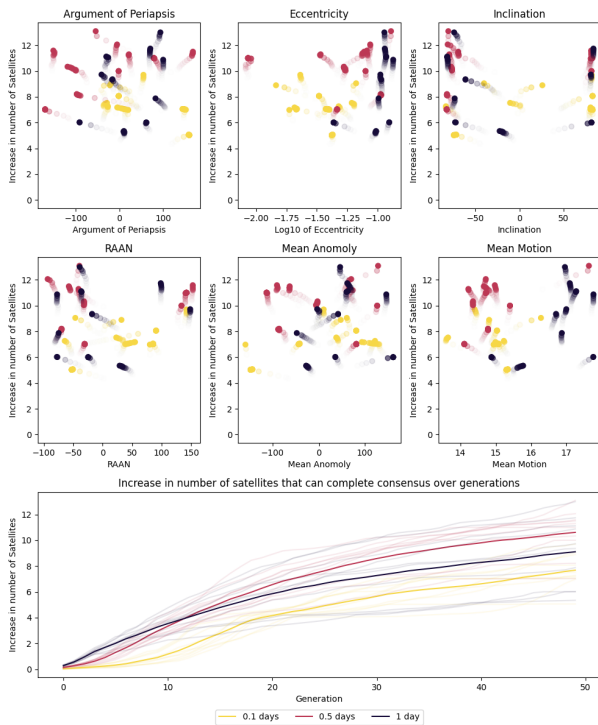


Fig. 3. 50 generations of 200 new theoretical satellites evaluated against the fitness function. Yellow has value t_{max} of 0.1 days, red of 0.5 days and black of 1 day.

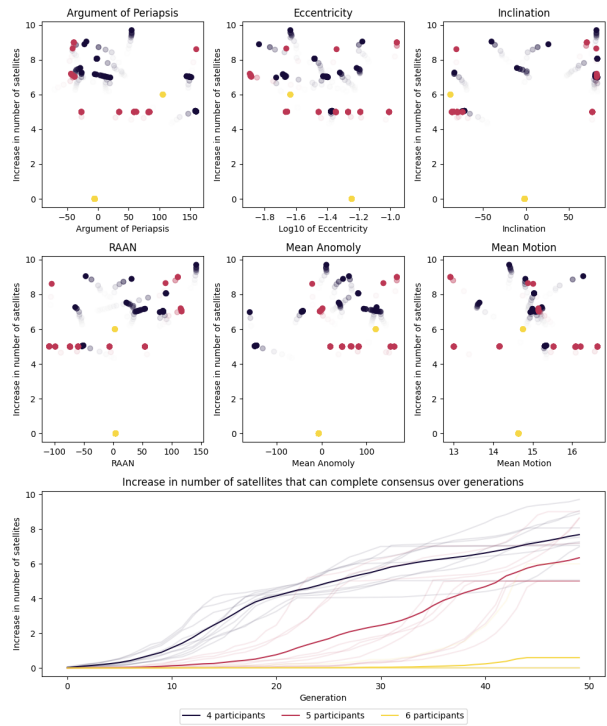


Fig. 4. GA effectiveness with different number of required participants. Each orbital element shown in the top 6 graphs, and generational improvement of the GA shown in the bottom graph. Where $t_{max} = 0.1$ days.

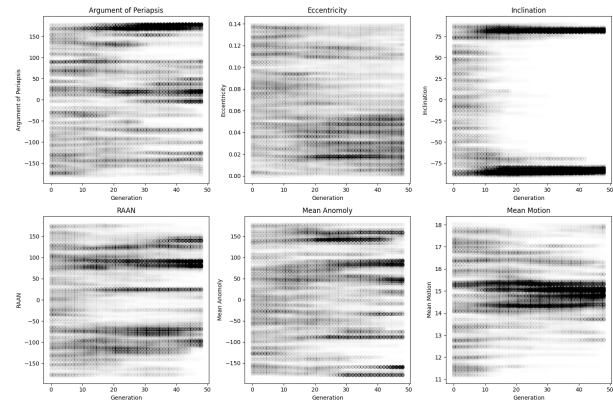


Fig. 5. The orbital parameters of the population in the GA for all generations where $t_{max} = 0.1$ days. This GA is trained on each individual starting date.

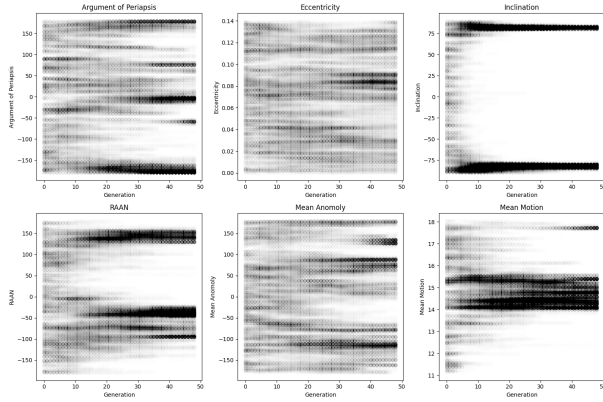


Fig. 6. The orbital parameters of the population in the GA for all generations where $t_{max} = 0.5$ days. This GA is trained on each individual starting date.

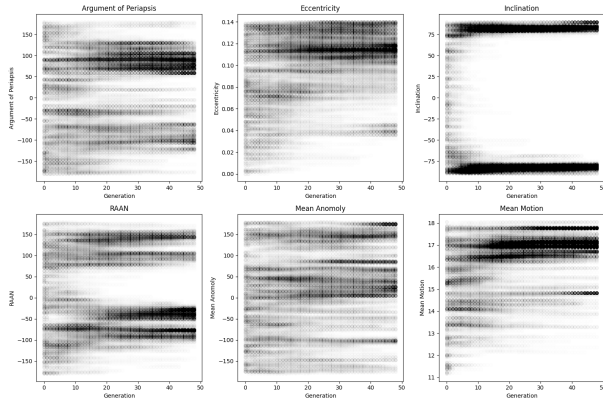


Fig. 7. The orbital parameters of the population in the GA for all generations where $t_{max} = 1$ day. This GA is trained on each individual starting date.

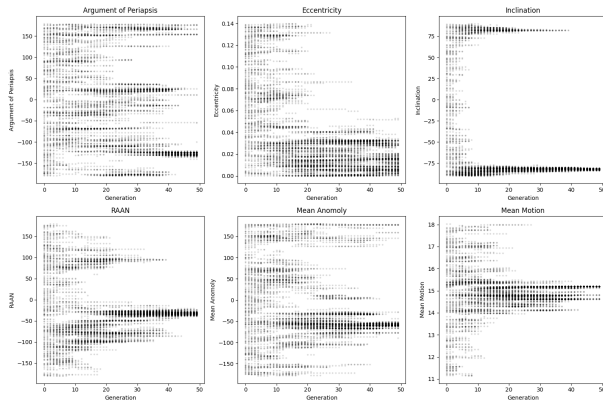


Fig. 8. The orbital parameters of the population in the GA for all generations where $t_{max} = 0.1$ days. This GA is trained on all starting dates.

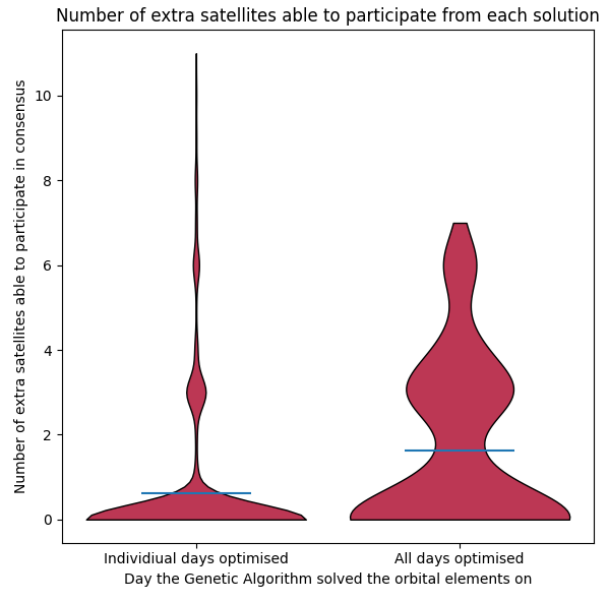


Fig. 9. The distribution of the number of extra satellites from the baseline able to participate at each timestep. All GA generated satellites in scenario 1 are plotted on the left being tested on all starting days. The GA generated satellite in scenario 2 is plotted on the right and tested on all timesteps. The timestep in this case is 12 minutes and $t_{max} = 0.1$ days.

higher concentrations of individuals within the population, while the lighter areas represent regions of the search space with fewer individuals. Figure 8 follows a similar pattern to figures 5 6 and 7, the difference is that the genetic algorithm optimises the orbital parameters across all starting days. This links to figure 9 which shows the distribution of number of satellites added to the baseline due to different GA scenarios. All GA generated satellites with $t_{max} = 0.1$ days are tested on all starting days and the number of timesteps where there are added consensus completed satellites is plotted. On the left it shows how this single day optimisation overfits to a single day and does not perform well on all other days. Whereas on the right, it can be seen that optimising the GA over all days in the second scenario provides a more consistent number of satellites added but without the same maximum improvement on any specific day. Figure 10 shows the final results from this GA optimisation across all starting days in scenario 2, displaying the orbital parameters of the new theoretical satellite against the orbital parameters of all IC-SMD subset satellites.

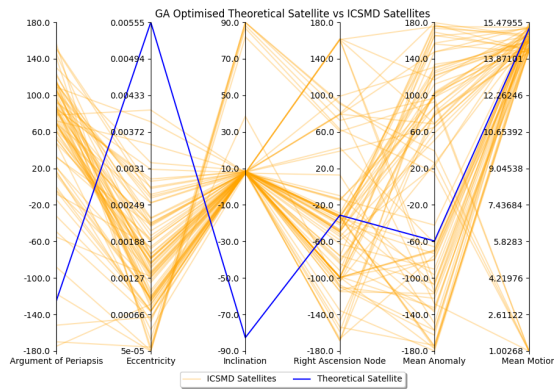


Fig. 10. Final orbital parameters of the new theoretical satellite from Scenario 2 GA optimisation against orbital parameters of all ICSMD subset satellites. Orange shows ICSMD satellites, blue shows Scenario 2 GA optimised new theoretical satellite.

4. Discussion

Although on each individual day in scenario 1, inclination swings between positive and negative values, the genetic optimisation strategy across all days in scenario 2 tends to negative values. This contrasts with the inclination of ICSMD satellites, where the mean inclination is on average about positive 10 degrees above equatorial. A higher-than-average mean motion, as was hypothesised, allows the new theoretical satellite to observe more satellites within the same time period, as it would pass and revisit other satellites more frequently. Eccentricity consistently trends toward zero across all cases, as most satellites operate in circular orbits. Increasing eccentricity would cause the new theoretical satellite to spend more time away from others, thereby reducing the opportunities for inter-satellite interactions. Argument of periapsis and right ascension of the ascending node will perturbate due to J2 perturbation over time and therefore will require alignment with the desired launch time of a satellite that resembles this new theoretical satellite. Increasing maximum consensus time t_{max} reduces the distribution of the results for both parameters and optimising with the genetic algorithm across all starting dates further narrows the distribution. Mean anomaly is time dependent and is therefore a harder parameter to design in a satellite mission.

Increasing the number of participants in a given consensus round makes it more challenging for all satellites to successfully participate. As shown in figure 4, raising the number of participants from 4 to 6 across 10 starting days results in an average of fewer than 1 additional participant. This indicates that, in most cases, the new theo-

retical satellite provides little to no added value compared to the scenario with 4 participants, which contributes an average of approximately 8 additional participants.

While optimizing across all starting days results in a lower maximum number of added satellites compared to optimizing for individual days in scenario 1, it would be costly or impractical to design a satellite mission with a unique orbit for each day. Therefore, optimizing across all starting days offers a feasible satellite mission with a higher average number of added consensus participants, even on days when the satellite's orbit is not specifically optimized. For this reason, the genetic algorithm is more effective when optimized over the full range of starting days rather than focusing on individual days such as in scenario 1. This can be seen in figure 9.

This GA optimization method demonstrates that with 50 generations and a population size of 200, using the previously discussed hyperparameters, orbital parameters can be effectively refined and selected. Although more generations could be used to confirm that further learning yields minimal improvement, the figures 5 6 7 8 show that the orbital parameters have sufficiently converged, indicating that an optimal solution has been reached.

5. Conclusion

This study demonstrates that it is feasible to design a new satellite specifically to improve participation in a given consensus round. For the case of reaching consensus within a day among the ICSMD charter, the orbital parameters of inclination and mean motion have the most significant impact on whether a new satellite can increase the number of participants. Other parameters, such as eccentricity, argument of periapsis, and right ascension of the ascending node, have a smaller effect on the fitness function and the number of satellites involved in the consensus, though they are more influential than mean anomaly, which is highly time-dependent. High inclination and mean motion enable the new theoretical satellite to cover more ground quickly, allowing for more frequent revisits and interactions with other satellites.

Using this method of identifying theoretical satellite trajectories allows for future satellite orbits to be determined to improve decision making and decentralisation of satellite communication.

Future work could study perturbation of the new theoretical satellite compared to the ICSMD subset as well as a larger subset of participating satellites than the ICSMD subset could also be tested however this would be computationally expensive due to the more combinations of subnetworks and therefore more orbit propagations and comparisons required.

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