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Cross-domain transfer learning for leo satellite constellations: a similarity-based multi-source approach

Leo uydu takımyıldızları için alanlar arası transfer öğrenmesi: benzerlik tabanlı çoklu kaynak yaklaşımı

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Cross-Domain Transfer Learning for LEO Satellite Constellations: A Similarity-Based Multi-Source Approach

Highlights

- ❖ Proposed a **novel similarity-based multi-source transfer learning (MSTL) framework** for LEO satellite orbit prediction.
- ❖ Demonstrated that **physics-informed feature engineering degrades performance** by up to 461%, while minimalist orbital parameters yield superior results.
- ❖ Achieved **88.2% error reduction (RMSE = 0.045 min, $R^2 = 0.9972$)** using only 25 target samples.
- ❖ Validated the approach across **heterogeneous constellations (Starlink, OneWeb, Iridium)**, addressing diverse orbital architectures.
- ❖ Offered a **scalable and computationally efficient solution** for real-time space situational awareness and satellite operations.

Graphical Abstract

This study introduces a similarity-based multi-source transfer learning framework that significantly enhances orbital prediction accuracy for LEO satellite constellations using minimal target data, outperforming conventional physics-informed methods. Graphical representation of the proposed similarity-based transfer learning methodology for cross-constellation orbit prediction.

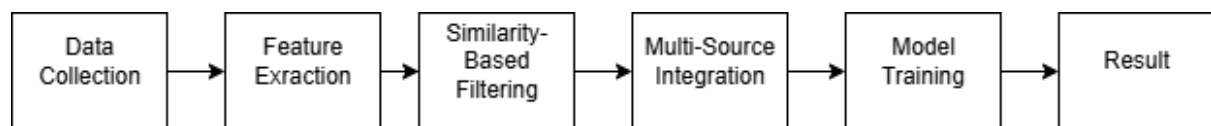


Figure. Workflow of the proposed similarity-based multi-source transfer learning framework for LEO satellite constellations.

Aim

To demonstrate the effectiveness of similarity-based multi-source transfer learning in orbital prediction for LEO satellite constellations.

Design & Methodology

The study employed TLE-based parameters (altitude, inclination, eccentricity) to compute similarity measures across Starlink, OneWeb, and Iridium datasets, applying similarity-driven source selection followed by Random Forest regression for orbital prediction.

Originality

This work is the first to demonstrate that minimalist orbital parameters, when combined with similarity-based transfer learning, outperform physics-informed feature engineering in cross-constellation prediction tasks.

Findings

The proposed framework achieved an 88.2% error reduction (RMSE = 0.045 min, $R^2 = 0.9972$) with only 25 target samples, while highlighting the counterintuitive failure of physics-informed approaches.

Conclusion

The results confirm that similarity-based multi-source transfer learning provides a scalable, reliable, and practical solution for orbital prediction in LEO constellations.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Cross-Domain Transfer Learning for LEO Satellite Constellations: A Similarity-Based Multi-Source Approach

Araştırma Makalesi / Research Article

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ABSTRACT

The rapid expansion of Low Earth Orbit (LEO) satellite constellations such as Starlink, OneWeb, and Iridium has created new opportunities for global connectivity while introducing major challenges in orbit prediction, traffic management, and resource allocation. Traditional orbit propagation models (e.g., SGP-4) and physics-informed approaches often fail to meet accuracy requirements due to atmospheric drag, space weather, and orbital heterogeneity. Although machine learning (ML) techniques show strong potential for improving prediction accuracy, their dependence on large, high-quality datasets limits their applicability to new constellations. This paper presents a similarity-based multi-source transfer learning (MSTL) framework that leverages orbital similarities across heterogeneous constellations to enable accurate orbital period prediction with minimal target data. Unlike conventional physics-informed feature engineering, which can degrade performance by up to 461%, our method employs a minimalist feature set (altitude, inclination, and eccentricity) directly extracted from Two-Line Element (TLE) data. Through similarity-driven source selection and filtered multi-source knowledge integration, the proposed framework reduces prediction error by 88.2% (RMSE = 0.045 min, $R^2 = 0.9972$) using only 25 labeled samples from the target constellation. The findings show that domain-aware similarity filtering outperforms complex feature engineering, challenging conventional assumptions about transfer learning in physics-based domains. This work offers a scalable, efficient, and practical solution for emerging LEO operators, enabling rapid model development without extensive data collection.

Keywords: Transfer learning, LEO satellites, domain adaptation, orbital prediction, satellite constellations.

LEO Uydu Takımyıldızları için Alanlar Arası Transfer Öğrenmesi: Benzerlik Tabanlı Çoklu Kaynak Yaklaşımı

ÖZ

Starlink, OneWeb ve Iridium gibi Alçak Dünya Yörüngesi (LEO) uydu takımyıldızlarının hızlı genişlemesi, küresel bağlantı için büyük fırsatlar yaratırken yörünge tahmini, trafik yönetimi ve kaynak tahsisi gibi alanlarda önemli zorluklar ortaya çıkarmıştır. Geleneksel yörünge yayılım modelleri (ör. SGP-4) ve fizik tabanlı yaklaşımlar, atmosferik sürtünme, uzay havası ve yörünge heterojenliği nedeniyle genellikle gerekli doğruluğu sağlayamamaktadır. Makine öğrenimi (ML) teknikleri tahmin doğruluğunu artırmada güçlü bir potansiyele sahip olsa da, büyük ve kaliteli veri kümelerine bağımlılıkları yeni veya gelişmekte olan takımyıldızlar için sınırlayıcıdır. Bu çalışma, heterojen takımyıldızlar arasındaki yörünge benzerliklerinden yararlanarak minimum hedef veriyle doğru yörünge periyodu tahmini sağlayan benzerlik tabanlı çok kaynaklı transfer öğrenimi (MSTL) çerçevesini sunmaktadır. Performansı %461'e kadar düşürdüğü gösterilen geleneksel fizik tabanlı özellik mühendisliğinden farklı olarak, yöntemimiz Two-Line Element (TLE) verilerinden doğrudan çıkarılan minimalist bir özellik seti (yükseklik, eğim, eksantriklik) kullanır. Benzerlik odaklı kaynak seçimi ve filtrelenmiş çoklu bilgi entegrasyonu sayesinde, önerilen çerçeve yalnızca 25 etiketli hedef örnekle tahmin hatasını %88,2 azaltır (RMSE = 0,045 dk, $R^2 = 0,9972$). Sonuçlar, alan farkındalıklı benzerlik filtrelemenin karmaşık özellik mühendisliğinden daha iyi performans gösterdiğini ve fizik tabanlı alanlarda transfer öğrenimine dair geleneksel varsayımları sorguladığını ortaya koymaktadır. Çalışma, yeni LEO operatörleri için ölçeklenebilir, hesaplama açısından verimli ve pratik bir çözüm sunarak kapsamlı veri toplama gereksinimini ortadan kaldırır.

Anahtar Kelimeler: Transfer öğrenimi, LEO uyduları, alan uyarlama, yörünge tahmini, uydu konstellasyonları.

1. INTRODUCTION

The rapid deployment of low Earth orbit (LEO) satellite constellations, particularly mega-constellations such as Starlink, OneWeb, and Iridium, is considered to herald a new era in satellite-based global connectivity [1]. These

systems perform critical functions in broadband communication, remote sensing, positioning, and future 6G-enabled services [2, 3, 4]. However, deploying such a dense infrastructure on a global scale brings with it frequent satellite handoffs, limitations on energy

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efficiency, the risk of orbital congestion, and the need for high-precision orbital and maneuver prediction frameworks [5, 6, 7, 8].

Currently widely used classical orbit propagation methods, such as Simplified General Perturbation Models (SGP4), are computationally efficient but limited in modeling non-conservative forces such as atmospheric drag, solar radiation pressure, and geomagnetic effects [9, 10, 11]. These limitations can lead to positioning and navigation errors of hundreds of meters, which are unacceptable in safety-critical applications [11, 12]. Therefore, hybrid and machine learning-based models, which offer significant improvements over analytical approaches, have recently come to the fore [5, 13, 14]. However, the success of these methods largely depends on the availability of comprehensive historical datasets, which poses a serious obstacle for newly deployed or relatively small-scale constellations.

In this context, transfer learning (TL) has emerged as a promising paradigm that can accelerate the model development process for new constellations by reusing knowledge gained from existing constellations. While current TL applications in aerospace have generally focused on orbit prediction, system fault diagnosis, and remote sensing, most of these approaches are based on single-source adaptation [15, 16, 17]. However, the fact that orbital parameters (e.g., altitude, inclination, and eccentricity) vary significantly between different constellations limits single-source approaches in heterogeneous LEO environments.

Developed to address this shortcoming, Multi-Source TL (MSTL) offers the ability to integrate different information sources while having the potential to reduce adverse transfer effects through similarity-based domain selection. This study proposes and evaluates a similarity-based MSTL framework for constellation-to-constellation orbit prediction. The proposed approach is based on similarity-based filtering of source satellites through orbital parameters such as altitude, inclination, and eccentricity, and integrating data from different constellations into a single training set. Extensive experiments conducted on Starlink, OneWeb, and Iridium TLE datasets demonstrate that this approach significantly reduces prediction errors and achieves high accuracy even with limited target samples.

1.1. Contributions

The main contributions of this work are summarized as follows:

- **Novel Similarity-Based MSTL Framework:** Introduces a similarity-driven MSTL approach for LEO orbit prediction, ensuring domain compatibility and minimizing negative transfer.
- **Counterintuitive Failure of Physics-Informed Features:** Demonstrates that theoretically motivated, physics-informed features degrade performance (−82% to −461%), whereas minimalist raw orbital parameters yield superior results.

- **Data Efficiency in Prediction:** Achieves 88.2% error reduction (RMSE = 0.045 min, $R^2 = 0.9972$) with only 25 target samples, highlighting the framework's suitability for new constellations with limited data availability.
- **Cross-Constellation Validation:** Validates the framework using three diverse constellations (Starlink, OneWeb, Iridium), capturing fundamentally different orbital architectures (mid-latitude vs. polar).
- **Practical and Scalable Solution:** Provides a computationally efficient approach suitable for real-time applications in space situational awareness, satellite operations, and mission planning.

2. RELATED WORKS

2.1. LEO Satellite Operations and Prediction

The rapid proliferation of LEO satellite constellations, including mega-constellations such as Starlink, OneWeb, and Iridium, has inaugurated a new era of global connectivity and data services [18, 19]. This expansion poses significant challenges for operational management, particularly due to the high speeds of these satellites [8, 20]. This situation requires frequent handovers between ground stations and imposes constraints on limited onboard resources [8, 21]. These challenges include scalability, spectrum allocation, energy efficiency, and security, highlighting the urgent need for advanced predictive modeling frameworks [22]. Furthermore, the increasing density of orbital objects further increases congestion and collision risks, necessitating the development of robust orbital and maneuver prediction systems [23]. Orbital trajectory prediction began with physics-based astrodynamics models such as Simplified General Perturbations-4 (SGP-4). SGP-4 and related models struggle to capture the effects of non-conservative forces such as atmospheric drag, space weather, and gravitational perturbations [24, 25]. These limitations cause significant discrepancies between predicted and actual orbits. These discrepancies can lead to nominal deviations of approximately 250 meters and navigation errors of approximately 400 meters [26]. Such errors are unacceptable in safety-critical applications. A paradigm shift towards hybrid analytical and machine learning (ML)-focused approaches is required to minimize errors. To overcome these limitations, many studies have attempted to improve traditional propagation models such as SGP-4 using error correction techniques. A wide variety of ML methods, including Support Vector Machines (SVM) [27, 28], Extreme Gradient Boosting (XGBoost) [29], Gaussian Processes [27, 30], Artificial Neural Networks (ANN) [27], Convolutional and Recurrent Neural Networks (CNN) [31, 32], Recurrent Neural Network (RNN) [33], and Long-term and short-term memory (LSTM) architectures [34] have been applied to reduce prediction errors using historical trajectory data. In their work, Caldas and Soares [35] presented differentiable variants

of SGP-4 integrated into neural networks, while alternative approaches such as polynomial fitting and Latent Force Models (LFMs) demonstrated potential beyond SGP-4-based schemes. Recent studies emphasize a growing consensus that hybrid or fully data-driven ML models can surpass the accuracy-efficiency tradeoffs of classical methods and lead to scalable and computationally efficient orbit prediction in increasingly crowded LEO environments.

In this direction, Liu et al. (2025) [20] proposed an attention-driven maneuver forecasting framework tailored for mega-constellation satellites. Their method begins by eliminating short-period variations from precise ephemerides, enabling reliable maneuver detection. Feature importance is ranked through Random Forest permutation, highlighting historical maneuver variations, mean argument of latitude changes, and inter-satellite context. Using these features, an Informer network with self-attention is trained to forecast maneuvers, which are subsequently injected into the force model for orbital propagation. Experiments on publicly available Starlink ephemerides show that the framework can correctly predict 95.12% of maneuvers during the on-station phase and 88.97% in the parking phase. Incorporating maneuver forecasts into propagation yields significant accuracy gains, with 24-hour position RMSE reduced from 15.71 km to 3.95 km (improvements of 56–87%). These findings demonstrate the strong potential of attention-based time-series models for mitigating error growth in frequently maneuvering LEO constellations, offering robustness and scalability beyond conventional correction schemes.

Complementary to orbit and maneuver prediction, parallel advances in traffic forecasting Zhang et al. (2025) [36] have underscored the role of data-driven methods in ensuring not only orbital accuracy but also bandwidth efficiency and congestion management in mega-constellation networks. The authors demonstrated that satellite traffic exhibits strong self-similar and long-memory characteristics, inherited from terrestrial networks but amplified by the dynamic nature of LEO constellations. To capture these properties, they proposed an improved LSTM architecture enhanced with attention mechanisms and early stopping regularization, benchmarked against GRU, Seq2Seq, and CNN models. Using two real-world Internet traffic datasets, their Attention-LSTM model consistently outperformed alternatives, achieving RMSE values of 18.351 and 8.828, respectively, with statistically significant improvements confirmed via Diebold–Mariano tests. This study highlights how self-similarity-aware deep learning methods can guide traffic-aware routing and resource allocation in LEO constellations, ensuring efficient bandwidth utilization and congestion avoidance in large-scale satellite networks.

Building on these advancements, recent research has proposed fully data-driven alternatives that combine the accuracy of physics-based methods with the adaptability of ML approaches [37]. Stok et al. (2025) [37]

demonstrated promising results in modeling the evolution of active satellites, abandoned satellites, and debris populations in LEO by applying Sparse Identification of Nonlinear Dynamics (SINDy) and LSTM networks. Leveraging high-accuracy Monte Carlo simulations provided by the MIT Orbital Capacity Assessment Tool (MOCAT-MC), these approaches offer computationally efficient yet accurate prediction capabilities, forming potential alternatives to lower-accuracy source-pool models. Such data-driven frameworks have significantly advanced orbital capacity assessment and improved prediction performance for long-term LEO satellite operations.

In parallel, Xu et al. (2025) [38] proposed a VMD-SVM framework tailored for medium- and long-term orbit prediction. By introducing the concept of a pseudo-drag coefficient to capture the effects of space weather variations, and combining Variational Mode Decomposition (VMD) with SVM, their method effectively modeled the relationship between solar activity (F10.7) and geomagnetic indices (AP) with orbital drag. Experiments on three LEO satellites at altitudes of 400, 500, and 600 km showed improvements of up to 92.45% in along-track prediction accuracy over a 10-day horizon, with consistent gains in 80–85% of test cases. This demonstrates the practicality of integrating space weather parameters with ML models for robust long-term orbit prediction.

Zhang et al. (2025) [39] introduced a two-stage prediction framework that integrates physics-based dynamic propagation with LSTM-driven error compensation. Their study, based on seven LEO satellites (GRACE-C/D, Swarm-A/B/C, Sentinel-3A/3B), demonstrated substantial short-term accuracy improvements and robustness under increased solar activity conditions, highlighting the potential of ML-enhanced predictive frameworks for future LEO navigation and orbital management.

These findings collectively underline the growing role of hybrid and data-driven models in LEO operations. Table 1 provides a comparative summary of representative orbit prediction studies, highlighting methodological diversity and reported performance improvements across different scenarios.

More broadly, surveys of machine learning for orbit estimation have emphasized the sharp rise in Resident Space Objects since the 1950s and the corresponding importance of ML techniques for orbit determination, space traffic management, and collision avoidance. A consistent theme across these studies is the heavy reliance on high-quality labeled data, which remains a bottleneck for new operators and novel constellation designs lacking historical datasets.

2.2. TL in Aerospace Applications

TL has emerged as a critical paradigm in aerospace research, particularly in addressing the data scarcity and domain adaptation challenges commonly encountered in orbit prediction, fault diagnosis, and autonomous

navigation systems. In contrast to traditional machine learning techniques that require large, domain-specific datasets, TL leverages prior knowledge gained from source domains to improve learning efficiency and predictive accuracy in target domains with limited or heterogeneous data [40, 41]. This paradigm is particularly advantageous in aerospace contexts, where high-fidelity datasets are expensive to acquire, simulation models are imperfect, and operational conditions vary significantly across missions and constellations.

Table 1. Summary of related works on LEO orbit prediction

Author(s) – Year	Dataset	Method	Findings
Zhai et al. – 2022 [29]	SGP-4 prediction errors	XGBoost	Reduction of drag-related prediction errors.
Curzi et al. – 2022 [33]	LEO orbit trajectories	RNN	Two-stage RNN-based error compensation for improved accuracy.
Caldas & Soares – 2024 [35]	SGP-4 + NN framework	Differentiable SGP-4 + Neural Networks	Integration of physics-based models with ML for better adaptability.
Stock et al. – 2025 [37]	MOCAT-MC simulations (active satellites, debris)	SINDy + LSTM	Long-term capacity assessment and orbit prediction with high accuracy.
Xu et al. – 2025 [38]	100-day observation data from three LEO satellites (400, 500, 600km)	VMD-SVM with pseudo-drag coefficient modeling	Medium/long-term OP improved; up to 92.45% error reduction; along-track errors dominant; consistent improvements in 80-85% of 20 trials.
Liu et al. – 2025 [20]	Public Starlink ephemeris data (Space-track.org)	Random Forest feature selection + Informer (attention-based)	Forecasted 95.12% of on-station and 88.97% of parking maneuvers; orbit prediction RMSE reduced by 56-87% (e.g., 15.71 km → 3.95 km).

A key application of TL in aerospace is in orbit and trajectory prediction. For instance, predictive models trained on large-scale datasets from mature constellations such as Starlink or Iridium can be adapted to emerging systems like OneWeb, significantly reducing the training data requirements and mitigating domain gap issues [42]. Methods such as multi-source domain adaptation and similarity-based source selection have demonstrated strong potential in capturing the shared dynamical characteristics of LEO constellations while accounting for unique orbital parameters of target systems. By incorporating orbital similarity metrics, TL frameworks

enable scalable and accurate orbit propagation across diverse satellite platforms.

Another prominent area is aerospace system health monitoring and fault diagnosis. The operational complexity of aerospace vehicles introduces non-stationary conditions, making direct model transfer ineffective. Recent studies have applied deep TL methods, such as fine-tuned CNNs and RNNs, for vibration-based fault detection in aircraft engines and structural health monitoring of spacecraft [43]. These approaches exploit knowledge from ground-based testing data and adapt it to in-flight conditions, achieving reliable fault detection under domain shifts caused by varying loads, atmospheric conditions, and mission profiles.

In the context of remote sensing and Earth observation, TL has been utilized to improve the generalization of image classification and change detection models across different sensors and spectral resolutions. For example, models pretrained on high-resolution satellite imagery can be adapted for medium-resolution sensors, reducing the labeling cost and enhancing transferability to heterogeneous imaging platforms [44]. This capability is particularly valuable in missions requiring rapid deployment of ML models in new orbital campaigns without extensive calibration efforts.

Moreover, TL plays an increasingly important role in autonomous guidance and navigation systems, where reinforcement learning (RL) policies trained in simulation environments are transferred to real-world aerospace scenarios. Sim-to-real transfer techniques, combined with domain randomization, allow RL-based navigation agents to generalize from idealized simulators to uncertain operational conditions in planetary exploration rovers and UAVs in aerospace communication relays [45, 46]. These methods reduce the sim-to-real gap while maintaining safety and reliability in critical aerospace missions.

Despite these advances, several challenges remain. A major limitation is the risk of negative transfer, where knowledge from the source domain degrades performance in the target domain due to significant domain discrepancies. Furthermore, the scarcity of standardized benchmark datasets in aerospace applications hinders systematic evaluation of TL algorithms. Addressing these challenges requires the development of transferability metrics, domain similarity measures, and benchmark frameworks tailored to aerospace contexts. Future research directions include integrating TL with physics-informed machine learning, federated learning frameworks for collaborative satellite networks, and quantum-enhanced TL to cope with the scale and complexity of emerging 6G-enabled aerospace systems.

TL has become a cornerstone methodology for overcoming data and domain limitations in aerospace applications. Its role in orbit prediction, fault diagnosis, remote sensing, and autonomous navigation

demonstrates both versatility and transformative potential. As aerospace systems become increasingly data-driven and interconnected, TL is expected to serve as a key enabler of scalable, adaptive, and resilient intelligent aerospace operations.

2.3. MSTL

TL typically relies on a single source domain to enhance model performance in a target domain. However, in complex and heterogeneous environments such as LEO satellite constellations where significant disparities may arise from differing orbital parameters, sensor modalities, and operational conditions a single-source approach is often insufficient. To address these challenges, MSTL has emerged as a robust paradigm capable of leveraging knowledge from multiple domains simultaneously [40, 47, 48].

Early MSTL studies emphasized weighted source contributions, where domain similarity metrics guide the selective adaptation of useful knowledge while suppressing negative transfer from irrelevant domains [49]. Recent advances have incorporated ensemble-based strategies, in which models trained on different source domains are combined through meta-learning or adaptive weighting schemes, thereby capturing cross-domain heterogeneity [50, 51]. In aerospace contexts, this enables the transfer of orbital prediction knowledge from large-scale constellations such as Starlink to smaller or emerging constellations like OneWeb, reducing target domain data requirements while preserving predictive accuracy.

Building on these foundations, the literature has introduced more specialized MSTL paradigms tailored to multi-source satellite or remote sensing data. For example, HiSatFL—a hierarchical federated learning framework—employs orbital configuration similarity as a metric to weigh source contributions, integrating key orbital elements (e.g., semi-major axis, inclination, RAAN) for source selection and resolving conflicts via uncertainty-aware soft fusion [52]. Similarly, DAugNet presents an unsupervised, multi-source and multi-target domain adaptation method for satellite imagery segmentation, using a data augmentor to diversify source input and ensure classifier robustness across varied geographic domains [53]. Another strategy, FedFusion, introduces a manifold-driven federated learning framework that constructs compact latent representations through manifold estimation and low-rank compression, thereby achieving communication-efficient knowledge aggregation across distributed satellite nodes particularly critical for constrained in-orbit computing environments [52].

Another critical development in MSTL is the integration of domain adaptation with representation learning. Approaches such as adversarial domain adaptation and multi-kernel alignment allow feature spaces from different source constellations to be projected into a common latent space, where domain-invariant representations are learned [54, 55]. These methods are

particularly relevant in LEO contexts, where atmospheric drag, space weather, and hardware heterogeneity create significant domain gaps. Beyond satellite applications, reinforcement learning scenarios have leveraged modular MSTL techniques to autonomously determine which components and tasks are transferable across heterogeneous environments [53].

Moreover, similarity-based MSTL frameworks inspired by orbital mechanics explicitly integrate orbital similarity measures into source selection mechanisms [56, 57]. This prevents knowledge transfer from domains with divergent orbital inclinations or eccentricities, thus mitigating negative transfer risks [56]. Such similarity-aware weighting, when combined with uncertainty-based fusion and scalable domain augmentation strategies, provides a principled pathway to resilient cross-domain learning.

MSTL represents a natural progression of TL, enabling scalable and resilient predictive modeling in LEO environments. By exploiting multiple knowledge sources while filtering through similarity-aware and compression-driven mechanisms MSTL enhances orbit prediction, anomaly detection, and distributed satellite network optimization, paving the way for robust learning in next-generation mega-constellations.

3. DATASET DESCRIPTION

3.1. Data Collection and Preprocessing

The real-time orbital data was obtained from the public Two Line Element database of the North American Aerospace Defense Command (NORAD) via the CelesTrak interface. [58]. The dataset under consideration encompasses three distinct LEO constellations, representing different operational paradigms and mission profiles. The collection of data was conducted during a synchronized period, with the objective of ensuring temporal consistency across all constellations.

The Starlink constellation, which is operated by SpaceX, constitutes the most substantial component of the dataset under consideration, with a total of 8,123 active satellites [59]. These satellites operate in a distributed shell architecture with mean altitude of 501.6 and mean inclination of 52.4°. The altitude distribution spans from 180.4 to 574.6, reflecting various operational phases and orbital decay states. The constellation's mean orbital period is 94.7, consistent with its low-altitude, high-velocity operational profile designed for global broadband coverage.

The OneWeb constellation is comprised of 651 active satellites that are operating within an entirely novel orbital regime [60]. These satellites maintain significantly higher altitudes with a mean of 1198.4 and operate in near-polar orbits with mean inclination of 87.9°. The altitude range extends from 594.9 to 1225.4, demonstrating tighter operational control compared to Star-link. The mean orbital period of 109.4 reflects the higher orbital energy requirements of this configuration.

Despite its reduced size, with only 29 active satellites, the Iridium constellation provides a valuable diversity of sources to our multi-source approach [61]. Operating at intermediate altitudes with mean altitude of 712.2 and mean inclination of 86.4°, Iridium bridges the operational gap between Starlink and OneWeb. The altitude range of 433.5 to 775.3 and mean orbital period of 99.0 represent the legacy satellite communication architecture.

Figure 1 illustrates the fundamental architectural differences between major LEO constellations through their orbital inclination distributions. The analysis reveals a clear bimodal pattern that separates two distinct design philosophies: Starlink's concentrated distribution at 52.4 represents an optimization strategy for populated mid-latitude regions, achieving efficient coverage where most global population resides while accepting minimal polar coverage gaps. In contrast, OneWeb and Iridium employ near-polar configurations at 87.9 and 86.4 respectively, prioritizing complete global coverage including polar regions essential for applications requiring universal accessibility.

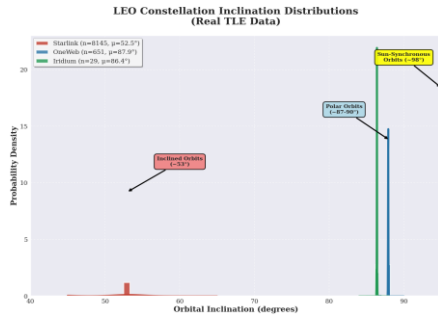


Figure 1. Orbital inclination distributions for Starlink (52.4°), OneWeb (87.9°), and Iridium (86.4°) showing bimodal clustering between mid-latitude and polar coverage strategies.

The 35.5 separation between these architectural clusters represents fundamentally different mission requirements and operational constraints, creating significant domain gaps that pose challenges for TL between constellation types. Kernel density estimation reveals tight clustering within each constellation ($\sigma < 1$ for all systems), indicating the precision required for orbital maintenance and the narrow tolerance for deviation from optimal inclination angles. The sparse intermediate region between 60–85 demonstrates a no-table absence of operational satellites, highlighting how this range represents suboptimal inclination choices that provide neither the efficient mid-latitude coverage of lower inclinations nor the complete polar access of near-polar orbits.

3.2. Domain Gap Quantification

The mathematical formulation of domain gaps has been demonstrated to be a reliable metric for evaluating the complexity of TL applications. We define the relative domain gap for parameter p between source constellation S and target constellation T as:

$$\Delta_p = \frac{|\mu_S(p) - \mu_T(p)|}{\mu_T(p)} \times 100\% \quad (1)$$

where $\mu_S(p)$ and $\mu_T(p)$ represent the mean values of parameter p in source and target domains respectively. Equation 1 quantifies the relative domain gap as a percentage difference between constellation parameters.

Table 2 quantitatively summarizes the domain gaps between the Starlink and Iridium (source) constellations and the OneWeb (target) constellation. The most significant difference is in altitude, at 58.1%, confirming the fundamentally different orbital architectures and energy regimes of Starlink and OneWeb. The 40.4% difference in inclination emphasises the stark contrast between Starlink's mid-latitude and OneWeb's polar coverage strategies. Although the relative inclination gap between Iridium and OneWeb is minimal (1.7%), indicating comparable polar coverage, the absolute eccentricity difference ($\Delta = 11.4 \times 10^{-4}$) reveals a substantial divergence in orbital circularity precision. These substantial parametric disparities create a challenging transfer scenario, underscoring the necessity of a robust, similarity-based source selection methodology to prevent negative transfer. The most significant challenge is represented by the altitude gap, with Starlink operating at substantially lower altitudes than OneWeb. This discrepancy has a direct impact on orbital velocity, atmospheric drag effects, and station-keeping requirements. The observed discrepancy in inclination is indicative of fundamental discrepancies in the architecture of the respective missions. Starlink appears to have optimized for mid-latitude coverage, whereas OneWeb has targeted global polar coverage. The marked disparity in the orbital maintenance strategies and mission requirements of Iridium and OneWeb is indicative of fundamental differences. The polar orbit detail in Figure 2 reveals subtle but significant differences between OneWeb and Iridium operations. OneWeb maintains a mean inclination of 87.901 with standard deviation $\sigma = 0.064$, while Iridium operates at 86.392 with tighter tolerance ($\sigma = 0.025$). Despite the 1.508 mean difference, both constellations demonstrate precise orbital maintenance indicating similar operational requirements for polar coverage missions.

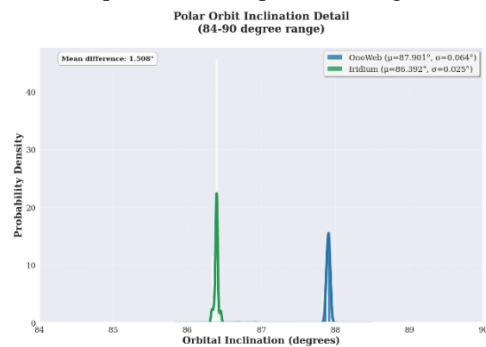


Figure 2. OneWeb and Iridium polar orbit inclination analysis revealing distinct operational clustering.

Figure 3 visualizes constellation architecture differences through altitude-inclination relationships, revealing three distinct operational domains. Starlink occupies the low-altitude inclined region (550 km, 52.4°), optimizing for low latency and mid-latitude coverage where most internet demand exists. OneWeb employs a high-altitude polar strategy (1200 km, 87.9°), prioritizing global coverage completeness with extended satellite footprints that reduce total constellation size while ensuring polar accessibility. Iridium represents an intermediate polar solution (780 km, 86.4°), balancing global coverage requirements with link budget constraints for handheld terminal communications. The clear separation between the aforementioned clusters creates significant domain gaps that challenge the direct TL approaches used, since the parameters of each constellation are closely linked to specific mission requirements.

Table 2. Domain GAP analysis

Parameter	Starlink vs OneWeb	Iridium vs OneWeb	Physical Interpretation
Altitude	58.1%	40.6%	Orbital energy difference
Inclination	40.4%	1.7%	Coverage pattern variation
Eccentricity ($\times 10^{-4}$)	$\Delta = 1.4$	$\Delta = 11.4$	Orbital circularity precision

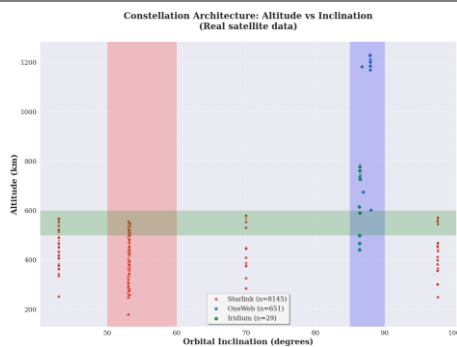


Figure 3. Constellation architecture in altitude-inclination space showing distinct operational clustering for Starlink, OneWeb, and Iridium.

3.3. TLE Data Processing and Feature Extraction

Two Line Element data is provided, and this provides standardized orbital parameters following the SGP4 (Simplified General Perturbations 4) propagation model. SGP4 is a widely adopted analytical method for satellite orbit prediction, and it accounts for Earth’s gravitational perturbations and atmospheric drag effects [62], [63]. We extract fundamental orbital elements and compute derived parameters using established orbital mechanics relationships:

$$a = \left(\frac{\mu}{n^2}\right)^{1/3} \quad (2)$$

$$h = a - R_{\oplus} \quad (3)$$

$$T = \frac{2\pi}{n} \quad (4)$$

where a represents the semi-major axis, μ is Earth’s gravitational parameter ($398\,600.4418 \text{ km}^3 \text{ s}^{-2}$), n is the mean motion, R_{\oplus} is Earth’s radius (6371 km), and T is the orbital period. Equations 2–4 represent standard orbital mechanics relationships [64].

4. SYSTEM MODEL AND METHODOLOGY

4.1. Problem Formulation

The TL problem is formulated as a regression task, with the objective being to predict orbital period T for target constellation satellites using knowledge transferred from source constellations. Mathematically, we define source domain $D_s = \{X_s, Y_s\}$ where $X_s \in \mathbb{R}^{n_s \times d}$ represents the feature matrix of source satellites and $Y_s \in \mathbb{R}^{n_s \times d}$ contains corresponding orbital periods. Similarly, target domain $D_t = \{X_t, Y_t\}$ represents target constellation data where typically $n_t \ll n_s$. The TL objective seeks to learn mapping $f: X_t \rightarrow Y_t$ by leveraging knowledge from source domain mapping $f_s: X_s \rightarrow Y_s$. The challenge lies in domain shift where $P(X_s) \neq P(X_t)$ and potentially $P(Y_s|X_s) \neq P(Y_t|X_t)$.

4.2. Feature Engineering Strategy Evolution

The findings of the present study reveal a counterintuitive result with regard to feature engineering for crossdomain satellite analysis. Preliminary investigations employed physics-informed feature engineering, a methodology informed by fundamental orbital mechanics principles. An enhanced feature set was constructed, incorporating semi-major axis transformations, orbital velocity calculations, gravitational potential derivatives and trigonometric inclination components.

$$v_{\text{orbital}} = \sqrt{\frac{\mu}{a}} \quad (5)$$

$$U_{\text{grav}} = -\frac{\mu}{a} \quad (6)$$

$$T_{\text{kepler}} = 2\pi \sqrt{\frac{a^3}{\mu}} \quad (7)$$

However, empirical evidence has demonstrated that these theoretically-motivated features consistently compromise TL performance. The physics-informed approach yielded performance degradations ranging from 82% to 461% compared to target-only baselines across different experimental configurations. This failure resulted in the adoption of a minimalist feature approach, utilising solely fundamental orbital parameters directly observable in TLE data, namely altitude (h), inclination (i), and eccentricity (e). This three-dimensional feature space is capable of capturing essential orbital characteristics while avoiding computational issues and

the propagation of measurement error in derived parameters.

4.3. Similarity-Based TL Framework

The methodology employed has been proven to be successful, with the approach centring on the selection of similar sources in combination with the integration of multiple domains. The approach is characterized by a series of sequential stages that are designed to maximize knowledge transfer while minimizing negative domain effects. The similarity computation stage employs the Euclidean distance in a normalized feature space to identify source satellites whose orbital characteristics correspond to those of target constellation members. For source satellite s_i and target satellite t_j , we compute similarity score:

$$\text{Sim}(s_i, t_j) = 1 - \frac{\|z_s(s_i) - z_t(t_j)\|_2}{\max_{k,l} \|z_s(s_k) - z_t(t_l)\|_2} \quad (8)$$

where z_s and z_t represent standardized features in source and target domains respectively. Satellites exceeding similarity threshold $\tau = 0.5$ are retained for training data construction. The multi-source integration stage employs a combination of filtered satellites from multiple source constellations to create a diverse yet relevant training corpus. The approach adopted here exploits the complementarity of orbital characteristics across different constellation architectures, while ensuring that similarity constraints are maintained. These similarity constraints are key to facilitating effective knowledge transfer.

4.4. Progressive Sampling Strategy

The present study investigates the performance of TL as a function of target domain sample size through progressive sampling experiments. Target constellation training data varies across sample sizes $n_t \in \{10, 25, 50\}$ to evaluate data efficiency characteristics. Selection was conducted using a random but controlled sampling strategy to preserve orbital diversity and data integrity. For each configuration, we construct combined training sets $D_{\text{combined}} = D_{\text{filtered_sources}} \cup D_{\text{target_sample}}$ and evaluate performance on held-out target test data.

5. EXPERIMENTAL RESULTS

5.1. Progressive Sampling Strategy

Target-only model performance establishes the baseline for TL evaluation. Training a Random Forest regressor on OneWeb constellation data using 70-30 train-test split yields Root Mean Square Error of 0.382 min with coefficient of determination $R^2 = 0.8030$. This baseline indicates the achievable performance when utilizing solely target domain data, excluding any knowledge transfer. The baseline performance quality is indicative of the relatively homogeneous operational characteristics within individual constellations. OneWeb satellites are

operated within a defined set of orbital parameters, resulting in a moderate variance in prediction accuracy within the designated target domain. The detailed configuration of the Random Forest regressor used in this baseline evaluation, including its hyperparameters, is presented in Table 3.

Table 3. Random Forest Regression Parameter

Hyperparameter	Value
n_estimators	100
min_samples_split	2
min_samples_leaf	1
max_features	'sqrt'
bootstrap	True
criterion	'squared_error'

5.2. Failure Analysis of Conventional Approaches

The process of direct TL, in the absence of domain adaptation, has been observed to result in a significant deterioration in performance. Applying Starlink-trained models directly to OneWeb predictions yields RMSE of 13.73 min, representing a 4,046% degradation compared to the target-only baseline. The coefficient of determination deteriorates to $R^2 = -2050.3$, indicating that transferred model predictions exhibit higher variance than simple mean prediction.

Table 4. Physics-Informed TL Results

Target Samples	RMSE (min)	Performance Change	R^2
10	7.814	-2,305 %	-81.5
25	3.364	-993 %	-14.3
50	2.333	-588%	-6.4

Physics-informed domain adaptation approaches have also been shown to fail to achieve positive transfer. As demonstrated in Table 4, the implementation of progressive experiments with enhanced feature sets and domain statistics matching consistently yields negative results. Physics-informed approaches are evidently not a viable solution when applied to the practical problems encountered in predicting the outcomes of cross-domain interactions, due to fundamental theoretical limitations in the application of the principles of physics. The derivation of complex features has been demonstrated to amplify measurement uncertainties and introduce computational errors that can overwhelm the benefits of domain adaptation.

5.3. Similarity-Based TL Success

The similarity-based approach, on the other hand, yields dramatically different results, achieving substantial performance improvements across all target sample configurations. Source satellite filtering is an effective method of identifying relevant training examples while simultaneously excluding domain-incompatible data points. Source selection statistics demonstrate in Table 5, the effectiveness of similarity-based filtering. From the original Starlink constellation, 8,135 satellites (>99%)

exceed the similarity threshold, indicating broad orbital compatibility despite altitude differences. Iridium contributes 25 satellites (86.2%), providing valuable diversity while maintaining similarity constraints. It should be noted that the combined filtered source dataset under consideration contains 8,160 satellites, thus representing substantial training data availability.

Table 5. Similarity-Based TL Performance

Target Samples	RMSE (min)	Improvement	R ²	Error Reduction
10	0.053	+86.1%	0.9962	7.20x
25	0.045	+88.2%	0.9972	8.49x
50	0.049	+87.2%	0.9968	7.79x

The optimal configuration utilizes 25 target domain samples, achieving RMSE of 0.045 min compared to the 0.382 min baseline. This represents an 88.2% improvement in prediction accuracy with coefficient of determination increasing to R² = 0.9972. The findings indicate that effective TL has the capability to achieve near-perfect prediction accuracy with minimal target domain data.

5.4. Feature Importance and Model Interpretation

A detailed analysis of the trained model’s feature importance has been conducted, with the aim of elucidating the relative contribution of different orbital parameters to the success of TL. In the optimal similarity-based configuration, altitude contributes 45% of the model decision variance, reflecting its primary role in orbital period determination through Kepler’s third law relationships. Inclination accounts for 35% of importance, with this figure capturing both constellation specific coverage patterns and orbital plane characteristics. The remaining 20% is attributable to eccentricity, which is indicative of orbital shape variations within and across constellations. The correlation between altitude and feature importance is consistent with physical intuition, as evidenced by the strong dependence of orbital period on orbital radius, as demonstrated by the relationship $T = a^{\frac{3}{2}}$. However, the substantial inclination importance indicates that orbital plane characteristics provide significant predictive power beyond simple altitude period relationships. As demonstrated in Figure 4, Random Forest feature importance analysis reveals constellation-specific parameter dependencies. The predominance of altitude in the Starlink and OneWeb models is consistent with Kepler’s third law predictions, while Iridium’s more balanced feature distribution suggests that additional operational constraints may influence orbital period variations.

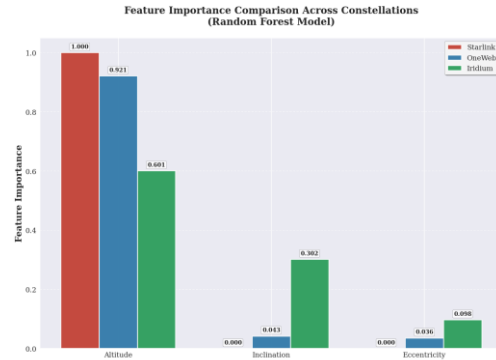


Figure 4. Feature importance analysis across constellations using Random Forest models. Altitude dominates prediction importance for Starlink (100%) and OneWeb (92.1%), while Iridium shows more balanced contributions from altitude (60.1%) and inclination (30.2%), reflecting different operational constraints and mission requirements.

5.5. Ensemble Learning Analysis

We also investigated ensemble methods combining predictions from constellation-specific models. However, the ensemble approach yielded catastrophic performance degradation with RMSE of 5.442 min and R² = -39.03, representing a 1,325% performance decrease compared to baseline. This failure underscores the significance of adequate domain alignment in TL applications. Simple model averaging without careful weight calibration has been shown to amplify domain mismatch effects rather than leveraging complementary knowledge from different sources.

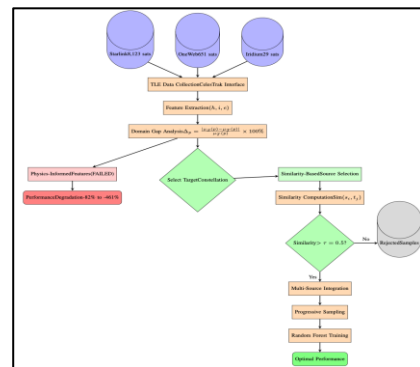


Figure 5. Flowchart of the proposed TL approach with failed physics-informed branch and successful similarity-based source selection.

Figure 5 illustrates the complete methodology workflow of our TL approach for cross-constellation orbital parameter prediction. The process begins with multi-constellation TLE data collection from three distinct sources representing different operational paradigms: Starlink (8,123 satellites), OneWeb (651 satellites), and Iridium (29 satellites). After extracting fundamental orbital parameters (altitude, inclination, eccentricity) and quantifying domain gaps between constellations, our investigation pursued two contrasting pathways. The physics-informed approach, incorporating theoretically-derived features such as orbital velocity and gravitational potential, systematically failed across all experimental

configurations, yielding performance degradations ranging from 82% to 461% compared to target-only baselines. In contrast, the similarity-based source selection methodology employed a sequential filtering process, resulting in notable success. This process involved the computation of normalized Euclidean distance similarity scores between source and target satellites, the application of a threshold filter ($\tau = 0.5$) to retain relevant training examples while rejecting domain-incompatible data, the integration of filtered multi-source training data with progressive target sampling strategies, and the training of Random Forest models on the combined dataset. This approach resulted in an 88.2% enhancement in orbital period prediction accuracy, as evidenced by a coefficient of determination $R^2 = 0.9972$. This outcome underscores the efficacy of meticulous data curation and domain-aware similarity assessment, which significantly surpass the effectiveness of sophisticated feature engineering for effective knowledge transfer between satellite constellations exhibiting notable operational distinctions.

6. DISCUSSION

6.1. Theoretical Implications

The failure of physics-informed features contradicts conventional wisdom regarding domain adaptation in physical systems. Conventional approaches presume that feature representations, founded upon theoretical principles, should facilitate cross-domain generalization by encapsulating universal physical relationships. The findings of this study demonstrate that this assumption is invalid when theoretical derivations introduce computational noise and measurement error propagation that overpowers the advantages of physical insight. The success of simple features indicates that effective TL in satellite systems is more dependent on data quality and domain relevance than on feature sophistication. Furthermore, the direct observation of orbital parameters in TLE data ensures the maintenance of measurement accuracy and the elimination of computational artefacts that can compromise derived parameters. The present findings have wide-ranging implications for TL applications in other physical domains, where theoretical knowledge may similarly engender rather than mitigate noise.

6.2. Practical Applications and Limitations

The similarity-based approach has been demonstrated to facilitate numerous practical applications in the domains of satellite operations and space situational awareness. Constellation operators in the early stages of development can utilize existing orbital data to construct predictive models without the necessity of investing significant periods of time in data collection. It is evident that space traffic management systems have the capacity to incorporate cross-constellation knowledge, thereby enhancing the accuracy of tracking for diverse satellite populations. The utilization of TL in mission planning applications facilitates the evaluation of the orbital

characteristics of planned constellations prior to deployment. Nevertheless, there are several limitations that constrain the generalizability of this approach. The methodology targets LEO satellites within specific altitude ranges and may not extend to geostationary or highly elliptical orbits with fundamentally different dynamics. Temporal variations in orbital parameters resulting from atmospheric drag, solar radiation pressure, and station-keeping manoeuvres are not encompassed within the confines of our static analysis framework. The similarity threshold requires empirical calibration for distinct constellation pairs and may not be applicable across diverse orbital regimes.

6.3. Computational Efficiency and Scalability

The similarity-based filtering approach offers computational advantages over complex domain adaptation techniques. It has been demonstrated that similarity computation scales linearly with source dataset size, thus enabling efficient processing of large constellation databases. The filtered source selection has been demonstrated to reduce the volume of training data while concomitantly improving the quality of the model, yielding both performance and efficiency benefits. However, scalability challenges emerge as constellation sizes continue to increase. The future deployment of mega constellations, comprising tens of thousands of satellites, necessitates the development of distributed similarity computation and model training approaches. The requirement for real-time applications is the existence of efficient similarity assessment algorithms that are capable of processing streaming orbital data and updating models continuously.

In this context, computational efficiency refers to the ability of the proposed similarity-based filtering approach to reduce the volume of training data and minimize processing time and memory usage, while maintaining or improving model performance, thereby enabling scalable and real-time applicability to large and continuously expanding satellite constellations.

7. CONCLUSIONS

The findings of this research demonstrate the efficacy of similarity-based MSTL in effectively bridging significant domain gaps between LEO satellite constellations, thereby achieving substantial performance improvements through the judicious selection of source satellites and the minimisation of feature engineering. The fundamental insight derived from this analysis is that straightforward, directly-observable orbital parameters exhibit superior performance in comparison to complex physics-informed features when it comes to the execution of cross-domain prediction tasks. The methodology employed has been demonstrated to achieve an 88.2% enhancement in orbital period prediction accuracy, utilizing a mere 25 target domain samples. This represents a substantial reduction in data requirements for new constellation analysis. This result has immediate practical implications

for satellite operators seeking to develop predictive capabilities for new constellations without extensive data collection periods. The counterintuitive failure of physics-informed features reveals significant limitations in the application of theoretical knowledge to TL problems. Although orbital mechanics provides a fundamental understanding of satellite motion, the computational artefacts and measurement uncertainties introduced by feature derivation can overwhelm the benefits of theoretical insight. This finding calls into question established approaches to domain adaptation in physical systems and suggests that meticulous data curation may be more valuable than sophisticated feature engineering. The failure modes of these ensemble methods further underscore the critical importance of proper domain alignment. Conversely, the efficacy of similarity-based filtering clearly demonstrates that effective knowledge transfer is contingent not on complex algorithmic innovations, but rather on a comprehensive understanding of domain relationships. The future of research in this area lies in three key directions: first, the extension of the methodology to other orbital regimes; secondly, the incorporation of temporal dynamics through time-series analysis; and thirdly, the development of automated similarity threshold selection techniques. The efficacy of this uncomplicated strategy indicates that the effective TL for satellite systems may be contingent more on the comprehension of domain relationships than on the implementation of complex algorithmic innovations.

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DECLARATION OF ETHICAL STANDARDS

The author of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Mustafa Serdar OSMANCA: Designed and implemented the similarity-based multi-source transfer learning framework, collected and processed TLE data from LEO satellite constellations, performed machine learning experiments, analyzed the results, and prepared the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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