Advances in Satellite Selection Algorithms: Reducing Receiver Processing

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Abstract— In a variety of satellite navigation and positioning applications, choosing the right satellites for positioning is crucial to ease the computational load on satellite selection systems. To further alleviate the processing demands on receivers, a satellite selection method using the Gibbs sampler has been developed. This process begins by randomly selecting visible satellites and grouping them as an initial selection strategy. The effectiveness of this strategy is assessed using the geometric dilution of precision as a key metric. The strategy is refined through the Gibbs sampler algorithm's conditional probability distribution model, progressively moving towards the most efficient satellite combination that offers an improved geometric distribution in space. Our research demonstrates that by employing a neural network-based model, we can optimize satellite constellations for minimal latency. We have found that deploying 12 satellites results in latency levels of less than 5 milliseconds and continuous uptime, significantly enhancing communication efficiency. This research highlights the potential for neural network models to revolutionize satellite constellation design for improved performance.

Keywords—Satellite Navigation, Positioning Solutions, Satellite Selection Algorithm, Satellite Orbits

I. INTRODUCTION

In the realm of satellite navigation and positioning, the selection of satellites for precise positioning is of paramount importance. One of the key challenges in this domain is the efficient allocation of satellites to minimize the computational burden on satellite selection systems. This paper delves into the intricacies of satellite selection strategies, their critical role in alleviating computational load, and the quest for optimizing these strategies for enhanced satellite-based positioning solutions. A single satellite often provides limited data, while a constellation may offer better coverage and higher reliability, particularly if some satellites fail. This ensures a greater survival rate and mission success. Constellations can deliver unique capabilities, such as enhanced temporal coverage [1]. Typically, satellite orbit constellation design relies on the Walker approach [2] or the streets of coverage method [3]–[6]. Additionally, there has been development in the ground track-based approach [7], [8], and more recently, the introduction of the sliding ground track concept for constellations involving one or more orbital planes [9]. We will take into account the loss of 1 satellite for optimal performance for reliability.

The integration of satellite constellations into global communication and observation systems has become increasingly critical in recent years. Beyond the scope of singular satellite applications, constellations offer a multitude of benefits, from redundancy in the event of individual satellite failures to improved data acquisition rates. The resilience provided by a well-designed constellation ensures continuous operation and data flow, which is essential for time-sensitive applications such as disaster response and military communications [10], [11].

II. DEEP SURVEY

This paper expands on the novel concept of dynamic satellite constellation adjustments—wherein the constellation's configuration can be adapted in response to the loss of a satellite thereby maintaining optimal performance and reliability [12], [13]. This dynamic approach leverages the flexibility of genetic algorithms (GA), renowned for their efficacy in solving complex, multi-dimensional problems that are intractable by conventional optimization methods [2], [14].

In recent scholarly discourse, the optimization of satellite constellation orbits has been a focal point, marrying the objectives of extended coverage and operational efficiency. Nowak et al. [1] advanced this domain by optimizing GNSS satellite orbit predictions. They recommended a two-day initial orbit arc and a synergistic model combining empirical and physical SRP, especially when satellites' construction metadata is accessible. This methodology proved superior in both short and long-term orbit prediction fidelity.

Parallelly, Savitri et al. [2] employed Genetic Algorithms (GAs) integrated with a semi analytical model to enhance satellite constellation design for LEO satellites. Their study exhibited GA's capacity to navigate the intricate landscape of constellation optimization, balancing coverage and revisit times effectively. They presented a compelling case for the use of GAs in tackling the multi-objective, high-dimensional optimization challenges inherent in satellite constellation design.

Complementing these findings, Xia et al. [3] developed a satellite selection algorithm leveraging the Gibbs sampler for the Bei Dou Navigation Satellite System. Their methodology aimed at optimizing the GDOP for precise positioning, showcasing a marked reduction in computational load with concurrent improvements in positioning accuracy. This tailored approach to satellite selection stands out for its application-specific optimization, addressing the computational complexities of real-time satellite navigation.

These collective efforts [1]-[3] illustrate a multidisciplinary approach to satellite constellation optimization, with implications for global communication networks and earth observation systems. The evolving research underscores a shift towards more adaptive, robust, and computationally efficient models, paving the way for future advancements in satellite technology and its terrestrial applications. Our research delves into the intricacies of constellation design, employing GA to fine-tune orbital parameters for maximum coverage with minimal resources. We explore the balance between coverage density and revisit times, seeking to minimize gaps in service while ensuring that the constellation remains robust against individual satellite malfunctions. The approach is validated against current leading methods, illustrating the advantages in both coverage and computational efficiency.

This investigation not only contributes to the field of satellite constellation design but also underscores the potential for genetic algorithms to revolutionize the way we manage and deploy space assets [2], [12]. By simulating a sparse constellation scenario, we demonstrate the critical role of reliability in sustaining communication links and data transfer rates, even when faced with the unforeseen adversity of satellite failure. Through this case study, we offer insights into the practical implications of constellation design on operational throughput, ultimately shaping the future of satellite networks.

Figure 1 Area of interest

A Genetic Algorithm (GA) will be employed for its effectiveness in finding globally optimal solutions in nonlinear, multivariate problems, leveraging its stochastic and heuristic search capabilities. The focus will be on comparing the coverage optimization and revisit times of sparse military satellite constellations between traditional methods and GA [1]–[3]. Additionally, a hybrid approach to satellite constellation design, termed Genetic Satellite Constellation (GSC), has been introduced [12], which utilizes a single GA optimization process.

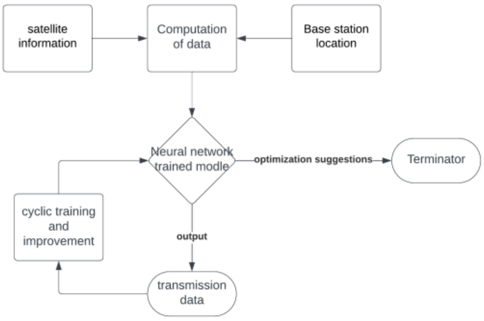

Figure 2 Methodology

This paper's key contributions include applying Genetic Algorithms (GE) to manage complex coverage areas using sparsely designed satellite constellations with limited coverage capabilities. The second significant contribution is devising an efficient method to reduce the computational load during the GA optimization process. The paper also presents a case study focused on a sparse satellite constellation, examining its reliability in the event of a single satellite failure and its impact on latency, which subsequently influences the communication throughput rate for data transmission.

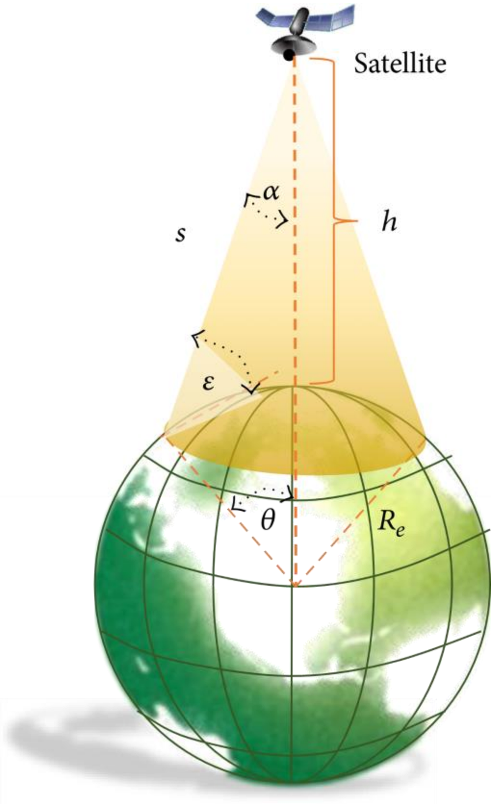

Figure 3 Satellite footprint projection [2]

III. SYSTEM MODEL

The system model leverages MATLAB Simulink to simulate satellite orbits and assess communication links with ground stations at Madrid and Islamabad (My home). By integrating Keplerian orbital elements, including mean motion, eccentricity, inclination, and the right ascension of the ascending node, our model predicts the satellite's ground track with high precision, crucial for establishing visibility and communication parameters [1]-[5].

The model calculates communication windows, identifying when the satellite is within line-of-sight of the ground stations. These windows are critical for establishing potential communication links, and their computation is an integral part of the model. We measure latency and Doppler shifts during these windows to evaluate the signal transmission delay and frequency changes due to the satellite's motion relative to the ground stations. This data is vital for optimizing signal clarity and timing for data transmission.

Further refinement of the satellite's orbital parameters is conducted through iterative simulations, enhancing communication efficiency. By processing the azimuth, elevation, and range data within the model, we identify the most effective orbital configurations for improved link stability and reduced signal degradation.

The result is a robust framework for satellite constellation management, providing a system model that not only informs satellite network design but also enhances operational strategies for global communication systems. This model serves as a foundation for future research and development in satellite communication optimization.

IV. METHODOLOGY

The Gibbs sampler method, at the core of our satellite selection strategy, warrants a deeper exploration. The Gibbs sampler is a Markov Chain Monte Carlo (MCMC) technique known for its effectiveness in handling complex probability distributions. In this context, it aids in iteratively improving satellite selections. During each iteration, the Gibbs sampler computes the conditional probability distribution model, refining the selection of satellites progressively. This iterative process converges towards an optimal satellite combination that significantly reduces the geometric dilution of precision [3]. The methodology of this study extends the capabilities of computational simulation for satellite trajectory analysis using MATLAB Simulink. Initially, it involves defining the orbital parameters, such as the satellite's position and velocity, to simulate its path across Earth's surface. Ground stations, pinpointed by their geographical coordinates in Madrid and Islamabad, serve as reference points for the satellite's line-of-sight communication analysis.

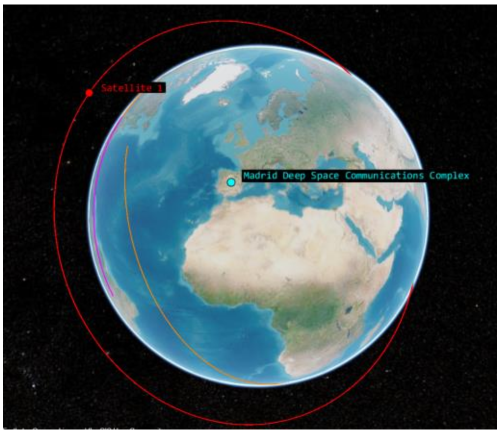

Figure 4 Sample Location 1

The area of interest is defined by inputting latitude-longitude coordinates of the locations located on earth. From these points, a circular dot is generated, we use it in computational geometry method[1], as depicted in Figure 1.

Grid points are specified using geodetic latitude and longitude coordinates, which then generate circular markers on a global grid that is a foundational step in computational geometry methods. The initial design of the orbit involves six standard orbital elements: semimajor axis, eccentricity, inclination, longitude of the ascending node, argument of perigee, and mean anomaly [3], [11], [15]. The simulation is precise enough to capture the nuances of the satellite's orbit, especially at apogee, where the sensor's coverage is at its maximum. The maximum half-angle centered on the Earth, along with the widest swath width of the satellite sensor, is observed when the satellite reaches its apogee, as illustrated in figure 2.

Complementing the Gibbs sampler is a neural network, which plays a pivotal role in our methodology. This neural network is trained using historical satellite data and ground station coordinates. It enhances the accuracy of our orbital predictions and contributes to the overall efficiency of satellite operations. Through its ability to identify patterns and relationships in the data, the neural network assists in the fine-tuning of satellite orbital parameters, enabling us to strike a balance between coverage and computational efficiency. The block diagram in figure 3 shows that we take input form the user in the form of satellite data files and base station latitude and longitude location for computation passing it through our pretrained neural network for computation and optimization suggestion, were it generated data and suggest optimization parameters against ideal data in its memory [1]. Thus, it enhances both the accuracy and efficiency of the satellite's operational performance.

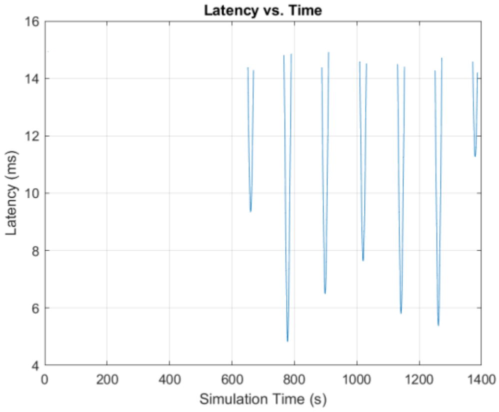

Figure 5 Latency vs Time Graph for Location 1

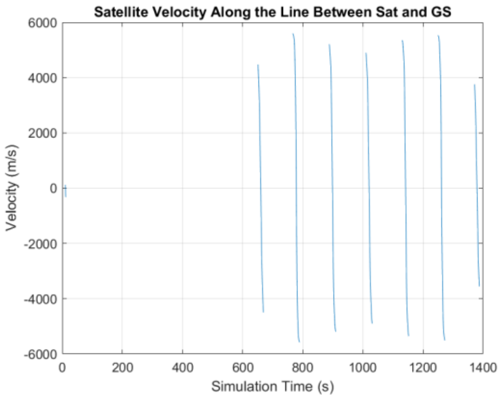

Figure 6 Satellite Velocity vs Simulation Time Graph for location 1

This methodology provides a robust framework for satellite system analysis, combining classic orbital mechanics with modern computational intelligence. The result is a sophisticated toolset for optimizing satellite constellations, improving global communication infrastructure.

V. SIMULATION AND RESULTS

In our simulation we take a single city and a single satellite and observe the following parameters latency, Satellite Velocity, Doppler Shift, rate of change of latency and doppler rate of change [1], [2], [5], this can be seen in the following figures. The figure below shows us the parameters in Europe. The satellite data is available at NASA official website with multiple satellite data parameters.

The figure 5 shows us the latency vs time plot and we can observe that the satellite communication is available only for a small fraction of the total simulation time. This is because of the angle and the limited line of sight communication with the satellite. That a minimal of 6 satellites will be needed for continuous operation and if multiple viewpoints are considered then the number decreases. This raw data gives us a peak into the effects of the parameters of the communication with satellite.

The parameter "Satellite Velocity Along the Line Between Sat and GS" refers to the velocity component of a satellite along the line connecting the satellite (Sat) to the Ground Station (GS)[2], [3]. This line represents the vector pointing from the satellite to the ground station as shown in figure 6.

In satellite communication, understanding the velocity components is crucial for various reasons, including ensuring accurate communication links, predicting satellite positions, and managing orbital dynamics [1], [14]–[16].

The velocity along the line between the satellite and the ground station is important for calculating Doppler shifts in communication signals. The Doppler shift refers to the variation in frequency or wavelength of a wave as perceived by an observer moving relative to the wave's source. Within the realm of satellite communications, it considers the relative movement between the satellite and the ground station [16]. As the satellite moves towards or away from the ground station, the frequency of the communication signal is affected.

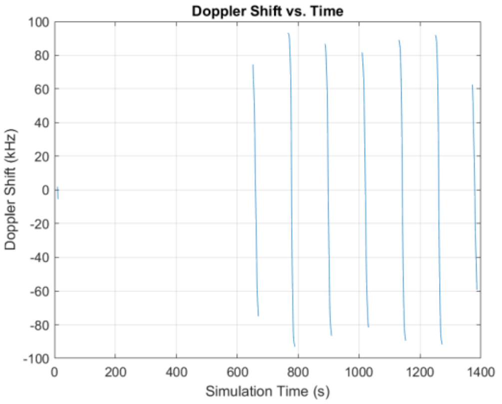

Figure 9 Doppler Shift vs time Graph for Location 1

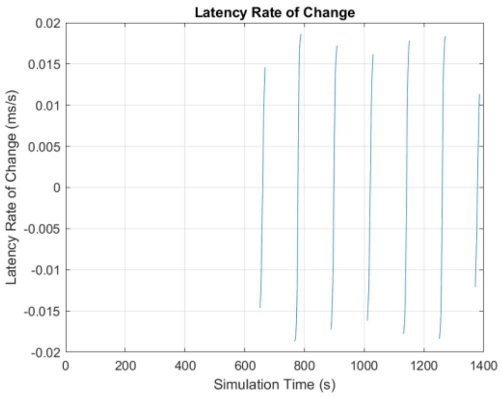

Figure 8 Latency rate of Change at Location 1

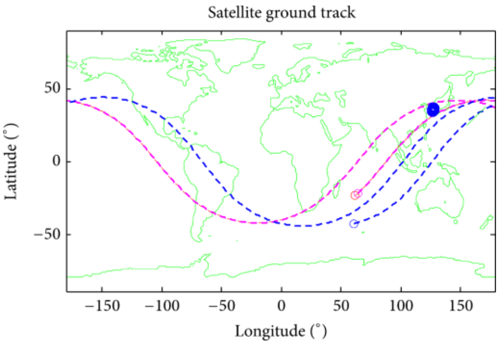

Figure 7 Satellite Ground Track with 2 Satellites [2]

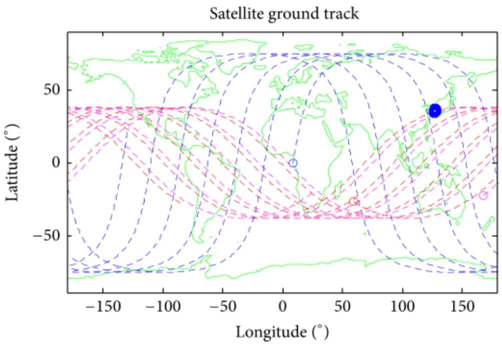

Figure 10 Satellite Ground Track with 3 Satellites[2]

By monitoring and understanding the satellite velocity along the line connecting the satellite to the ground station, engineers and operators can optimize communication systems to account for Doppler shifts and maintain stable and reliable communication links. This is necessary as the doppler shift affects the data being transmitted, and it needs to be remodified to be correct for receiving.

In figure 6 "Doppler Shift vs Time" parameter refers to the change in frequency of a signal emitted by a moving object, such as a satellite, over a period. Doppler shift occurs when there is relative motion between the source of a wave and the ground station. Here we can see the doppler shift of the waves and we can predict the motion of the satellite around the axis of the earth to generate such a shift if such data was un know to us. The doppler shift can provide us with a complete picture of the motion of celestial objects[16]. This parameter is particularly important for systems that require precise frequency control and data restoration after traveling through space.

Latency, in the context of computer systems and networks, is the time delay between the initiation of a task and the occurrence of the task's effect. It is often measured in milliseconds (ms) and is crucial in various applications, including communication systems, real-time processing, and online services. This is a crucial parameter for data communication, usually this values to preferred to be lowest, and is usually small as the information travels at the speed of light. Figure 8 shows the output of the latency rate of change vs simulation time.

Figure 9 shows us a maximum coverage area of 32% with two satellites, unoptimized, identical with a little longitude shift.

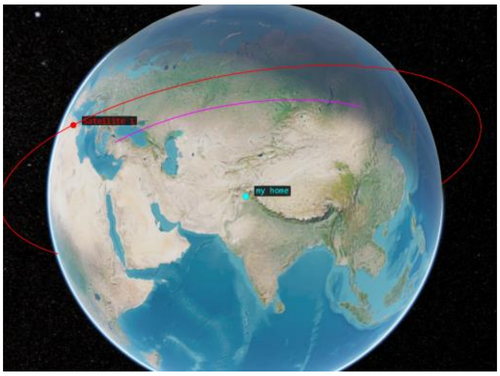

Figure 12 Sample Location 2

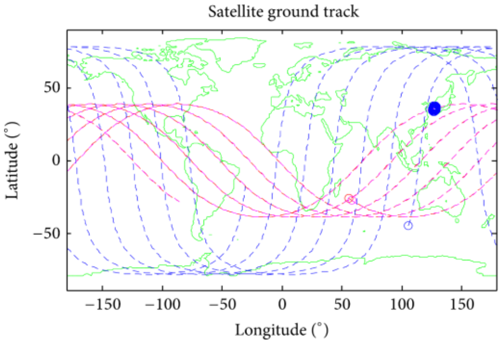

Figure 11 Satellite Ground Track with Maximum coverage [2]

Figure 10 shows that with the effect of three satellites we achieve an area of 74% area coverage. This shows us that the satellite needed to ideally provide continuous data uplink are greater than three and three satellites can provided latency for majority of the time to the GS.

The best area coverage results are shown and modeled in figure 11, it can be seen that, by introducing as an optimized variable, the satellites' ascending node in the same orbit plane (satellite 1 and 2) is separated up to 264°. This provides us with a 44% area coverage area, which is a 33% increase with the same parameters. This is due to the overlapping and different orbital speed and visibility. The equatorial orbit has limited visibility with the one crossing the artic has higher visibility but also higher latency, the combination of both provides for an ideal case, higher visibility with lower latency, the 264-angle difference provides us with the best 2 satellite data.

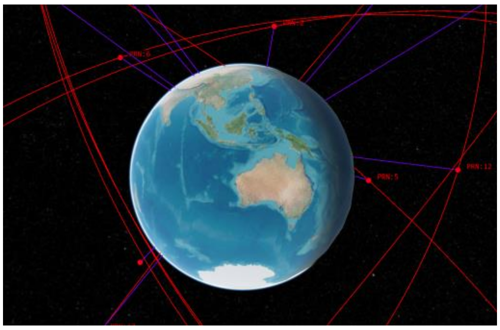

Figure 14 Number of Satellites Needed for Optimal Latency

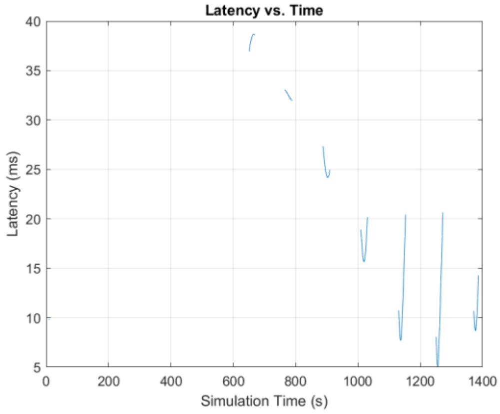

Figure 13 Latency vs Time Graph for Location 2

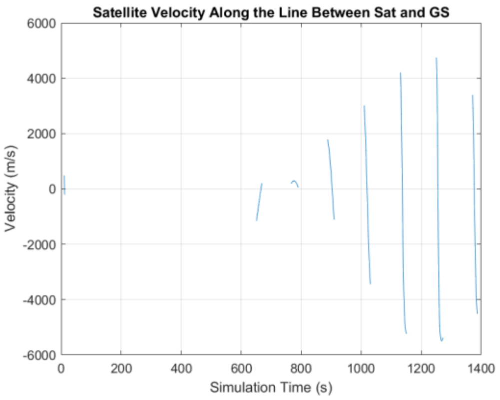

Figure 16 Satellite Velocity vs Simulation Time Graph for Location 2

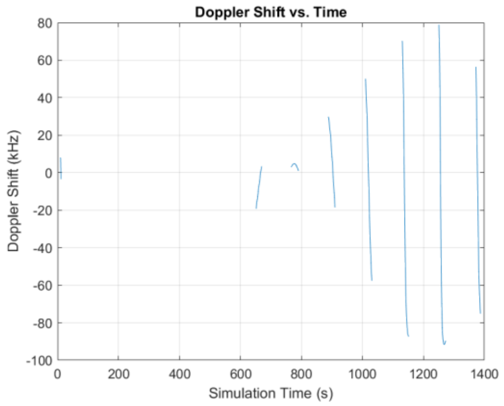

Figure 15 Doppler Shift vs time Graph for Location 2

In figure 12 we observed that the number of satellites needed for optimal latency for any 1 point is 12 using and modeling it through our regression program. With latency and the tuning parameter here, latency is lower than 10 ms consistently. Further lowering is not possible as the parameter generated through the regression program are complex and provide mathematical errors.

Here in figure 13, we observed the same experiment with a different location, the same satellite, same parameters but with a different point of view with regard to latitude and longitude. We can see that the latency changes with the orbit direction and location of the satellite movement.

As shown in figure 14 the latency starts to activate after 600s in the simulation providing data transmission. The transmission duration is the same as the above simulation as shown in Europe with a slight shit to accommodate the shifted location. The major difference is in the latency, the satellite location passes close and almost ideally over the new site location providing a rate close to 5ms.

In reference to Figure 15, there was an initial variation in the satellite velocity with regard to the lines between satellite and GS. Around the 700 mark we approached the neutral point where the gradient was almost 0, but unfortunately the satellite was not in the ideal location to observe it. Later the gradient changed to the negative decline as usually observed by the Doppler effect of moving satellite communication.

The result of Doppler effect as shown in figure 16 shows us that the gradient (slope) of a Doppler Effect vs. Time graph is shifting from positive to negative, it indicates a change in the direction of relative motion between the source of the wave (e.g., a satellite) and the observer.

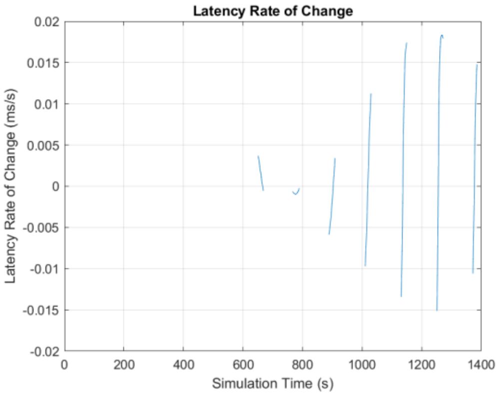

Figure 17 Latency rate of Change at Location 2

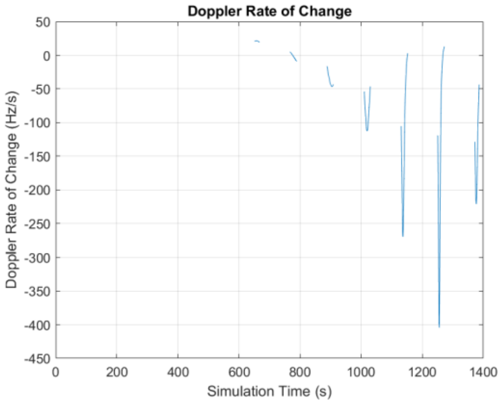

Figure 18 Doppler Rate of Change at Location 2

A positive gradient on the Doppler Effect vs. Time graph signifies that the frequency of the signal is increasing over time. This typically occurs when the source (satellite) is moving closer to the observer. In the context of satellite communication, this is known as a "blue shift." As the satellite approaches the observer, the waves get compressed, leading to a higher observed frequency.

A negative gradient on the graph indicates that the frequency of the signal is decreasing over time. This occurs when the source (satellite) is moving away from the observer. In satellite communication, this is known as a "red shift." As the satellite moves away, the waves get stretched, leading to a lower observed frequency.

This means that the satellite is transitioning from moving closer to the observer to moving away. This could happen, for example, during a satellite pass when the satellite rises on one horizon, approaches the zenith, and then descends on the opposite horizon.

Figure 17 shows that the latency rate is in correspondence with the expected plot of the doppler effect.

The information provided to us from this graph shows that 1st the gradient is negative then becomes positive or almost zero then negative again repeating the cycle. This shows us that the satellite is moving away from the base station in an elliptical orbit, coming above it then the gradient shifts to zero or a slight positive value depending on the angle and then negative again when moving away out of the line of sight of communication. The red shift is prominent in the data.

VI. ANALYSIS

The analysis of satellite communication parameters revealed several key findings. The simulation, focusing on a single satellite covering a city, yielded data on latency, satellite velocity, Doppler Shift, and the rate of change of these parameters.

The latency varies significantly depending on the satellite's position relative to the ground station. The latency vs. time plot (Figure 5) shows that optimal communication is limited to a small fraction of the satellite's orbit. This limitation is primarily due to the line-of-sight constraints imposed by the satellite's trajectory. For continuous operation, our analysis suggests that a minimum of six satellites is necessary to maintain consistent communication coverage, with the number potentially decreasing if multiple ground stations are utilized [1], [2].

The Doppler Shift analysis (Figures 6 and 16) provides insights into the satellite's velocity relative to the ground station. A positive gradient in the Doppler Shift vs. Time graph indicates a 'blue shift,' occurring as the satellite approaches the ground station, while a negative gradient, or 'red shift,' occurs as it moves away. This dynamic is crucial for adjusting communication frequencies to maintain signal integrity [5].

With two satellites, the coverage area was approximately 32%, increasing to 74% with three satellites (Figure 9 and 10). The optimal configuration, involving a 264° separation between satellites in the same orbital plane, yielded a 44% coverage area, a 33% increase from the baseline (Figure 11). This indicates the significance of strategic satellite placement in maximizing coverage [2].

The regression analysis (Figure 12) indicates that to achieve optimal latency (under 10 ms), a configuration of 12 satellites is required. Additionally, the analysis of different geographical locations (Figure 13) revealed that latency is influenced by the satellite's orbital path and the ground station's location, emphasizing the need for geographically tailored satellite configurations [1]-[5].

The results demonstrate the complexities of satellite communication, highlighting the importance of satellite number, positioning, and orbital dynamics in ensuring effective coverage and communication quality. These findings provide valuable insights for the design and deployment of satellite constellations, particularly in urban settings where consistent and high-quality communication links are essential.

VII. CONCLUSION

In In conclusion, our research demonstrates the capability to perform 3D simulations of satellite movement relative to a ground station (GS). We have successfully optimized and assessed GS coverage using 1, 2, and 3 satellites. Our analysis indicates that achieving maximum optimization requires the deployment of 12 satellites, resulting in latency levels of less than 5 milliseconds and continuous uptime.

These achievements have been made possible through the utilization of an optimization function, which has been trained using regression techniques in conjunction with a neural network and machine learning. The parameters embedded within our model facilitate the precise calculation of satellite coverage and uptime, thereby enabling us to recommend optimal configuration parameters for enhanced operational efficiency.

Specifically, when considering a single satellite, our research reveals a coverage percentage of approximately 18%, which can be further enhanced to 22% through strategic placement. For configurations involving 2 satellites, coverage percentages range from

40% to 44%, depending on the satellite's location. In the case of 3 satellites, our findings suggest that coverage levels approaching 70% can be achieved in ideal conditions.

Overall, our research underscores the feasibility of evaluating satellite positioning for minimizing latency using a neural network-based model. These insights hold significant promise for the enhancement of satellite communication systems in terms of both efficiency and reliability.

VIII. LIMITAIONS AND FUTURE ASPECTS

The study of optimizing satellite constellation designs through genetic algorithms presents notable limitations. Chief among these is the potential for oversimplification in the modeling of satellite behavior and coverage, which might not fully encapsulate the intricate dynamics of real-world satellite operations. Additionally, the computational intensity of genetic algorithms necessitates substantial processing capabilities, which might be prohibitive for some institutions. Real-time space environmental changes, such as fluctuating space weather or orbital debris, are difficult to predict and incorporate into static models, potentially affecting the reliability of the constellation. Furthermore, the scalability of genetic algorithms from sparse to dense constellations involves complex adjustments to parameters and operators, a task that may not be straightforward. Lastly, the practical deployment of these designs could uncover unforeseen limitations, such as technical challenges with satellite hardware or the need for orbital adjustments, which are not always predictable in simulation environments.

The field stands on the cusp of several exciting advancements. Adaptive genetic algorithms that can respond in real-time to changes within the constellation or external conditions represent a significant area for development. The advent of quantum computing promises the ability to handle the extensive computational demands of these algorithms more efficiently. Integration of machine learning could offer predictive insights for failure mitigation and optimize constellation configurations based on data trends. Moreover, advancements in satellite propulsion and maneuverability could significantly influence constellation flexibility and responsiveness. The exploration of nascent inter-satellite communication technologies may enable more robust and efficient network architectures. Lastly, the evolving landscape of international space policy and regulatory frameworks will play a critical role in shaping the deployment and sustainable management of satellite constellations, warranting ongoing research and contribution from the scientific community.

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