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Latency Minimization for hybrid LEO-MEO Satellite Constellations using Dynamic Routing and Machine Learning Algorithm

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Abstract

The contemporary worldwide network is connected to satellite communication systems which provide services, such as internet connection, television broadcasting, and emergency calls, over large geographical zones. In satellite communication, latency is one of the major challenges affecting time-sensitive communications and high-speed data transfer requirements. This work focuses on minimizing latency in satellite communication through the Dynamic Routing (DR) algorithm and Image Compression (IC) technique. The work presents a model that integrates Low Earth Orbit (LEO) and Medium Earth Orbit (MEO) satellite constellations, emphasizing Inter-Satellite Links transmission to ensure efficient data dependency. Data transmission speed is improved through edge computing involving image processing and compression which are conducted at the transmitting node. The model is simulated using Python to analyse its performance. Results demonstrate an improvement of 36.19%, 46.84% and 68.56 % in latency minimization for small, medium and large sized image, respectively. Furthermore, the study reveals that the compression factor increases with data size, making this technique more effective for big data.

Keywords

Data Compression
Dynamic Routing Algorithm
Inter-satellite communications
Latency Minimization
Machine learning
Satellite Communications

1. Introduction

Over the past two decades, satellite communication systems have gained considerable attention in enhancing global communication. Communication drives an increased demand for

interest in diverse applications, such as resource exploration and mining, environmental monitoring, disaster response and management, transportation, traffic management, telecommunications, and internet connectivity. Most modern wireless communication networks leverage satellite systems as their backbone [1, 2]. While Optical Fiber Cables (OFC) offer high capacity and speed, their susceptibility to damage during disasters such as floods and fires limits their reliability, thereby reinforcing the importance of satellite communication. Moreover, their high deployment costs have reaffirmed the critical role of satellite communications [3, 4].

Despite their vital importance, satellite communication systems face several persistent issues, including management of space debris, optimization of radio resources, such as spectrum utilization and power management, cybersecurity, and synchronization. Among these, latency stands out as a critical cross-cutting challenge, significantly detrimental to overall system performance and usability [5,6]. Latency in satellite communications is primarily caused by the time signals take to travel between ground stations and satellites, or between satellites themselves in an intersatellite communication, in addition to processing delays.

Addressing the pervasive issue of latency in satellite communications has spurred various research efforts. Existing solutions broadly include the use of satellite swarms and constellations, inter-satellite links (ISLs), and the application of machine learning (ML) and artificial intelligence (AI) techniques for routing optimization [7–9].

For instance, authors proposed a low-latency routing scheme for Low Earth Orbit (LEO) satellites communicating with ground stations, employing propagation, transmission, and queuing delays as routing metrics [10]. While the approach demonstrates effectiveness in static, single-path routing scenarios, its reliance on average delay estimates assumes traffic patterns remain relatively stable-an assumption rarely valid in highly dynamic satellite networks. Such simplifications risk masking short-term congestion spikes and rapid topology changes, potentially degrading performance under real-world conditions. These limitations point toward the need for routing strategies that incorporate Dynamic Routing (DR) to improve responsiveness and efficiency.

Bhattacharjee et al. [11] quantified the impact and tolerable limits of laser inter-satellite link (LISL) delays, calculating end-to-end latency in free-space optical satellite networks (FSOSNs) and proposing design guidelines for laser communication terminal manufacturers. While these guidelines are valuable for hardware optimization, their tolerable limits are derived under controlled conditions and may not fully capture the variability of real-world network dynamics. Consequently, their applicability to latency-sensitive addressed in this study remains uncertain.

Furthermore, Lu et al. [12] developed an algorithm for link failure detection and dynamic link switchover between the shortest and the alternative path to minimize the end-to-end delay.

Despite the best performance obtained, the algorithm is based on LEO orbit satellite constellations only. This limitation calls for further studies to enhance communication in LEO-MEO satellite constellations. Other studies discuss various methods for reducing latency in LEO satellites [13-16].

Lazzaro et al. [17] propose an algorithm for communication in LEOMEO satellite networks. Accordingly, the algorithm ensures minimal onboard intelligence at the satellite, as it simply forwards data based on a predefined routing table without requiring additional protocol

implementation or a specific number of ISLs terminals. While the latter two claims are acceptable, the first remains questionable-particularly regarding how data can be forwarded when the link between satellites has failed. In such scenarios, a mechanism should be in place to reroute data via an alternative shortest path, directing it to a specific satellite rather than broadcasting it across the entire network, thereby optimizing power utilization. Furthermore, the study does not address how high-volume, high-latency data is handled.

Lastly, Kumari and Sriramulu [1] propose an algorithm using k-means clustering to generate lossless images for various applications, including satellite communications. We argue that dividing images into batches prior to clustering could achieve greater size reduction than applying k-means alone.

In this work, we introduce a novel approach to minimize latency and data loss in intersatellite communications, especially the LEO-MEO satellite constellations using (ISLs) and advanced machine learning algorithms. Our proposed method aims to dynamically optimize routing paths and resource allocation to significantly reduce energy utilization, propagation and processing delays across LEO-MEO satellite networks.

2. Methods and Materials

2.1 Dynamic Routing (DR) Algorithm

This work adopts a two-tier constellation consisting of LEO and MEO orbits. Due to their altitudes, LEO satellites provide low latency while MEO provides long coverage. Dynamic routes account for how the satellites in the orbits can switch communication from one satellite to the other without sending the signal back to the ground station. This section focuses on distance calculation, shortest path establishment, placement of the satellite in the orbits, and algorithm development.

2.1.1 Satellite Placement in Orbits

The placement of the satellite in the orbit depends on the shape of the orbit itself. For circular orbits, satellites are placed at equal distances while this is not the case for elliptical orbits. We focus on circular orbits only. Let r be the radius of the orbit and n be the number of satellites. The angular position θ_i of the i^{th} satellite in a circular orbit is given by Eq. (1).

$$\theta_i = \frac{2\pi i}{n}, \text{ for } i = 1,2,3,\dots,n-1 \quad (1)$$

After obtaining an angular separation, the cartesian coordinates (x_i, y_i, z_i) are obtained using Eq. (2).

$$\begin{aligned} x_i &= r\cos(\theta_i) \\ y_i &= r\sin(\theta_i) \\ z_i &= 0 \end{aligned} \quad (2)$$

The value of r depends on the radius of the earth (R_E) and the orbit's altitude h as indicated in Eq. (3). The maximum altitude for LEO and MEO is 2,000 km and 35,786 km respectively.

$$r = R_E + h \quad (3)$$

2.1.2 Distance Calculation and Shortest Path

Once the satellites have been placed in orbits, the Euclidean distance, d, from each of LEO satellites to all MEO satellites is calculated using Eq. (4).

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \quad (4)$$

Where:
i and j: Indices of the satellites in LEO and MEO
(x_i, y_i, z_i): Coordinates of LEO satellites
(x_j, y_j, z_j): Coordinates of MEO satellites

The shortest communication path from any LEO satellite to any MEO satellite and vice versa is then calculated using Eq. (5) and Eq. (6).

$$Shortest\ Distance = min\{d_{ij}\} \quad (5)$$

$$Shortest\ Index = arg\ min\{d_{ij}\} \quad (6)$$

To reduce the satellite's processing time, the distances are sorted in ascending order using Eq. (7) and stored on the satellite's routing table.

$$Sorted\ Indices = argsort\{d_{ij}\} \quad (7)$$

2.1.3 Proposed Dynamic Routing Algorithm

The DR algorithm was developed based on the workflow depicted in Figure 1. This flowchart clearly illustrates the sequential steps and decision points involved in its operation, specifically how it dynamically assigns the optimal route, performs error checking, and seamlessly redirects to an alternative route if a fault in the existing path is detected.

2.2 Image Compression (IC) Algorithm

To achieve an efficient latency minimization, this work employs a combined approach of DR and IC algorithms. Specifically, a mini-batch k-means clustering method is used to compress and reduce the size of the transmitted images. The optimal number of clusters, K, for this compression is determined using the elbow method. The implementation flowchart for the elbow method is illustrated in Figure 2.

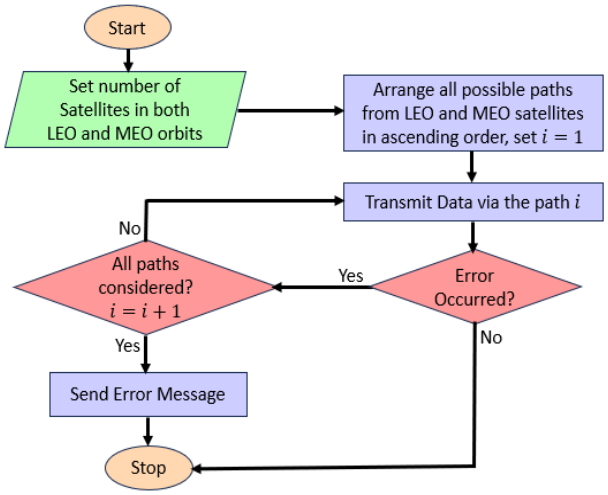


Figure 1. Dynamic routing algorithm.

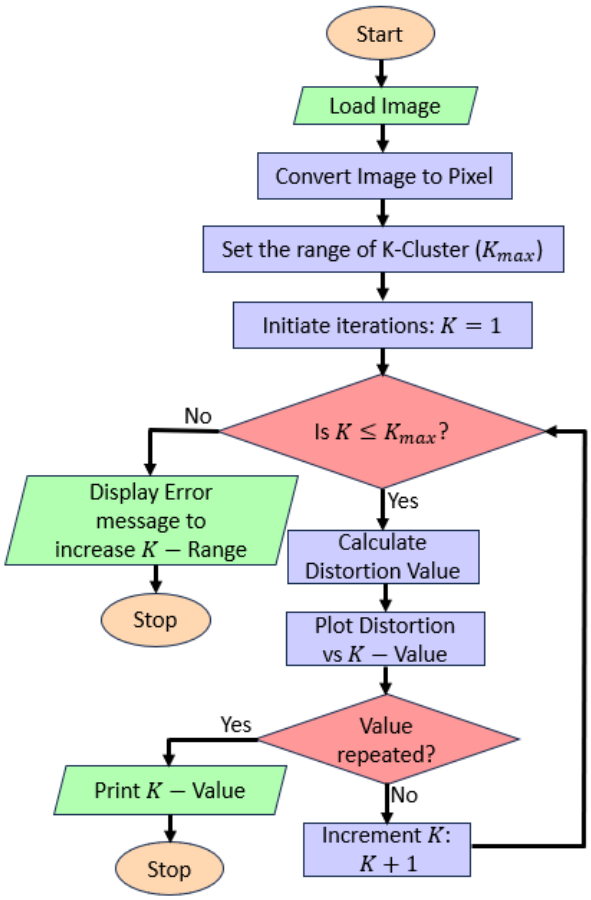


Figure 2. Elbow method for determining optimal K in image compression.

After the determination of the optimal K value, the image compression phase starts using the unsupervised machine learning algorithm, that is the mini-batch k-means algorithm. In the mini-batch k-means algorithm, the convergence criteria were maximum iterations reached, centroid stability and cluster assignment stability. The centroid stability and cluster assignment stability are governed by equations (8) and (9), respectively. For both centroid and cluster assignment stability, a typical threshold value was set at 1×10^{-5}. The overall algorithm is summarized in Figure 3.

$$max\ _change = max_i||c_{t+1}(i) - c_t(i)|| \quad (8)$$

Where:
$c_t(i)$ is the centroid stability at iteration t
$c_{t+1}(i)$ is the centroid stability at iteration $t + 1$
$||\cdot||$ denotes the Euclidean distance

$$change_rate = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(A_t(i) \neq A_{t+1}(i)) \qquad (9)$$

Where $A_t(i)$and $A_{t+1}(i)$denote the cluster assignments of data point i at iterations t and $t+1$, respectively. The function $\mathbf{1}(\cdot)$ is an indicator function that takes the value of 1 if the condition is true and 0 otherwise. Here, n represents the total number of data points.

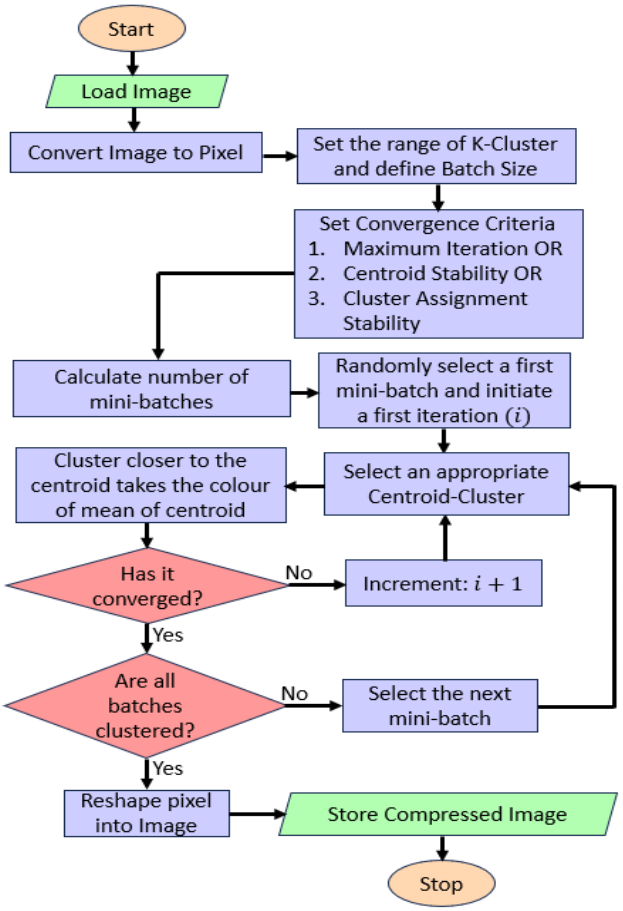


Figure 3. Image compression (IC) algorithm.

The total number of mini-batches in a mini-batch k-means algorithm is given by Eq. (10): M is the total number of mini-batches, N is the size of the dataset, and B is the size of each mini-batch. In this mini-batch k-mean algorithm, the like-colored pixels are grouped by an iterative process that seeks to minimize the distance between data points (pixels) and cluster centroid (representative colors).

$$M = \frac{N}{B} \qquad (10)$$

The combined operation and interaction of these two mechanisms are comprehensively summarized in Figure 4.

2.3 Performance Evaluation

The performance of the developed algorithms was evaluated using five performance metrics: compression factor (CF), compression ratio (CR), saving percentage (SP), propagation delay, and transmission time. The image compression metrics are given in Eq. (11) through Eq. (13).

$$CF = \frac{Original\ \ size}{Compressed\ \ size} \qquad (11)$$

$$CR = \frac{Compressed\ \ size}{Original\ \ size} \qquad (12)$$

$$SP = \left(\frac{Original - compressed}{Original\ \ size}\right) \times 100 \qquad (13)$$

Transmission metrics, such as transmission time, T_x, which depends on the size of the data packet being transmitted and propagation delay, P_D, are as in Eq. (14) and Eq. (15), respectively.

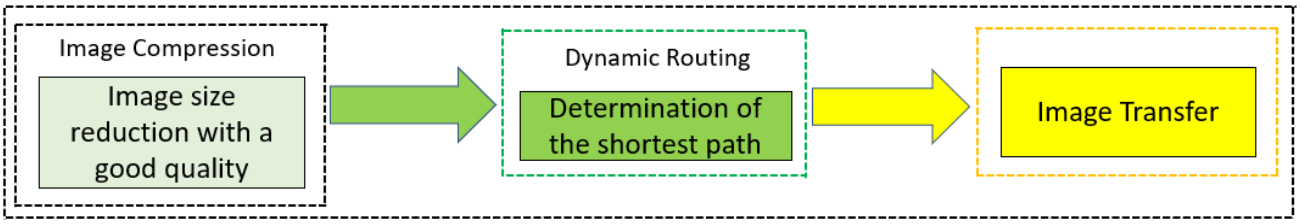


Figure 4. Architecture of the proposed model.

$$T_x = \frac{s}{b} \quad (14)$$

$$P_D = \frac{d}{c} \quad (15)$$

From Eq (14) and (15), s and b stand for the size of the data packet being transmitted and the data rate of the communication link, respectively; d is the distance between communicating satellites; c is the speed light in vacuum. While transmission time accounts for the time that data travels from the source to the destination, propagation delay is the time that data takes to move between satellites in the constellation of satellites before reaching the destination.

3. Results and Discussions

3.1 Dynamic Routing

Initially, the developed algorithms were validated for their ability to deploy satellites into both LEO and MEO constellations. This deployment was achieved using the satellite placement equations defined in Eq (1) through Eq, (4). Figure 5(a) illustrates a sample resulting constellation, comprising 10 LEO and 22 MEO satellites. Subsequently, the inter-satellite distances between each LEO and all MEO satellites were calculated to establish a routing table. This routing table enables efficient communication by providing prior distance knowledge, thereby minimizing data retransmission and eliminating the need for automatic repeat requests (ARQs).

Table 1 shows the routing table of the first LEO satellite, which stores information to be used during communication. The link with the shortest distance will be given the highest priority for data transmission. In case of link failure, the developed algorithm will dynamically select the next shortest link. For satellite number one, the shortest distance was 18014.46 km. The satellite transmits a communication signal via this path. Upon encountering challenges on that path, the next-best shortest is chosen, as shown in Figure (5b).

Table 1. Routing table for satellite 1 in LEO.

No.	Communication Links	Distance (km)
1.	LEO1 to MEO1	18014.46
2.	LEO1 to MEO2	18424.96
3.	LEO1 to MEO3	19903.26
4.	LEO1 to MEO4	22112.35
5.	LEO1 to MEO5	24674.74
6.	LEO1 to MEO6	27277.55
7.	LEO1 to MEO7	29688.13
8.	LEO1 to MEO8	31738.97
9.	LEO1 to MEO9	33311.62
10.	LEO1 to MEO10	34258.37
11.	LEO1 to MEO11	34706.52
12.	LEO1 to MEO12	34639.30
13.	LEO1 to MEO13	34059.20
14.	LEO1 to MEO14	32988.10
15.	LEO1 to MEO15	31468.34
16.	LEO1 to MEO16	29565.01
17.	LEO1 to MEO17	27370.17
18.	LEO1 to MEO18	25009.79
19.	LEO1 to MEO19	22653.82
20.	LEO1 to MEO20	20526.62
21.	LEO1 to MEO21	19904.26
22.	LEO1 to MEO22	18781.08

The dynamic selection process continues until a clear communication channel is established and the data are transmitted via that channel. In circular orbits, the process is generally less time-consuming compared to the elliptical orbits, as the path closer to the shortest path is assumed to be the next shortest, unlike in elliptical orbits.

3.2 Image Compression Comparison

The three different metrics for image compression, namely the ratio of compression, saving percentage, and compression factor, were used for comparison with other available compression techniques. These techniques are RLSDLA, VQ, and K-means [1]. The set of data used for satellite communication ranges from low-sized to high-sized data. RLSDLA shows a compression ratio of 1.3, which suggests that it compresses less compared to the other methods. Moreover, the proposed model has the lowest ratio of 0.218, indicating that it achieves the highest level of compression. The K-means approach saves 71.49 %, whereas the proposed model shows the greatest results with a saving percentage of 78.2 %. As a result, a factor that measures the total

effectiveness of the compression process is the compression factor.

The proposed study results in the highest efficiency with a Compression Factor of 4.58, indicating it not only compresses effectively but also maintains a balance between compression and image quality. K-means has a Compression Factor of 3.50, while the VQ method shows the lowest performance across all metrics. The overall comparison is represented in Table 2.

Table 2. Compression performance comparison

Comparison Methods	RLSDLA	VQ	K-mean	Proposed
Compression Ratio	1.3	0.5053	0.285	0.218
Saving Percentage	30%	49.7%	71.49%	78.2%
Compression Factor	3.507	0.0785	3.5	4.58
File Type	JPEG	JPG/TIF	All	All

A sample of the compressed image alongside the original image is demonstrated in Figure 6.



(a) Original Image (8764 KB) (b) Compressed Image (1914 KB)

Figure 6. Image compression comparison.

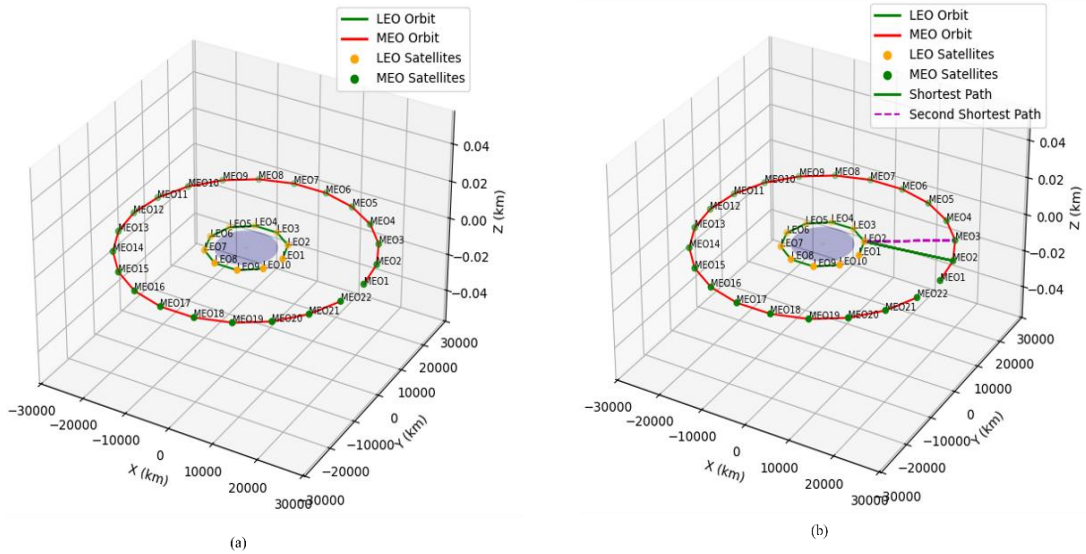


Figure 5. Satellite constellation deployment and dynamic routing path selection.

3.3 Transmission Time

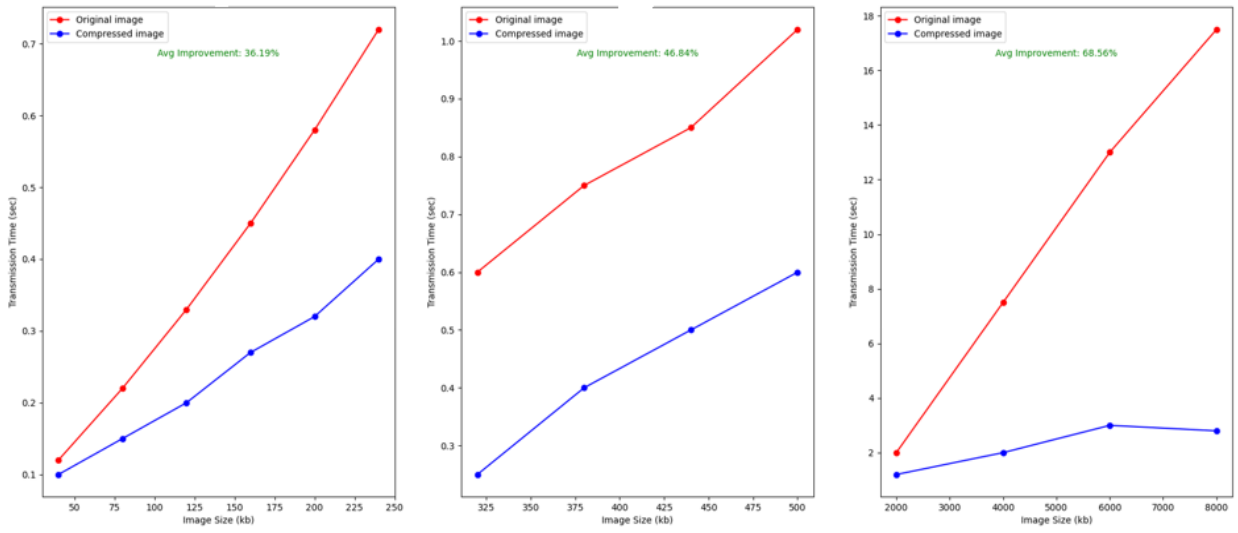
This section demonstrates the overall latency improvement achieved in LEO-MEO satellite constellations. This is realized by integrating two key mechanisms, namely Dynamic Routing (DR) and Image Compression (IC). The performance of the proposed model is analysed in terms of transmission time by comparing compressed and uncompressed data across various image sizes through an ISL employing an S-band of 25 Mbps (Figure 7).

Figure 7 presents the transmission time performance across different data size ranges. Figure 7(a) specifically shows results for low data sizes, ranging from 0 kb to 250 kb. In this range, the transmission time for compressed and uncompressed images does not differ significantly, primarily because the original data sizes are already minimal. Only an average of 36.19 % improvement is observed. As data size transits from low to medium, increased performance is also observed as demonstrated in Figure 7(b).

The average improvement of 46.84 % is observed with the medium data size. At certain points, the transmission time for compressed data might initially show a slight increase or deviation from its ideal trend; this phenomenon is attributed to the additional processing overhead incurred during the compression phase itself. Nevertheless, the overall trend clearly indicates a net benefit in transmission efficiency for medium-sized datasets.

Crucially, Figure 7(c), which considers large-sized data, demonstrates a very significant improvement of 68.56 % in transmission time. For data ranging from 1000 kb to nearly 6500 kb, a substantial reduction in transmission time is observed for compressed images compared to their uncompressed counterparts.

For data sizes beyond approximately 6500kb the proposed model achieves a near-constant transmission time, regardless of the original data size. This remarkable effect occurs because the algorithm efficiently compresses large datasets to a consistently small final size, providing a distinct advantage over handling uncompressed low-sized data. This capability represents a significant strength of this study in advancing satellite communications.



7(a) 7(b) 7(c)

Figure 7. Comparison of transmission time performances of the proposed model across varying data sizes.

4. Conclusion and Future Works

From this study, it can be concluded that the developed DR algorithm effectively chooses the shortest path dynamically in satellite networks where both LEO and MEO orbit satellites are in constant motion. This algorithm incorporates an error tolerance mechanism that includes a path-switching technique, ensuring that if an error occurs in the shortest communication path, data is automatically shifted to the next shortest available path rather than requiring re-transmission. This significantly expedites data requests between satellites and reduces time spent on error detection and correction, thereby enhancing communication efficiency.

This approach complements recent efforts, such as the multi-agent deep reinforcement learning-based routing, in integrated satellite-terrestrial networks proposed by Wang et al. [18], which optimizes routing paths through constrained collaborative agents. However, unlike their model, which is focused primarily on terrestrial handoffs, our system targets dynamic adaptation in hybrid LEO-MEO constellations, addressing inter-orbit discrepancies and switching overheads in a more latency-sensitive context.

The results of the unsupervised machine learning image compression algorithm clearly demonstrate that image compression significantly reduces latency, particularly for large data sizes. The image size is reduced to 1.15× and 1.37× compared to the original image for low-size data. Additionally, the compression factors are 1.92× and 2.05× for medium-size data and 2.93× and 4.58× for high-size data, respectively. For very small data sizes, the compression factor is less noticeable, with minimal transmission time differences between original and compressed data; indeed, excessive compression can negatively impact image quality. In the medium data size range, there is a considerable decrease in transmission time, demonstrating the efficiency of the approach for this dataset due to its consistent performance in data compression and transmission time.

These results contrast favorably with the latency optimization framework introduced by Wang et al. [15], who proposed a stochastic geometry-based latency model for LEO networks. While their model provides strong theoretical bounds, it lacks dynamic adaptability under changing traffic loads and orbital configurations—a gap our compression-aware, real-time DR scheme attempts to address.

The benefits of compression become more pronounced with larger data sizes, leading to faster transmission times. Greater size datasets typically include larger levels of repetitious information that can be eliminated or decreased, raising the compressibility factor. As a result, compressed data travels across networks faster and requires shorter transmission times than uncompressed data. Furthermore, this research effectively addresses the large size and high latency limitations identified by Lazzaro *et al.* [17], by demonstrating how large-size data can be compressed more effectively to achieve superior results at the same bandwidth.

The developed DR algorithm, while effective in reducing overall transmission time, faces increased complexity and a higher risk of data transfer loss when there is a significant velocity disparity between LEO and MEO orbit satellites, particularly in scenarios involving multiple MEO satellites communicating with a single LEO satellite. Additionally, for very large data sizes, the compression time can still be considerable. Furthermore, it is important to acknowledge that this study's technical derivations, Python implementation, and evaluation metrics (compression ratio, factor, saving percentage) provide an appropriate approach, but our simulation environment relied on simplifying assumptions such as circular orbits and a static setting. These assumptions inherently limit the direct applicability of our findings to highly dynamic, real-world satellite network scenarios,

which involve more complex elliptical orbits and unpredictable satellite movements.

Comparable models, such as SkyOctopus [19], which improve latency via multi-anchor relay schemes, or DRL-SR [20], which uses deep reinforcement learning to route multi-commodity flows across LEO satellites, have demonstrated valuable improvements in end-to-end performance. However, our approach introduces a unique integration of ML-based image compression with dynamic inter-orbit routing, a combination not explored in those models. It is worth noting that in this study, the use of the elbow method and mini-batch K-means for image compression, along with the reliance on distance-based Euclidean metrics for the DR method, are standard approaches within their respective fields.

For future work, we suggest several promising directions. Firstly, developing a formal mathematical model for latency estimation that comprehensively integrates both data size (like image size) and dynamic routing paths would provide a more robust theoretical framework for predicting and optimizing latency. Secondly, exploring hybrid optimization approaches is crucial; this could involve combining various machine learning paradigms, such as integrating supervised learning for traffic prediction with unsupervised learning for compression, or incorporating metaheuristic optimization algorithms into the current routing scheme. The developed model should extend beyond image-based data to explore other data types common in satellite systems, such as real-time telemetry or video. Additionally, future research should aim to enhance the real-world applicability of these models by incorporating more realistic simulation parameters, including elliptical orbits, dynamic traffic loads, and ISL failures. Further investigations into the impact of different constellation designs and the integration of advanced channel coding techniques with data compression could also lead to significant latency reductions.

While our model facilitates effective intersatellite communication, its implementation on an orbiting satellite would increase energy consumption due to onboard processing of image compression and determination of best route. Therefore, any direct implementation of the model would need to consider this trade-off.

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CONTRIBUTIONS OF CO-AUTHORS

Joseph S. Mwakijale	[ORCID: 0000-0001-6257-6986]	Identification of the research gap and proposed the conceptual solution.
Ibrahim A. Mwammenywa	[ORCID: 0000-0003-2735-643X]	Provided technical details and insights into the methodology and materials used in this study
Neky V. Chaniyara	[ORCID: 0009-0002-6491-2570]	Conducted simulations and analysis of results

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