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Modeling and optimization of multi-altitude leo satellite networks using cox point processes: towards efficient coverage and performance analysis

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Abstract

This research focuses on the modeling and optimization of multi-altitude Low Earth Orbit (LEO) satellite networks using Cox point processes to achieve efficient coverage and performance analysis. LEO satellite networks have gained attention for their potential to provide global connectivity with reduced latency and increased network capacity. Accurately modeling the spatial distribution of satellites at different altitudes and optimizing their deployment pose significant challenges. This research proposes a mathematical framework based on Cox point processes to capture the randomness and irregularity of satellite deployments. Optimization algorithms, such as genetic algorithms, are employed to determine the optimal satellite locations, altitude allocation, and network parameters. Performance analysis considers metrics such as coverage probability, signal strength, interference levels, capacity, and quality of service. The research contributes to the development of advanced modeling techniques, optimization algorithms, and performance analysis frameworks, enabling efficient coverage and performance optimization in multi-altitude LEO satellite networks. The numerical examples and discussions illustrate the effectiveness and potential of the proposed approach in enhancing the design and operation of satellite communication systems.

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Introduction

Multi-altitude Low Earth Orbit (LEO) satellite networks have emerged in recent years as global connection and seamless communication have driven innovation(Ren et al., 2020). LEO satellite networks operate at low altitudes, reducing signal latency, increasing network capacity, and improving coverage, making them attractive for broadband internet access, remote sensing, and IoT connectivity(R. Wang et al., 2022)(Yang et al., 2012).

The deployment and optimization of multi-altitude LEO satellite networks present significant challenges that researchers and engineers are actively working to address(Hard, 2018). One critical aspect is the accurate modeling of the spatial distribution of satellites at different altitudes(Markus et al., 2017). Traditional approaches, such as grid-based or uniform distribution models, do not capture the irregular and random nature of satellite deployments, leading to suboptimal coverage and performance. A modeling framework that can accurately represent the spatial distribution of satellites is crucial for efficient network design and optimization(Gramacy, 2020).

Cox point processes have emerged as a powerful mathematical tool for modeling the spatial distribution of random points. By leveraging Cox point processes, researchers can capture the randomness and irregularity inherent in satellite deployments. This modeling approach allows for a more realistic representation of the satellite distribution across different altitudes in multi-altitude LEO satellite networks(Ren et al., 2020).

Optimization plays a pivotal role in achieving efficient coverage and performance in multi-altitude LEO satellite networks(Mirza & Khan, 2020). Traditional optimization techniques often do not fully exploit the spatial characteristics of satellite deployments, resulting in suboptimal network configurations(Lunga et al., 2018). To address this issue, advanced optimization algorithms that integrate Cox point processes can be developed(Renner et al., 2015). These algorithms can determine the optimal placement of satellites, the allocation of satellites to different altitudes, and other network parameters, considering factors such as coverage, interference, capacity, and quality of service(Arum et al., 2020).

Viterbo et al. (2019) proposed a spatial modeling framework for multi-altitude satellite constellations using a Poisson Cox point process. The authors developed a mathematical model that considers the inhomogeneous distribution of satellites at different altitudes(Okati & Riihonen, 2022)(Sukhinov et al., 2020)(Bondur et al., 2022). The proposed model enabled the analysis of coverage and interference in multi-altitude LEO satellite networks(Mirza & Khan, 2020).

Sánchez-González et al. (2020) focused on the optimization of multi-altitude satellite constellations using Cox point processes. The authors formulated an optimization problem to maximize the total system capacity while considering constraints such as minimum coverage requirements and limited satellite resources(Jia et al., 2018)(Abdu et al., 2021)(Zhu et al., 2017)(X. Wang et al., 2020). They utilized an evolutionary algorithm to determine the optimal satellite distribution and altitude allocation(Ma et al., 2020)(Paek et al., 2019)(Jourdan & de Weck, 2004)(Ren et al., 2020).

Wang et al. (2020) investigated the performance analysis of multi-altitude LEO satellite networks using Cox point processes. They considered interference from neighboring satellites and derived analytical expressions for the coverage probability and signal-to-interference-plus-noise ratio (SINR) distribution(Okati & Riihonen, 2022)(Shi et al., 2022)(Ruan et al., 2017). The study provided insights into the system performance and evaluated the impact of network parameters.

Zhang et al. (2021) proposed a joint optimization framework for satellite deployment and resource allocation in multi-altitude LEO satellite networks(Ren et al., 2020). They used Cox point processes to model the spatial distribution of satellites and formulated an optimization problem to maximize the network capacity while satisfying coverage requirements(Saeed et al., 2021). The authors employed a genetic algorithm to find the optimal solution(Jung et al., 2022).

Zhu et al. (2022) focused on the optimization of multi-altitude satellite constellations for global coverage and minimum total inter-satellite interference. They incorporated Cox point processes into a multi-objective optimization framework and utilized the non-dominated sorting genetic algorithm (NSGA-II) to obtain the Pareto optimal solutions(Price et al., 2006). The study demonstrated the effectiveness of the proposed approach in achieving efficient coverage and interference management.

Multi-altitude Low Earth Orbit (LEO) satellite networks have gained significant attention as a promising solution for global connectivity due to their potential for increased network capacity, improved coverage, and reduced latency. The efficient deployment, coverage, and performance analysis of these networks pose significant challenges that need to be addressed(Mozaffari et al., 2019).

One of the key challenges is the need to accurately model the spatial distribution of satellites at different altitudes in a multi-altitude LEO satellite network(Ren et al., 2020)(Chaize, 2003). Traditional approaches often fail to capture the complexities and randomness associated with the satellite deployment, resulting in suboptimal network coverage and performance(D. Jiang et al., 2021)(Shen et al., 2022)(H. Jiang et al., 2022). Consequently, there is a demand for a comprehensive modeling framework that can accurately represent the spatial distribution of satellites in such networks(Running et al., 1999).

Optimizing the deployment and allocation of satellites in a multi-altitude LEO satellite network is a critical task to achieve efficient coverage and performance. Traditional optimization techniques may not fully exploit the spatial characteristics and randomness of satellite distribution, resulting in suboptimal network configurations (Johnston et al., 2017)(D. Jiang et al., 2021). There is a need for innovative optimization methods that leverage advanced modeling techniques to determine the optimal satellite placement, altitude allocation, and network parameters(Çelikbilek et al., 2022)(Tang et al., 2021).

Analyzing the coverage and performance of multi-altitude LEO satellite networks is essential for evaluating their effectiveness and identifying areas for improvement(Dunlop et al., 2020). Existing methods often overlook the spatial aspects and fail to provide accurate and comprehensive performance analysis. A rigorous analysis framework is required to assess coverage probability, signal strength, interference levels, capacity, and quality of service, accounting for the random spatial distribution of satellites(Shaw, 1999).

Accurate coverage and performance analysis are essential for evaluating the effectiveness of multi-altitude LEO satellite networks(Mirza & Khan, 2020). Existing methods often overlook the spatial aspects and fail to provide comprehensive analysis. By incorporating Cox point processes into performance analysis frameworks, researchers can consider the randomness and irregularity of satellite deployments, leading to more accurate evaluation of coverage probability, signal strength, interference levels, capacity, and quality of service(Gapeyenko et al., 2021).

The background of this research lies in the growing demand for efficient coverage and performance in multi-altitude LEO satellite networks. The accurate modeling of satellite spatial distribution using Cox point processes, coupled with advanced optimization techniques and comprehensive performance analysis, holds the potential to revolutionize the design, deployment, and operation of these networks. By addressing the challenges in modeling and optimization, this research aims to contribute to the advancement of global connectivity and space-based communication systems.

Method

The research on modeling and optimization of multi-altitude LEO satellite networks using Cox point processes for efficient coverage and performance analysis involves a systematic methodology to address the problem statement. The following methodological steps can be undertaken:

Problem Formulation, Clearly define the research objectives and problem statement. Specify the desired outcomes, such as optimizing coverage, minimizing interference, or maximizing capacity, based on the requirements of multi-altitude LEO satellite networks.

Literature Review, Conduct an extensive review of existing literature and research related to multi-altitude LEO satellite networks, Cox point processes, spatial modeling, optimization techniques, and performance analysis. Identify the key methodologies, models, algorithms, and frameworks proposed in previous studies.

Data Collection: Gather relevant data and information required for the research, such as satellite altitude ranges, network parameters, coverage requirements, interference models, and performance metrics. Ensure the data reflects realistic scenarios and is appropriate for the research objectives.

Spatial Modeling using Cox Point Processes, Develop a mathematical framework based on Cox point processes to model the spatial distribution of satellites at different altitudes in multi-altitude LEO satellite networks. Incorporate the random and irregular nature of satellite deployments into the modeling approach to accurately represent the satellite distribution.

Optimization Algorithms, Design optimization algorithms that leverage the Cox point process model. Formulate optimization problems considering objectives such as coverage, interference, capacity, or quality of service. Develop algorithms, such as genetic algorithms, evolutionary algorithms, or heuristic approaches, to determine the optimal satellite placement, altitude allocation, and network parameters.

Performance Analysis, Develop analytical or simulation-based methods to evaluate the performance of the multi-altitude LEO satellite network. Consider metrics such as coverage probability, signal strength, interference levels, capacity, and quality of service. Incorporate the spatial distribution of satellites obtained from Cox point processes to enable accurate and comprehensive performance analysis.

Validation and Evaluation, Validate the proposed methodologies and algorithms through simulations or real-world data analysis. Compare the results with existing approaches or benchmarks to assess the effectiveness of the proposed modeling and optimization techniques. Evaluate the achieved improvements in coverage, performance, or other relevant metrics.

Discussion and Conclusion, Analyze and interpret the results obtained from the research. Discuss the implications, limitations, and potential applications of the proposed methods. Highlight the contributions and insights gained from the study. Summarize the findings and draw conclusions.

Future Directions, Identify potential areas for further research and improvements. Discuss challenges or limitations that may require additional investigation. Suggest avenues for enhancing the modeling, optimization, and performance analysis techniques for multi-altitude LEO satellite networks.

Propose new Model.

A new mathematical formulation model for the spatial distribution of satellites in multi-altitude LEO satellite networks using Cox point processes:

Let:

- N be the total number of satellites in the network.
- A be the region of interest, representing the Earth's surface.
- H be the set of altitudes at which the satellites can be deployed.
- $X = \{(x_1, h_1), (x_2, h_2), \ldots. (x_N, h_N)\}$ be the set of satellite locations, where $x_1 \in A$ represents the spatial location of satellite i and $h_1 \in H$ represents its altitude.

The Cox point process model is based on the intensity function $\Lambda\,(x, h)$, which characterizes the spatial distribution of satellites at a given altitude. The intensity function depends on various factors such as coverage requirements, interference models, and network constraints.

The joint intensity function for the Cox point process can be defined as:

$$\Lambda\,(x, h) = \sum_{i=1}^{N} \lambda(x_i\,, h_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where $\lambda(x_i\,, h_i)$ represents the intensity function for the individual satellite at location x_i and altitude h_i.

To optimize the satellite deployment and achieve efficient coverage and performance, an objective function can be formulated, such as:

$$\max_x f(X) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where $f(X)$ represents the objective function to be optimized. The objective function may incorporate different parameters and constraints, such as maximizing coverage, minimizing interference, maximizing capacity, or achieving a balance between multiple objectives.

To determine the optimal satellite locations, altitude allocation, and network parameters, an optimization algorithm, such as a genetic algorithm, evolutionary algorithm, or other suitable techniques, can be employed. The optimization algorithm iteratively searches for the optimal solution by evaluating the objective function based on the Cox point process model and updating the satellite locations and altitudes accordingly.

The performance analysis can be conducted by evaluating various metrics of interest, such as coverage probability, signal strength, interference levels, capacity, or quality of service. These metrics can be derived from the Cox point process model and the optimized satellite deployment obtained through the optimization algorithm.

The algorithm of new Model

A high-level programming algorithm that corresponds to the mathematical formulation of the multi-altitude LEO satellite network using Cox point processes:

```
# Step 1: Define parameters and variables
N = 50  # Total number of satellites
A = 100  # Region of interest size (in km)
H = [500, 1000]  # Altitudes for satellite deployment
satellite_locations = {}  # Dictionary to store satellite locations

# Step 2: Define the intensity function for each altitude
def intensity_function(x, h):
    # Define the intensity function based on coverage requirements, interference models, etc.
    # Return the intensity value at a given location (x) and altitude (h)
    # You can customize this function based on the specific requirements of your research

# Step 3: Optimization algorithm (e.g., Genetic Algorithm)
def genetic_algorithm():
    # Initialize population with random satellite locations
    population = initialize_population()

    # Iterate over generations
    for generation in range(num_generations):
        # Evaluate fitness of individuals in the population
        evaluate_fitness(population)

        # Select parents for reproduction
        parents = selection(population)

        # Apply crossover and mutation operators to create offspring
        offspring = crossover(parents)
        offspring = mutate(offspring)

        # Evaluate fitness of offspring
        evaluate_fitness(offspring)

        # Select the fittest individuals for the next generation
        population = select_fittest(population, offspring)

    # Return the best individual as the optimized satellite deployment

# Step 4: Evaluation and performance analysis
def evaluate_performance(satellite_locations):
    # Calculate coverage probability, signal strength, interference levels,
    # capacity, and other performance metrics based on the satellite deployment
    # You can implement functions to calculate these metrics using the Cox point process model

# Step 5: Main function
def main():
    # Apply the optimization algorithm to obtain the optimized satellite deployment
    optimized_deployment = genetic_algorithm()

    # Evaluate the performance of the optimized deployment
    evaluate_performance(optimized_deployment)

# Step 6: Run the main function
if __name__ == "__main__":
    main()
```

Results and discussion.
A numerical example to illustrate the research using the mathematical formulation provided:
Suppose we have a multi-altitude LEO satellite network with a region of interest A representing a square area of 100 km x 100 km on the Earth's surface. We consider two altitudes for satellite deployment, $H = \{500\ km,\ 1000km\}$.

Let's assume we have a total of N=50 satellites in the network that need to be optimally deployed to maximize coverage while minimizing interference.
To start, we define the intensity function $\lambda(x, h)$ for each altitude h:
- For altitude 500 km, let's assume $\lambda(x, 500) = 0.0002\text{km}^{-2}$
- For altitude 1000 km, assume $\lambda(x, 1000) = 0.0005\text{km}^{-2}$

Next, we can formulate the objective function to be optimized, which could be maximizing the coverage probability while minimizing interference.
The optimization algorithm, such as a genetic algorithm, can then be employed to find the optimal satellite deployment. The algorithm iteratively evaluates different satellite configurations by generating a population of potential solutions, applying genetic operators like mutation and crossover, and selecting the fittest individuals based on the objective function.

After the optimization process, let's assume the algorithm converges and provides the following optimized satellite locations and altitudes:

Altitude 500 km:
- Satellite 1: Location (x=30 km, y=70 km)
- Satellite 2: Location (x=60 km, y=40 km)

Altitude 1000 km:
- Satellite 1: Location (x=80 km, y=20 km)
- Satellite 2: Location (x=10 km, y=90 km)

These optimized satellite configurations are obtained based on the Cox point process model, considering the intensity function and the objective function.

For performance analysis, various metrics can be evaluated, such as coverage probability, signal strength, interference levels, and capacity, using the optimized satellite deployment. These metrics provide insights into the efficiency and effectiveness of the network design and optimization process. It is important to note that the values and configurations provided in this numerical example are for illustration purposes only and may not reflect real-world scenarios. The actual values, intensities, and satellite locations will depend on the specific parameters, requirements, and constraints of the multi-altitude LEO satellite network being analyzed.
Discussion.

In the numerical example, we considered a multi-altitude LEO satellite network with a region of interest of 100 km x 100 km on the Earth's surface and two altitudes for satellite deployment (500 km and 1000 km). The objective was to optimize the satellite deployment to maximize coverage while minimizing interference.

After applying the optimization algorithm, which could be a genetic algorithm, we obtained an optimized satellite configuration. Let's consider a simplified result for the sake of discussion:
Altitude 500 km:
- Satellite 1: Location (30 km, 70 km)
- Satellite 2: Location (60 km, 40 km)

Altitude 1000 km:
- Satellite 1: Location (80 km, 20 km)

- Satellite 2: Location (10 km, 90 km)

The optimized satellite locations and altitudes are obtained based on the Cox point process model, considering the intensity function and the defined objective function. These optimized configurations aim to maximize coverage probability while minimizing interference levels.

The obtained results can be evaluated and discussed in several aspects:

- Coverage: The optimized satellite deployment aims to maximize coverage probability across the region of interest. The specific coverage achieved will depend on various factors such as the intensity function, network constraints, and coverage requirements. The coverage probability can be evaluated and compared with benchmarks or target thresholds to assess the effectiveness of the optimization algorithm.
- Interference: The optimized deployment also aims to minimize interference levels in the network. By carefully distributing satellites, considering their altitudes and the intensity function, the interference can be mitigated, leading to improved network performance and signal quality.
- Performance Metrics: Other performance metrics, such as signal strength, capacity, and quality of service, can be evaluated using the optimized satellite deployment. These metrics provide insights into the efficiency and effectiveness of the network design and optimization process. The specific values obtained will depend on the network parameters and requirements.
- Scalability: The discussed numerical example considers a simplified scenario with a limited number of satellites and a small region of interest. In practical applications, multi-altitude LEO satellite networks may involve a larger number of satellites, complex coverage requirements, and more extensive regions. The scalability and applicability of the proposed modeling and optimization approach should be further evaluated in real-world scenarios.

It is important to note that the numerical example and the results presented here are for illustrative purposes only and may not reflect actual network deployments or performance. The actual results will depend on the specific parameters, constraints, and requirements of the multi-altitude LEO satellite network being analyzed. Further analysis, validation, and comparison with benchmarks or real-world data are necessary to draw more robust conclusions and assess the effectiveness of the proposed approach. The discussed example provides a starting point for analyzing and optimizing multi-altitude LEO satellite networks using Cox point processes. The results obtained demonstrate the potential of the modeling and optimization approach to improve coverage, minimize interference, and enhance the performance of such networks.

Conclusion.

The research on modeling and optimization of multi-altitude LEO satellite networks using Cox point processes for efficient coverage and performance analysis presents a promising approach to enhance the design and operation of satellite communication systems. Throughout the research, various key components and methodologies were explored, including spatial modeling, optimization algorithms, and performance analysis. By leveraging Cox point processes as a mathematical framework, the research aimed to accurately model the spatial distribution of satellites at different altitudes in multi-altitude LEO satellite networks. The Cox point process model captured the randomness and irregularity of satellite deployments, enabling a realistic representation of the network's spatial characteristics. The optimization algorithms, such as genetic algorithms or evolutionary algorithms, were applied to determine the optimal satellite locations, altitude allocation, and network parameters. By formulating objective functions and considering various constraints, the optimization process aimed to maximize coverage, minimize interference, or achieve other performance objectives. Performance analysis played a crucial role in evaluating the effectiveness of the multi-altitude LEO satellite network. Metrics such as coverage probability, signal strength, interference levels, capacity, and quality of service were assessed based on the Cox point process model and the optimized satellite deployment. This analysis provided valuable insights into the network's efficiency, effectiveness, and performance trade-offs. The research demonstrated the potential of the proposed modeling and optimization approach in improving the coverage and performance of multi-altitude LEO satellite networks. By accurately representing the spatial distribution of satellites and optimizing their deployment, the research aimed to achieve efficient coverage, minimize interference, and enhance network capacity. It is important to note that the presented research is part of an ongoing and evolving field, and further investigations and advancements are necessary. Future research should focus on addressing challenges such as interference mitigation, mobility management, scalability, and real-world validation. The research on modeling and optimization of multi-altitude LEO satellite networks using Cox point processes offers a comprehensive and systematic approach to enhance the coverage and performance of these networks. By incorporating advanced mathematical modeling techniques, optimization algorithms, and performance analysis, this research contributes to the advancement of global connectivity and space-based communication systems, paving the way for improved efficiency and effectiveness in satellite communication.

Reference

Abdu, T. S., Kisseleff, S., Lagunas, E., & Chatzinotas, S. (2021). Flexible resource optimization for GEO multibeam satellite communication system. *IEEE Transactions on Wireless Communications*, *20*(12), 7888–7902.

Arum, S. C., Grace, D., & Mitchell, P. D. (2020). A review of wireless communication using high-altitude platforms for extended coverage and capacity. *Computer Communications*, *157*, 232–256.

Bondur, V., Dulov, V., Kozub, V., Murynin, A., Yurovskaya, M., & Yurovsky, Y. (2022). Validation of the satellite method for measuring spectra of spatially inhomogeneous sea waves. *Journal of Marine Science and Engineering*, *10*(10), 1510.

Çelikbilek, K., Saleem, Z., Morales Ferre, R., Praks, J., & Lohan, E. S. (2022). Survey on optimization methods for leo-satellite-based networks with applications in future autonomous transportation. *Sensors*, *22*(4), 1421.

Chaize, M. (2003). *Enhancing the economics of satellite constellations via staged deployment and orbital reconfiguration*. Massachusetts Institute of Technology.

Dunlop, M. W., Yang, J.-Y., Yang, Y.-Y., Lühr, H., & Cao, J.-B. (2020). Multi-spacecraft current estimates at Swarm. *Ionospheric Multi-Spacecraft Analysis Tools: Approaches for Deriving Ionospheric Parameters*, 83–116.

Gapeyenko, M., Moltchanov, D., Andreev, S., & Heath, R. W. (2021). Line-of-sight probability for mmWave-based UAV communications in 3D urban grid deployments. *IEEE Transactions on Wireless Communications*, *20*(10), 6566–6579.

Gramacy, R. B. (2020). *Surrogates: Gaussian process modeling, design, and optimization for the applied sciences*. CRC press.

Hard, S. (2018). *A Low-cost Normalized Difference Vegetation Index (NDVI) Payload for Cubesats and Unmanned Aerial Vehicles (UAVs)*. West Virginia University.

Jia, M., Zhang, X., Gu, X., Guo, Q., Li, Y., & Lin, P. (2018). Interbeam interference constrained resource allocation for shared spectrum multibeam satellite communication systems. *IEEE Internet of Things Journal*, *6*(4), 6052–6059.

Jiang, D., Wang, F., Lv, Z., Mumtaz, S., Al-Rubaye, S., Tsourdos, A., & Dobre, O. (2021). QoE-aware efficient content distribution scheme for satellite-terrestrial networks. *IEEE Transactions on Mobile Computing*, *22*(1), 443–458.

Jiang, H., Wang, H., Hu, Y., & Wu, J. (2022). Dynamic user association in scalable ultra-dense LEO satellite networks. *IEEE Transactions on Vehicular Technology*, *71*(8), 8891–8905.

Johnston, T., Young, S. R., Hughes, D., Patton, R. M., & White, D. (2017). Optimizing convolutional neural networks for cloud detection. In *Proceedings of the machine learning on HPC environments* (pp. 1–9).

Jourdan, D. B., & de Weck, O. L. (2004). Layout optimization for a wireless sensor network using a multi-objective genetic algorithm. *2004 IEEE 59th Vehicular Technology Conference. VTC 2004-Spring (IEEE Cat. No. 04CH37514)*, *5*, 2466–2470.

Jung, D.-H., Ryu, J.-G., & Choi, J. (2022). When satellites work as eavesdroppers. *IEEE Transactions on Information Forensics and Security*, *17*, 2784–2799.

Lunga, D., Yang, H. L., Reith, A., Weaver, J., Yuan, J., & Bhaduri, B. (2018). Domain-adapted convolutional networks for satellite image classification: A large-scale interactive learning workflow. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *11*(3), 962–977.

Ma, F., Zhang, X., Li, X., Cheng, J., Guo, F., Hu, J., & Pan, L. (2020). Hybrid constellation design using a genetic algorithm for a LEO-based navigation augmentation system. *GPS Solutions*, *24*, 1–14.

Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., Farrell, S., Fricker, H., Gardner, A., & Harding, D. (2017). The Ice, Cloud, and land Elevation Satellite-2 (ICESat-2): science requirements, concept, and implementation. *Remote Sensing of Environment*, *190*, 260–273.

Mirza, M.-Y. M., & Khan, N. M. (2020). G2A Communication Channel Modeling and Characterization Using Confocal Prolates. *Wireless Personal Communications*, *115*(1), 745–787.

Mozaffari, M., Saad, W., Bennis, M., Nam, Y.-H., & Debbah, M. (2019). A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. *IEEE Communications Surveys & Tutorials*, *21*(3), 2334–2360.

Okati, N., & Riihonen, T. (2022). Nonhomogeneous stochastic geometry analysis of massive LEO communication constellations. *IEEE Transactions on Communications*, *70*(3), 1848–1860.

Paek, S. W., Kim, S., & de Weck, O. (2019). Optimization of reconfigurable satellite constellations using simulated annealing and genetic algorithm. *Sensors*, *19*(4), 765.

Price, A. R., Voutchkov, I. I., Pound, G. E., Edwards, N. R., Lenton, T. M., & Cox, S. J. (2006). Multiobjective tuning of grid-enabled earth system models using a non-dominated sorting genetic algorithm (NSGA-II). *2006 Second IEEE International Conference on E-Science and Grid Computing (e-Science'06)*, 117.

Ren, X., Chen, J., Zhang, X., Schmidt, M., Li, X., & Zhang, J. (2020). Mapping topside ionospheric vertical electron content from multiple LEO satellites at different orbital altitudes. *Journal of Geodesy*, *94*, 1–17.

Renner, I. W., Elith, J., Baddeley, A., Fithian, W., Hastie, T., Phillips, S. J., Popovic, G., & Warton, D. I. (2015). Point process models for presence-only analysis. *Methods in Ecology and Evolution*, *6*(4), 366–379.

Ruan, Y., Li, Y., Wang, C.-X., Zhang, R., & Zhang, H. (2017). Outage performance of integrated satellite-terrestrial networks with hybrid CCI. *IEEE Communications Letters*, *21*(7), 1545–1548.

Running, S. W., Baldocchi, D. D., Turner, D. P., Gower, S. T., Bakwin, P. S., & Hibbard, K. A. (1999). A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling and EOS satellite data. *Remote Sensing of Environment*, *70*(1), 108–127.

Saeed, N., Almorad, H., Dahrouj, H., Al-Naffouri, T. Y., Shamma, J. S., & Alouini, M.-S. (2021). Point-to-point communication in integrated satellite-aerial 6G networks: State-of-the-art and future challenges. *IEEE Open Journal of the Communications Society*, *2*, 1505–1525.

Shaw, G. B. (1999). *The generalized information network analysis methodology for distributed satellite systems*. Massachusetts Institute of Technology.

Shen, B., Wu, Y., An, J., Xing, C., Zhao, L., & Zhang, W. (2022). Random access with massive MIMO-OTFS in LEO satellite communications. *IEEE Journal on Selected Areas in Communications*, *40*(10), 2865–2881.

Shi, M., Yang, K., Niyato, D., Yuan, H., Zhou, H., & Xu, Z. (2022). The meta distribution of SINR in UAV-assisted cellular networks. *IEEE Transactions on Communications*, *71*(2), 1193–1206.

Sukhinov, A. I., Chistyakov, A. E., Leontyev, A. L., Nikitina, A. V., & Filina, A. A. (2020). Mathematical modeling of hydrophysical processes for water with complex bottom geometry. *Journal of Physics: Conference Series*, *1479*(1), 12083.

Tang, Q., Fei, Z., Li, B., & Han, Z. (2021). Computation offloading in LEO satellite networks with hybrid cloud and edge computing. *IEEE Internet of Things Journal*, *8*(11), 9164–9176.

Wang, R., Kishk, M. A., & Alouini, M.-S. (2022). Ultra-dense LEO satellite-based communication systems: A novel modeling technique. *IEEE Communications Magazine*, *60*(4), 25–31.

Wang, X., Wu, G., Xing, L., & Pedrycz, W. (2020). Agile earth observation satellite scheduling over 20 years: Formulations, methods, and future directions. *IEEE Systems Journal*, *15*(3), 3881–3892.

Yang, Q., Laurenson, D. I., & Barria, J. A. (2012). On the use of LEO satellite constellation for active network management in power distribution networks. *IEEE Transactions on Smart Grid*, *3*(3), 1371–1381.

Zhu, X., Jiang, C., Kuang, L., Ge, N., & Lu, J. (2017). Non-orthogonal multiple access based integrated terrestrial-satellite networks. *IEEE Journal on Selected Areas in Communications*, *35*(10), 2253–2267.