ORACLE: QoS-aware Online Service Provisioning in Non-Terrestrial Networks with Safe Transfer Learning

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IEEE INFOCOM 2025 - IEEE Conference on Computer Communications | 979-8-3315-4305-1/25/$31.00 ©2025 IEEE | DOI: 10.1109/INFOCOM55648.2025.11044634

***Abstract*—Emerging mega-constellations consisting of numerous Low Earth Orbit (LEO) satellites are actively providing pervasive Internet services worldwide, which are usually considered crucial components of Non-Terrestrial Networks (NTNs). However, the high mobility and limited coverage of LEO satellites can introduce frequent handovers, causing network interruptions and degrading Quality of Service (QoS). While many efforts have been made to alleviate the impact of handovers on service provisioning from NTNs, they usually assume channel conditions are pre-determined and remain unchanged as satellites move, which is different from real situations and thus may experience significant performance degradation compared to theoretical analysis. In this paper, we propose ORACLE to promise QoS-aware service provisioning in NTNs under dynamic channel conditions. Specifically, we mathematically formulate a channel model to characterize channel conditions in NTNs and develop a QoS maximization problem considering handover frequency and transmission capacity. To accommodate the dynamic nature of NTNs, we introduce a Model Predictive Control (MPC)-based controller to predict future dynamic network status and generate control strategies correspondingly, and leverage Digital Twin (DT) for real-time network status consideration. For higher efficiency, we further employ Generative Artificial Intelligence (GAI) with a safe transfer learning-based framework to enhance model adaptivity to environmental uncertainties and ensure feasible control decisions in real-world NTNs. Extensive simulation results under real-world constellation demonstrate that ORACLE can enhance up to 3× QoS during service provisioning compared with baseline approaches.**

I. INTRODUCTION

Utilizing mega-constellations consisting of numerous Low Earth Orbit (LEO) satellites in space to build Non-Terrestrial Networks (NTNs) is viewed as a promising solution for providing pervasive Internet services worldwide. Existing LEO mega-constellations (*e.g.*, SpaceX's Starlink [1], OneWeb [2], and Amazon's Project Kuiper [3]) usually operate as Internet Service Providers (ISPs) and possess the ability to furnish pervasive Internet services across the globe [4], specifically in remote regions. These LEO mega-constellations play an integral role in developing future networks by offering ubiquitous and low-latency on-demand network services [5], [6]. Commencing with Release 15, the 3rd Generation Partnership Project (3GPP) has initiated research on NTNs to formulate standards and protocols that facilitate the amalgamation of satellite communications with terrestrial 5G networks [7], [8]. In addition, recent 6G standards also emphasize the NTN as a fundamental component of the entire communication system since it bridges the gap between traditional terrestrial networks and new space-based communications [9]. NTNs extend beyond Earth's surface, providing global or regional connectivity, and are expected to be a native component of 6G systems, offering increased performance and service provisioning capabilities [10].

Unlike traditional terrestrial networks consisting of ground facilities in fixed locations, LEO satellites are essential components for User Terminals (UTs) access to NTNs, moving at extremely high velocity in Space [11]. These satellites typically operate at relatively low orbits compared to Geostationary Earth Orbit (GEO) satellites, resulting in limited coverage of ground UTs [12]. Thus, due to the high mobility and limited coverage of LEO satellites, the connection between each satellite and UT can only last for a few minutes in most terrestrial locations, and thus frequent handover between the satellite and UT will occur [13], [14]. Such handover can cause short but non-negligible network interruptions, severely decreasing users' Quality of Service (QoS) [15]. Specifically, substantial latency and possible data transmission disruptions can be introduced since additional steps and procedures are required during handovers [7]. According to recent measurement work on Starlink's performance, the handover can lead to at most 80% network throughput degradation [16]. As a result, the influence of NTNs' dynamics is considerable, significantly undermining the normal service provisioning for users [17].

Many efforts have been made to mitigate the impact of handovers on network performance in various aspects, including maximizing network throughput [18], [19], [20], [21], [22], minimizing queueing delay [23], maintaining load balancing [24], improving random access efficiency [25], and increasing service time [26], [27], [28]. These works are usually designed under the assumption that Channel State Information (CSI) status can be pre-determined and remains unchanged as the satellite moves. Nevertheless, this assumption is far different from real situations and cannot satisfy the dynamic nature of the communication environment caused by the high mobility of NTNs. Due to the relatively long communication distance and harsh radiation environment in Space, the communication channel between the satellite and UT is susceptible to attenuation, obstructions, and weather variations [12]. Such vulnerabilities in the communication channel can trigger significant CSI fluctuations [29]. Thus, existing works may suffer from significant performance degradation compared to theoretical performance when applied to real-world NTNs. Recently, an offline Multi-Agent Deep Reinforcement Learning (MADRL) method has been proposed and tries to consider the dynamic

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channel condition [30]. However, accurately predicting long-term CSI status using an offline method may be infeasible since Out-of-Distribution (OOD) issues may occur [31], especially under highly dynamic NTN scenarios. Therefore, an online method that can perfectly grasp the high mobility of NTNs for QoS-aware service provisioning is necessary.

To this end, in this paper, we propose N**O**n-Terrestrial Netwo**R**ks-based Qu**A**lity of Servi**C**e-aware On**L**ine S**E**rvice Provisioning (ORACLE), which aims to maintain satisfactory QoS for users in NTNs under dynamic channel conditions. We mathematically formulate a channel model to characterize the dynamic CSI in NTNs. Further, a QoS maximization problem that jointly considers handover frequency and transmission capacity is formulated to maintain the QoS during the service provisioning in NTNs, and the definition of the QoS is detailed in Section IV-B. To capture the dynamic characteristics of NTNs due to their high mobility, we introduce a Model Predictive Control (MPC)-based dynamic controller to handle the fluctuating network status in NTNs. Given that predicting long-term further network status for decision-making is rendered infeasible, we propose to leverage Digital Twin (DT) for considering real-time network status. Furthermore, an extend-MPC algorithm is then proposed to use historical network information to predict short-term future network status. However, solving the formulated problem may be challenging since it is a non-convex problem. To tackle this issue, we implement Generative Artificial Intelligence (GAI) to efficiently solve this problem. Specifically, we design a safe transfer learning-based framework to improve the adaptivity of the training model to the environmental uncertainty of NTNs and ensure the calculated output control decisions are feasible to implement in real-world NTNs.

The contributions of this paper are summarized as follows:

- We identify that existing works may experience a significant performance gap between theoretical analysis and real-world performance since they usually neglect the dynamic channel conditions in NTNs.
- We design an MPC-based dynamic controller for predicting future channel status to accommodate the dynamic nature of NTNs and leverage DT to update real-time network status for making timely decisions by the controller.
- To efficiently generate control decisions, we introduce transfer learning to quickly learn and adjust to dynamic and uncertain environments. Safe learning is further implemented to ensure the generated control decisions are feasible for real-world implementation.
- Extensive simulation results under real-world constellation demonstrate that our proposed ORACLE can enhance up to 3× QoS during service provisioning compared with baseline solutions.

The rest of the paper is organized as follows. Section II provides background and motivation of this paper. Section III presents a comprehensive overview of ORACLE. Section IV mathematically formulates the channel model and the QoS maximization problem, which jointly considers handover frequency and transmission capacity. In Section V, we introduce the details of online service provision, including an MPC-based online controller, an extended-MPC algorithm, and a safe transfer learning-based framework. The performance of ORACLE is evaluated and analyzed in Section VI. Section VII explores existing works related to this research field. Finally, in Section VIII, we summarize our key findings and conclusions.

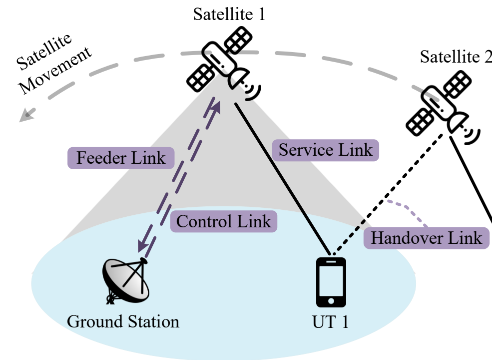

Fig. 1: Service Provisioning in NTNs.

II. BACKGROUND AND MOTIVATION

In this section, we introduce the background of NTNs, elaborate on the reason behind QoS degradation caused by the high mobility of satellites, and analyze the limitations of existing works.

A. High Mobility of Non-Terrestrial Networks

Unlike terrestrial networks consisting of fixed ground infrastructures [32], LEO satellites serve as essential elements for UTs access to the LEO satellite network, moving at high velocities and often at considerable distances from terrestrial networks [30]. Specifically, LEO satellites can reach speeds of approximately 27,000 km/hour (*i.e.*, 7.5 km/s) [11] and typically operate at relatively low orbits (*e.g.*, altitudes below 2,000 km), resulting in coverage of ground users for merely a few minutes in most terrestrial locations [33]. Consequently, connections between UTs and satellites exhibit highly dynamic properties, necessitating frequent handovers during the user's service duration. Fig. 1 is an example to show the high mobility and limited coverage of LEO satellites. The service link between Satellite_1 and UT_1 will become unavailable as the satellite moves. When this happens, a handover will occur, and Satellite_2 will continuously provide the service for UT_1. Moreover, the number of visible satellites for ground UTs increases substantially in LEO mega-constellations, leading to more frequent and complex satellite handovers [34].

B. User-Satellite Handovers Severely Decrease Users' QoS

We further delve into the details of user-satellite handovers and their potential impact on users' QoS. Take the Starlink constellation as an example. Theoretically, the Starlink constellation can cover a ground facility for less than three minutes, given its coverage radius of approximately 580 km [16]. However, practical factors such as Line-of-Sight (LoS)

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obstructions, weak signal strength, or dynamic weather conditions may necessitate frequent handovers for UTs. In the case of Starlink, the network needs to contemplate handover strategies every 15 seconds [13]. For each handover, considering that UTs typically possess a single antenna, the terminal must first disconnect from the current ingress satellite before establishing a connection with a new one. Such handovers can result in short but non-negligible network interruptions. When handovers take place between these two networks (*i.e.*, terrestrial networks and NTNs), additional steps and procedures, such as altering device settings or transitioning to a different network, are required. These complexities heighten the operational demands on the UT, contributing to substantial latency and possible data transmission disruptions. Experimental measurements on the existing Starlink constellation demonstrate that handovers can lead to severe throughput degradation [16]. The influence of these dynamics on the network is considerable, significantly undermining users' QoS, particularly for latency-sensitive applications [17].

C. Channel State Information Varies in Real Scenarios

In addition to handovers, the CSI between UTs and satellites varies significantly, which can also affect the user's QoS. CSI discloses the channel conditions of communication links, and is usually evaluated based on received known information at the receiver end and is relayed back to the transmitter for future transmission [35]. For higher capacity, the majority of LEO satellites operate in higher frequencies (*e.g.*, Ku/Ka bands), which makes maintaining QoS a more challenging task. This complexity predominantly arises due to the augmentation of tropospheric propagation impairments, which include both the amplification of attenuation magnitude and the variability of fading, compared with lower frequencies [36]. Moreover, these higher frequencies are also susceptible to obstructions (*e.g.*, occlusion or blocked by trees and buildings) and weather variations in lower orbits [12]. Such vulnerabilities in the communication channel can trigger significant CSI fluctuations [29]. Thus, to guarantee various QoS requirements of users, the dynamic CSI between UTs and satellites should also be considered in NTNs.

D. Solutions, Limitations, and Challenges

Existing Works. As mentioned earlier, many existing works propose to mitigate the impact of user-satellite handovers on the service provisioning of LEO constellations with different objectives, including maximizing network throughput [18], [19], [20], [21], minimizing queueing delay [23], maintaining load balancing [24], improving random access efficiency [25], and increasing service time [26], [27]. However, these existing handover schemes for NTNs are designed based on predetermined static CSI status. They usually assume the CSI remains unchanged as the satellite moves, which is far different from real situations and cannot satisfy the dynamic feature of the communication environment caused by the mobility of LEO satellites. Users may experience significant QoS degradation compared to the performance under theoretical analysis by utilizing the static CSI status to decide on a handover strategy.

Challenges. Due to the dynamic channel conditions, service providers of NTNs need to predict the fluctuating CSI status and adjust the handover policy based on this real-world channel status for QoS-aware service provisioning. Typically, CSI estimation methods predict future CSI status and accommodate potential CSI variations. However, while the routes of satellites are predictable in the short term by using methods like Two-Line Element (TLE) data, the CSI status is determined by many other important factors (*e.g.*, attenuation, obstructions, and weather conditions). Thus, CSI variations are challenging to predict and require more complex techniques [37].

Unlike terrestrial networks, LEO satellites move at a really fast speed, traveling different areas with various channel conditions, making CSI status estimation more complex. Thus, existing CSI estimation techniques are designed for terrestrial networks and thus may not be suitable for NTNs. Specifically, they may no longer accurately grasp the highly dynamic feature of the environment and depict the actual channel state, thereby impacting the estimation performance [38]. It is also challenging to account for dynamic CSI status in NTNs, as the vast number of satellites will substantially escalate the signaling overhead and computational complexity associated with acquiring and estimating CSI status.

To this end, existing work [30] tries to consider the dynamic channel condition in determining the handover strategy for NTNs by using an offline MADRL method. However, accurately predicting long-term CSI status using the offline method is rendered infeasible since it may not capture the dynamic characteristics of NTNs, and OOD issues may occur [31]. Moreover, the CSI status is highly relevant to that before the handover decision moment and affects that after the decision moment. It is difficult to make good handover decisions by just utilizing the predicted CSI status at the handover moment as a reference [39]. Therefore, an online method that can perfectly grasp the high mobility of NTNs to decide handovers for QoS-aware service provisioning is necessary.

III. Design Overview

In this section, we detail our QoS-aware online service provisioning approach, namely ORACLE, as shown in Fig. 2. The three main steps of ORACLEare presented as follows.

Step 1: Offline Training Process. The first step involves the offline training process, where a controller is trained by the offline dataset. This offline dataset could be generated according to the historical NTN network status (if available) or from parametric modeling. The main purpose of the offline training process is to provide the controller with a foundational understanding of online service provisioning before it is fine-tuned for specific tasks. In particular, pre-training allows the model to learn general temporal-spatial features from a large offline dataset. This includes understanding the CSI, weather conditions, and relative positions between UTs and satellites. By training on a diverse and extensive dataset, the model can acquire knowledge that can be transferred to various

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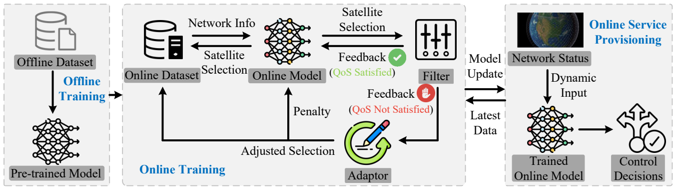

Fig. 2: Structure of ORACLE.

conditions. This reduces the amount of task-specific data needed for fine-tuning. Once a model is pre-trained, it can be fine-tuned for different tasks with relatively less data and computational power, making the online training process more efficient.

Step 2: Online Training with Few-Shot Dataset. After the offline training process, the pre-trained model is obtained. The second step is online training with a few-shot dataset. In particular, we froze the foundation modules in the pre-trained model and replaced the input/output layers according to the current task. Then, we fine-tune the pre-trained model with the online dataset generated by the historical network status and service provisioning tasks. This online training customizes the pre-trained model to perform well on a specific task. This adaptation helps the model learn the specific patterns of the target online service provisioning task. Moreover, online training allows continuous learning, enabling the model to stay up-to-date with new network status and user deployment. This is particularly important in NTNs where network status evolves over time.

Step 3: Deployment with DT. Finally, we deploy the fine-tuned model for online service provisioning in NTNs by leveraging DT. Unlike parametric simulations that generate or predict network status based on parametric modeling, DT facilitates dynamic adjustment of control decisions according to real-time network status. Specifically, in each time frame, the Ground Station (GS) collects the current network status and predicts the future network status over a short horizon. The controller then determines the short horizon based on the prediction results. A safe learning adaptor ensures that decisions made within this short horizon satisfy the QoS constraints. The controller's decision for the next frame is extracted from these short-horizon decisions and communicated to the NTNs.

In summary, our proposed ORACLE strategically combines MPC, DT, safe learning, and transfer learning to ensure the QoS of online service provisioning in NTNs. Note that our ORACLE is feasible to implement since it can be incorporated into the existing global controller, which current operational satellite constellations use to collect network information periodically [13]. The detailed design principles and structure of each step will be described in the following sections.

IV. Problem Formulation

In this section, we first formulate a mathematical model to characterize the scenario where a certain region is served by NTNs. The channel model between the satellite and UTs is described in detail. Further, a QoS maximization problem is formulated with practical constraints on NTN service capacities.

A. Channel Model

We consider a LEO mega-constellation, which consists of M LEO satellites indexed by $\mathcal{M} = \{1, \ldots, M\}$ and K mobile UTs indexed by $\mathcal{K} = \{1, \ldots, K\}$. Our primary focus is on the mathematical modeling of uplink communications, with the understanding that the downlink channel can be modeled in a similar fashion. As illustrated in Fig. 1, we assume that all the UTs access the LEO satellites for data service via an RF link during time period $[0, T]$, and the channel conditions remain constant throughout each discrete time frame t.

If a data stream, $s_k(t)$, is sent from UT-k to LEO-m at time frame t, the received signal could be expressed as

$$y_{k,m}(t) = h_{k,m}^H(t) P_k s_k(t) + n_k. \tag{1}$$

Here, P_k is the power burget of the UT, $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ signifies the Additive White Gaussian Noise (AWGN) at UT-k, and $h_{k,m}^H(t)$ represents the channel coefficient. Due to the considerable mobility of LEO satellites, the satellite channels experience both Doppler shift and delay effects [40], [41]. However, these effects can be anticipated and mitigated through meticulous time and frequency synchronizations [42], [43]. In this context, the channel coefficient can be calculated as

$$h_{k,m}(t) = \sqrt{\varpi_{k,m}(t) G^l G^{k,m} A_{k,m}(t)} \delta_{k,m}. \tag{2}$$

Here, G^l denotes the satellite's antenna gain, G^v signifies the receiver's antenna gain, $\varpi_{k,m}(t)$ corresponds to the free space loss, $A_m(t)$ is the atmospheric fading gain, and δ_k indicates the Shadowed-Rician large-scale fading. Following the formulation from [44], [45], [46], the free space loss $\varpi_{k,m}(t)$ is determined by

$$\varpi_{k,m}(t) = \left(\frac{c}{4\pi d_{k,m}(t) f_c} \right)^2, \tag{3}$$

where c is the speed of light, f_c is the carrier frequency and $d_{k,m}(t)$ is the relative distance between the UT and LEO satellite, which is expressed as

$$d_{k,m}(t) = \| \boldsymbol{l}_m(t) - \boldsymbol{l}_k(t) \|. \tag{4}$$

Here, $\boldsymbol{l}_{m/k}(t)$ are the dynamic location of the satellite/UT. Moreover, the atmospheric fading gain can be represented as

$$A_{k,m}(t) = 10^{-\frac{3\chi_m(t)}{10 \sin[\varphi_{k,m}(t)]}}, \tag{5}$$

where $\chi_m(t)$ is the attenuation of the weather condition and $\varphi_{k,m}(t)$ is the angle of elevation, which can be expressed as

$$\sin[\varphi_{k,m}(t)] = \frac{l_m^{al}(t) - l_k^{al}(t)}{d_{k,m}(t)}. \tag{6}$$

Here, $l_{m/k}^{al}(t)$ is the altitude of the satellite/UT. Furthermore, the Shadowed-Rician distribution is represented by a tuple $(\Omega_{k,m}, b_{k,m}, q_{k,m})$, where $2b_{k,m}$ represents the average power of the scatter, $q_{k,m}$ denotes the shape parameter of the

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Nakagami-m distribution and $\Omega_{k,m}$ stands for the average power of the LoS component. According to [47], we can express the Probability Density Function (PDF) and the Cumulative Distribution Function (CDF) of the channel fading factor $|\delta_{k,m}|^2$ as

$$f_{|\delta_{k,m}|^2}(x) = \alpha_{k,m} e^{-\beta_{k,m} x} {}_1F_1(q_{k,m}; 1; \delta_{k,m} x), \quad (7)$$

$$F_{|\delta_{k,m}|^2}(x) = \alpha_{k,m} \sum_{i=0}^{\infty} \frac{(q_{k,m})_i \delta_{k,m}^i}{(i!)^2 \beta_{k,m}^{i+1}} \gamma(i+1, \beta_{k,m} x). \quad (8)$$

The Signal-to-Noise Ratio (SNR) of the uplink communication can be calculated as

$$\gamma_{k,m}(t) = \frac{P_k |h_{k,m}^H(t)|^2}{\sigma_{k,m}^2}. \quad (9)$$

where P_b is the power budget. To guarantee successful decoding by the satellite-m, the achievable rates of s_k is bounded by

$$R_{k,m}(t) = B \log_2 \left(1 + \gamma_{k,m}(t)\right). \quad (10)$$

Here, B is the bandwidth of the uplink channel.

B. Quality of Service Maximization

Building upon the channel model mentioned above, we consider the QoS of service provisioning in NTNs. We assume K UTs access the Internet via M LEO satellites during T time frames. As illustrated in Fig. 1, we assume that the GS collects all the network status, including CSI, weather conditions, user deployment, and satellites' positions and capacities, via feeder link. GS then calculates the control decision for service provisioning and sends it to NTNs via the control link. Our goal is to maximize the QoS of the service provisioning dynamically during the T time frames, which consist of two aspects: the handover frequency and the transmission capacity.

In particular, we assume the historical channel coefficients, $\mathcal{H}_{k,m}^{\varsigma}(t) \triangleq \{\boldsymbol{h}_{k,m}(t-1), \ldots, \boldsymbol{h}_{k,m}(t-T_0)\}$, during the last T_0 time frames is available to GS, then the ergodic user rate between UT-k and LEO-m can be calculated as

$$\hat{R}_{k,n}(t) = \mathbb{E}_{\boldsymbol{h}_{k,m}(t)|\mathcal{H}_{k,m}^{\varsigma}(t)} \left(R_{k,m}(t)\right). \quad (11)$$

By leveraging this ergodic user rate, we formulate the QoS maximization problem for service provisioning in NTNs as

$$\textbf{P0}: \max_{\mathcal{X}} \quad \lambda \sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{0\le t\le T} x_{k,m}(t) \hat{R}_{k,m}(t) \Delta t + (\lambda - 1) \sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{1\le t\le T} |x_{k,m}(t) - x_{k,m}(t-1)|/2 \quad (12a)$$

$$\text{s.t.} \quad \sum_{m\in\mathcal{M}} x_{k,m}(t) \le 1, \quad \forall t \in [0,T], \forall k \in \mathcal{K} \quad (12b)$$

$$\hat{R}_{k,m}(t) \ge x_{k,m}(t) R_k^{\text{th}}(t), \quad \forall t \in [0,T], \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (12c)$$

$$\sum_{k\in\mathcal{K}} \hat{R}_{k,m}(t) x_{k,m}(t) \le C_k, \quad \forall t \in [0,T], \forall m \in \mathcal{M} \quad (12d)$$

Here, we denote the satellite selection of UT k in time frame t by $\mathcal{X} = \{x_{1,1}(0), \ldots, x_{k,m}(t), \ldots, x_{K,M}(T)\}$, where $x_{k,m}(t) \in \{0,1\}$. To be more specific, it implies $x_{k,m}(t) = 1$ that UT-k chooses satellite-m for service provisioning in time frame t and $x_{k,m}(t) = 0$ represents that UT-k does not choose satellite-m for service provisioning in time frame t. In this context, $|x_{k,m}(t) - x_{k,m}(t-1)| = 1$ implies handover event, and $|x_{k,m}(t) - x_{k,m}(t-1)| = 0$ represents that UT-k does not change satellite-m for service provisioning in time frame t. Therefore, $\sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{1\le t\le T} |x_{k,m}(t) - x_{k,m}(t-1)|/2$ is the total numbers of handover events during time frame T, $\sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} x_{k,m}(t) \hat{R}_{k,m}(t)$ is the transmission rate for service provisioning of UT-k in time frame t, and $\sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{0\le t\le T} x_{k,m}(t) \hat{R}_{k,m}(t) \Delta t$ is the total transmission capacity during time frame T. We also introduce a weighting factor $\lambda \in [0,1]$ to balance the enhancement of the transmission capacity and the number of handover events. Here, $\lambda = 0$ means only the transmission capacity is considered for QoS, and $\lambda = 1$ means the QoS only considers handovers. Thus, the overall QoS can be formulated as (12a). We aim to find the optimal strategy $\mathcal{X}^*$ to achieve maximum QoS under the dynamic network status.

Furthermore, (12b) constrains the UT-k can only select one satellite for service provisioning at each time frame t. (12c) guarantees that the transmission rate of UT-k satisfies the minimum transmission requirement for the service, $R_k^{\text{th}}(t)$. In particular, according to (10), $\hat{R}_{k,m}(t) \ge x_{k,m}(t) R_k^{\text{th}}(t) = 0$ always holds when $x_{k,m}(t) = 0$. And, when $x_{k,m}(t) = 1$, (12c) equals to $\hat{R}_{k,m}(t) \ge R_k^{\text{th}}(t)$, which guarantees that the transmission rate of UT-k satisfies the minimum transmission requirement for the service. Given the potential processing capacity and transmission capacity constraints of the LEO satellite, (12d) ensures the total amount of transmitted data to satellite m would not extend its processing limitation.

V. Online Service Provision

In this section, we detail the online service provisioning module in ORACLE. An MPC-based dynamic controller is designed for handling the varying network status in NTNs. Further, a time-window-based extended-MPC algorithm is proposed to enhance the quality of control decisions generated by ORACLE. Finally, a safe-learning-based framework is designed to enhance the robustness of decisions made by ORACLE.

A. MPC-Based Online Service Provision

Although **P0** formulates the QoS maximization problem for service provisioning problem in NTNs, it requires the knowledge of long-term future network status for deciding the service provisioning strategy. However, forecasting long-term network status in real-world implementation is challenging, if not infeasible. Therefore, we proposed an online service provisioning scheme by leveraging DT. The major difference between DT and simulators in existing studies is that DT considers real-time network status as inputs, making decisions accordingly. Meanwhile, the simulators in existing studies merely rely on the parametric modeling of future NTN

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status to make decisions. This difference enables our proposed ORACLE more adaptive and reliable to the dynamic NTNs.

To enable online service provisioning in NTNs, we propose to leverage DT to optimize the system performance via dynamic network status. Specifically, instead of parametric modeling/predicting the long-term future network status, we introduce a short-term prediction horizon with τ, during which the network status could be predicted according to the historical network status. Then, we introduce MPC to implement control law by solving a constrained optimization problem over this prediction horizon as

$$\mathbf{P1}: \max_{\mathcal{X}_{t_0+1}^{t_0+\tau}} \quad \Phi \tag{13a}$$

$$\text{s.t.} \quad \sum_{m\in\mathcal{M}} x_{k,m}(t) \leq 1, \quad \forall t \in [t_0+1, t_0+\tau], \forall k \in \mathcal{M} \tag{13b}$$

$$\hat{R}_{k,m}(t) \geq x_{k,m}(t) R_k^{\text{th}}(t), \quad \forall t \in [t_0+1, t_0+\tau], \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \tag{13c}$$

$$\sum_{k\in\mathcal{K}} \hat{R}_{k,m}(t) x_{k,m}(t) \leq C_k, \quad \forall t \in [t_0+1, t_0+\tau], \forall m \in \mathcal{M} \tag{13d}$$

$$x_{k,m}^*(t_0) = x_{k,m}(t_0), \forall k \in \mathcal{K}, \forall n \in \mathcal{N} \tag{13e}$$

Here, $\Phi = \lambda \sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{t_0+1\leq t\leq t_0+\tau} x_{k,m}(t)\hat{R}_{k,m}(t) \Delta t + (\lambda-1) \sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{t_0+1\leq t\leq t_0+\tau} |x_{k,m}(t) - x_{k,m}(t-1)|/2$, $\mathcal{X}_{t_0+1}^{t_0+\tau} \triangleq \{\boldsymbol{X}_{t_0+1}, \ldots, \boldsymbol{X}_{t_0+\tau}\}$ is the control decisions from time frame t_0+1 to $t_0+\tau$, and $\boldsymbol{X}_{t_0+1} \triangleq \{x_{1,1}(t_0+1), \ldots, x_{k,m}(t_0+1), \ldots, x_{K,M}(t_0+1)\}$. The optimal results of **P1** allow ORACLE to make a feasible decision, which accounts for both service provisioning constraints and the evolution of system state over the prediction horizon.

B. Extend-MPC Algorithm

Building upon the **P1**, we further propose an extend-MPC algorithm for service provisioning in NTNs. The key idea of this extend-MPC algorithm is to use the historical network status in the last T_0 time frames to predict the network status in the following τ prediction horizon. The controller optimizes the control decision for service provisioning in NTNs based on the prediction results.

In particular, as detailed in Algorithm 1, the GS collects the current network status (*i.e.*, CSI, weather condition, satellite orbit information, capacities of satellites, and motion of UTs) at each time frame t_0. The GS then combines the historical network status and control decisions in time frame t_0-T_0+1 to t_0-1, $\boldsymbol{\Psi}_{t_0-T_0+1}^{t_0-1} \triangleq \{\psi_{t_0-T_0+1}, \ldots \psi_{t_0-1}\}$, with the network status and control decision in current time frame, formulating $\boldsymbol{\Psi}_{t_0-T_0+1}^{t_0}$. By leveraging $\boldsymbol{\Psi}_{t_0-T_0+1}^{t_0}$, GS predicts the future network status in the t_0+1 to $t_0+\tau$ time frames. Notably, no exact T_0 time frame historical information is required for this prediction. Any historical time frames in the range $(0, T_0]$ can be utilized to predict the future network status. We consider T_0 as the maximum number of time frames information can be utilized to limit the storage space and computing complex.

Algorithm 1 Extend-MPC Algorithm

Input: Historical network status set $\boldsymbol{\Psi}_{t_0-T_0}^{t_0-1}$.
Output: Control decisions.

```
Initialize time frame t_0.
while Operating = True do
    Collect the current network status.
    Delete ψ_{t_0-T_0} in Ψ_{t_0-T_0}^{t_0-1}.
    Add ψ_{t_0} into Ψ_{t_0-T_0+1}^{t_0-1}.
    Predict the network status in the t_0+1 to t_0+τ time frames.
    Find optimal X_{t_0+1}^{t_0+τ} by solving P1.
    Return Control decision X_{t_0+1}.
    t_0 = t_0 + 1
end while
```

Subsequently, the GS optimizes the service provisioning decision by solving the maximization QoS problem in **P1**. If the results are feasible, the optimal service provisioning decision at time frame t_0+1 would be sent to NTN for online service provisioning.

C. Safe Learning Framework

Clearly, **P1** is a non-convex problem that is challenging to solve efficiently. Thanks to recent advances in AI, GAI has been widely utilized in communication and networking to enhance system performance and reduce processing delay, especially for solving non-convex problems (*e.g.*, **P1**). One of the major concerns regarding implementing GAI to solve these problems is that the GAI output may not be located in feasible regions. To tackle this problem, we design a safe learning-based framework in ORACLE. The key idea of safe learning is to transfer the **P1** into a trainable loss function and find a feasible control decision when the solver's output cannot satisfy the QoS constraints.

Specifically, as illustrated in Fig. 2, at time frame t_0, the controller has the knowledge of the network status and control decisions from t_0-T_0+1 to t_0 frames, $\Psi_{t_0-T_0+1}^{t_0}$. According to $\Psi_{t_0-T_0+1}^{t_0}$, the GAI model generates the possibility of control decisions from time frame t_0+1 to $t_0+\tau$, $P\mathcal{X}_{t_0+1}^{t_0+\tau} \triangleq \{P(x_{1,1}(t_0+1), \ldots, P(x_{k,m}(t)), \ldots, P(x_{K,M}(t_0+\tau))\} \in \mathbb{R}^{K\times M\times\tau}$. We assume $P(x_{k,m}(t))$ represent the possibility that $x_{k,m}(t) = 1$ is optimal decision. Therefore, the control decisions can be generated by

$$x_{k,m}(t) = \begin{cases} 1 \text{ if } P(x_{k,m}(t)) = \max_m P(x_{k,m}(t)) \\ 0 \text{ otherwise} \end{cases} \quad \forall k \in \mathcal{K}, \forall t \in [t_0+1, t_0+\tau] \tag{14}$$

By adding a small random noise with $\mathcal{CN}(0, 10^{-7})$ to $P\mathcal{X}_{t_0+1}^{t_0+\tau}$, (14) ensures $\mathcal{X}_{t_0+1}^{t_0+\tau}$ satisfies (13b) in most cases. For some extreme cases with $P(x_{k,m_1}(t)) = P(x_{k,m_2}(t)) = \max_m P(x_{k,m}(t))$, $m_1 \neq m_2$, we select the smallest m, satisfying $P(x_{k,m}(t)) = \max_m P(x_{k,m}(t))$, to make $x_{k,m}(t) = 1$. This control decision, $\mathcal{X}_{t_0+1}^{t_0+\tau}$, would then be sent to a safe filter. If this control decision satisfies the constraints (13c)

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and (13d), the $\boldsymbol{X}_{t_0+1}$ would then be sent to the NTNs as the control decision for t_0+1 time frame. Thus, the loss function could be expressed as

$$\mathcal{L} = -\Phi. \tag{15}$$

Otherwise, the UT-k would select the nearest satellite-m in the feasible region. A penalty is added to the loss function to enhance the efficacy of learning

$$\begin{aligned}\mathcal{L} = & -\Phi + \mu_1 \sum_{k\in\mathcal{K}} \sum_{m\in\mathcal{M}} \sum_{t_0+1\leq t\leq t_0+\tau} (x_{k,m}(t) R_k^{\text{th}}(t) - \hat{R}_{k,m}(t)) \\ & + \mu_2 \sum_{m\in\mathcal{M}} \sum_{t_0+1\leq t\leq t_0+\tau} (\sum_{k\in\mathcal{K}} \hat{R}_{k,m}(t) x_{k,m}(t) - C_k),\end{aligned} \tag{16}$$

where μ is the penalty factor for actions that do not satisfy QoS requirements. By leveraging the safe-learning framework, we transfer the original **P1** into a trainable problem while enhancing the efficacy of the training process.

VI. Performance Evaluation

A. Simulation Setup

We adopt a time-dynamic satellite system simulation tool Ansys STK [48] to calculate inter visibility and time-varying geo-locations of each satellite. Our simulations are based on SpaceX's operational LEO mega-constellation Starlink (Shell I of Phase I) [49]. Primary parameter settings used in our simulations are presented in Table I. To ensure our simulations' validity, we randomly generate the UTs within the coverage of the LEO mega-constellation. The operational scenario assumes an LEO satellite operating in the Ka-band, specifically employing a carrier frequency of 28 GHz [50]. As a cornerstone for our analysis, the channel model is generated based on the channel model delineated in Section IV. The weather condition factor $\chi_m(t)$ follows the uniform distribution in the range [0, 4]. Employing the Adam optimizer for efficient parameter updates, all learning models incorporate a progressively decreasing learning rate, commencing at 0.01 and decaying at a rate of 0.999. This strategy is employed to ensure stable convergence and avoid overshooting the minimum. During the offline training process, each training iteration involves a batch size of 512 sets of network status, and to guarantee convergence and optimal performance, all models undergo comprehensive training for 500 iterations. Moreover, for the online training process, we assume only one dynamic task of each condition (one-shot) is available for online training.

Due to the limited space, unless explicitly specified, default simulation settings are utilized. Specifically, the default length of the historical network status is set to $T_0 = 10$ second (s), and the default sampling frequency is set to 1 Hz. The default SNR of the LEO satellite is set to 50 dB, the default weight factor $\lambda = 0.3$, the default number of users considered is $K = 10$, the default time horizon is $\tau = 20$ s, and the default average processing capacity of the satellite is 10 Gbits/s.

TABLE I: Table of simulation parameters.

Carrier frequency	28 GHz
Bandwidth	500 MHz
Shape of Nakagami-m	10
Average power of LoS component	0.835
Operate altitude	550 km
Inclination	53°
Number of orbits	72
Number of satellites per orbit	22
Antenna gain	58.5 dBi
Average power of the scatter	0.126

B. Comparision Algorithm

1) Always Nearest Satellite (**ANS**) [21]: This scheme always finds the nearest satellite for each user and assigns each user to its nearest satellite.
2) Longest Visible Time (**LVT**) [27]: This scheme finds the satellite with the longest remaining visible time (according to parametric modeling), and only assigns each user to one satellite when the connection between the user and its previous connected satellite is no longer visible.
3) **ORACLE**: This scheme implements ORACLE with a 4-layer Convolutional Neural Network (CNN) as the predictor.

C. Simulation Results

In this subsection, we evaluate the QoS of online service provisioning under ORACLE in the NTN system. Our primary performance metric is the average QoS, $\bar{\Phi} \triangleq \Phi/|T|$, where $|T|$ is the simulation time. To approximate ergodic use rates during training, we employ a Monte Carlo method [51], leveraging the data set. Additionally, we insightfully examine the system performance by assessing the average handover times (per second) and average sum rates (per second). Finally, we investigate the efficiency of the ORACLEunder varying user configurations, paving the way for real-world implementation.

1) Effectiveness of ORACLE*:* Fig. 3 compares the performance of the proposed ORACLE with conventional service provisioning schemes, i.e., ANS and LVT. From the analysis presented in Fig. 3a, it becomes evident that our proposed ORACLE significantly outperforms the conventional schemes. ORACLE successfully balances the trade-off between handover and sum rate under dynamic network conditions. Specifically, with lower λ values (0, 0.3), indicating that QoS performance mainly relies on handover performance, ORACLE achieves handover performance almost equivalent to LVT, as illustrated in Fig. 3b. Concurrently, the sum rate performance is comparable to ANS, as demonstrated in Fig. 3c. At higher λ values (0.3, 1), where QoS performance primarily depends on sum rate performance, ORACLE achieves a much higher sum rate than ANS. This is accomplished by taking into account environmental uncertainty and load balancing issues in the satellite network.

Therefore, ORACLE is markedly more adaptive than conventional service provisioning schemes. Conventional schemes yield constant results regardless of varying service provisioning tasks and network status. In contrast, ORACLE dynamically

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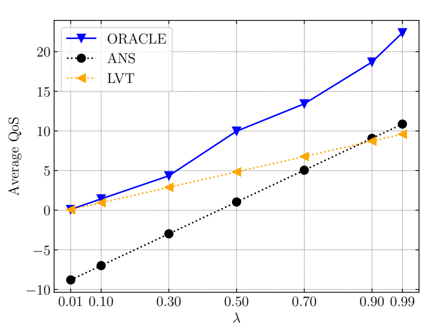
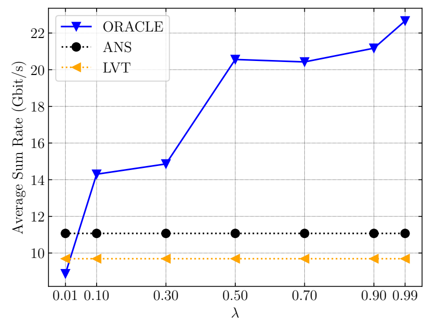
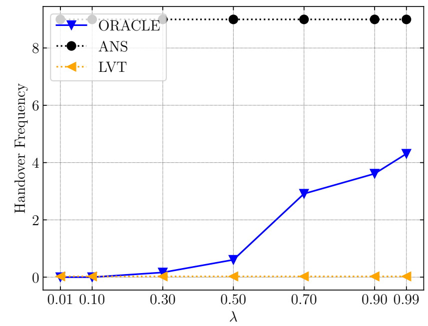


(a) Performance of average QoS.

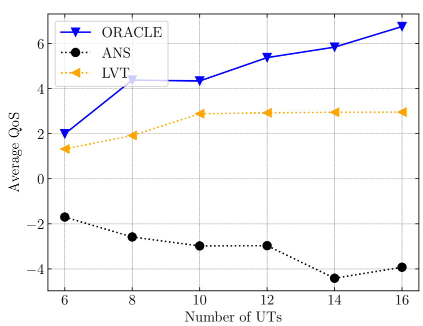


(b) Performance of average sum rates.

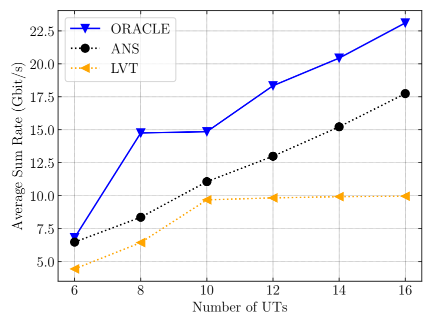


(c) Performance of handover frequency.

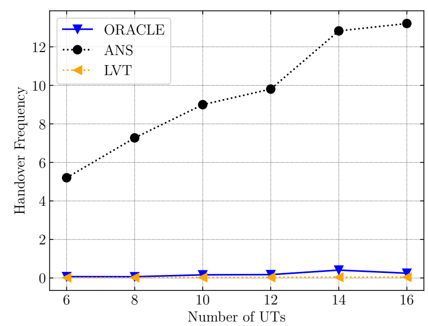
Fig. 3: Performance of ORACLE under different weighting factor λ.



(a) Performance of average QoS.

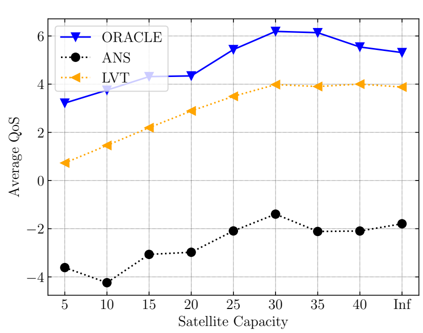


(b) Performance of average sum rates.

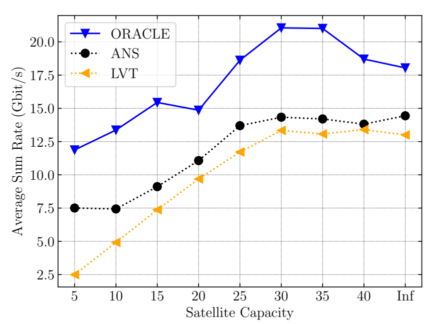


(c) Performance of handover frequency.

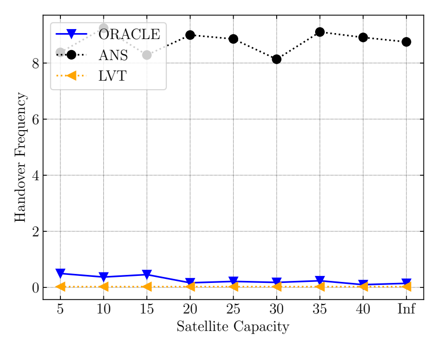
Fig. 4: Performance of ORACLE under different number of UTs.



(a) Performance of average QoS.



(b) Performance of average sum rates.



(c) Performance of handover frequency.

Fig. 5: Performance of ORACLE under different satellite capacities.

adjusts its strategies according to service requirements. For services necessitating ultra-reliable communications, ORACLE makes decisions at lower λ values with reduced handover frequency. Conversely, for tasks demanding higher bandwidth, ORACLE opts for higher λ values, achieving a larger sum rate.

2) Robustness of ORACLE*:* Fig. 4 illustrates the impact of varying user numbers on the performance of the proposed ORACLE. It is evident that our proposed ORACLE consistently outperforms conventional approaches across different configurations. This consistency affirms the robustness of the proposed ORACLE. Additionally, we investigated the impact of varying satellite capacities, as shown in Fig. 5. The term "Inf" denotes that the satellite capacity is unlimited and sufficient for service provisioning. Our proposed ORACLE clearly outperforms conventional approaches in this scenario as well, reaffirming the robustness of the proposed ORACLE. The sum rate of the system initially improves with increasing satellite capacities and reaches saturation when $C_k \geq 30$. This indicates that a capacity of 30 Gbits/s per satellite is sufficient for service provisioning under the given user deployment.

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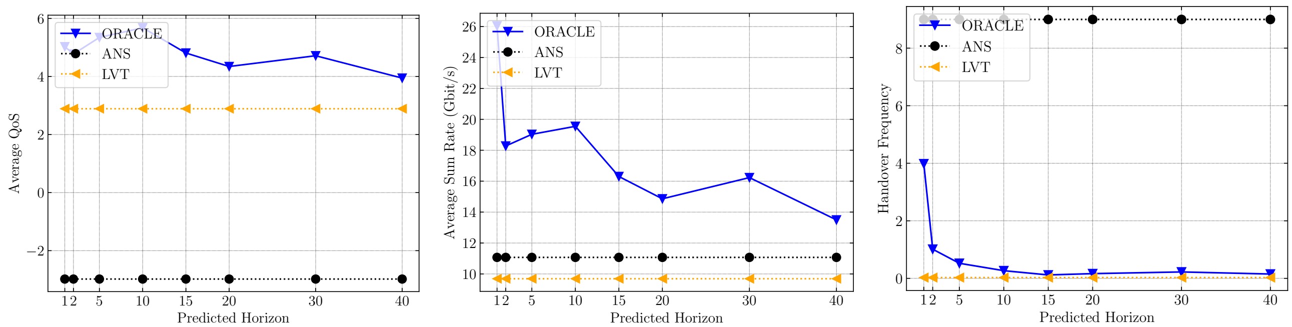

(a) Performance of average QoS (b) Performance of average sum rates. (c) Performance of handover frequency.

Fig. 6: Performance of ORACLE under different prediction horizon τ.

Furthermore, we assessed the performance of the system under different prediction horizons τ, as depicted in Fig. 6. Notably, when τ is small, the handover frequency is significantly high, indicating that ORACLE struggles to manage the handover problem effectively due to the limited prediction horizon, leading to poor QoS performance. Performance improves and stabilizes when $\tau > 10$ seconds. Interestingly, there is a slight performance drop when the prediction horizon τ is considerably larger. This phenomenon suggests that the prediction error in ORACLE increases with a larger τ, leading to suboptimal control decisions and subsequent performance degradation. In practical terms, our findings indicate that a prediction horizon of 10 seconds is optimal for our predictor. This choice ensures the model's effectiveness while limiting the scale and complexity of the training process.

VII. Related Work

Many efforts have been made to mitigate the impact of user-satellite handover on network performance degradation with different objectives. Wang *et al.* [19] propose a fuzzy-CNN-based multi-task routing method for integrated satellite-terrestrial networks to enhance traffic control and pathfinding flexibility. It combines Software-Defined Networking (SDN), convolutional neural network, and fuzzy logic to optimize routing decisions, ensuring both load balance and user Quality of Experience (QoE). Guo *et al.* [23] present a dynamic handover transmission control scheme for integrated satellite-terrestrial networks using a queuing game model to improve information transmission efficiency. They leverage SDN technology to enhance resource allocation and reduce the dependency on physical hardware. Liu *et al.* [25] introduce a new random access scheme for machine-type-communication devices in LEO satellite IoT networks to enhance efficiency. They also introduce a model-free DRL algorithm and a deep Dyna-Q learning algorithm to optimize random access control. Xu *et al.* [26] propose a QoE-driven intelligent handover mechanism for user-centric mobile satellite networks to ensure seamless connectivity. A spatial relationship coupling model and an available channel estimation model are proposed to predict handover factors, and reinforcement learning is also used to optimize handover decisions. However, most of these works usually overlook the dynamic CSI status due to the high mobility of NTNs and thus may experience a performance gap between theoretical analysis and real performance.

VIII. Conclusion

In this paper, we propose ORACLE for QoS-aware online service provisioning in NTNs. Given that frequent handovers in NTNs can lead to severe QoS degradation, we propose a QoS maximization problem to decide the optimal handover strategy. However, the channel conditions vary significantly as the satellite moves, which is usually overlooked by existing works and can cause performance degradation of the proposed handover strategy. We mathematically formulate a channel model and propose an MPC-based controller and an extended-MPC algorithm to predict future channel conditions and generate corresponding control decisions. To efficiently generate control decisions and make the model more adaptive to environmental uncertainty, we further design a safe transfer learning-based framework for improving training performance and reducing the training time for the new environment. Evaluation results under the Starlink constellation demonstrate that our proposed ORACLE can enhance up to $3\times$ QoS during service provisioning.

Acknowledgment

We thank anonymous reviewers for their valuable feedback. This work was supported in part by the National Research Foundation, Singapore, and the Infocomm Media Development Authority under its Future Communications Research and Development Program.

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