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Abstract

This deliverable E10 is the final version of the studies on the edge solutions for integration of terrestrial and non terrestrial networks, TN and NTN respectively. This document continues the work conducted in E9 and explore enabling technologies and algorithms for deployment edge computing within integrated TN and NTN.

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List of Acronyms

DRTO	Deep RL-based task offloading
GEO	Geostationary Earth Orbit
HAPS	High Altitude Platform System
LEO	Low Earth Orbit
LTE	Long Term Evolution
MEC	Mobile Edge Computing
MEO	Medium Earth Orbit
NTN	Non Terrestrial Networks
RIS	Reconfigurable Intelligent Surfaces
TN	Terrestrial Networks
UAV	Unmaned Aerial Vehicle

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1. Introduction

Technological advancements have propelled us into an era of unprecedented connectivity and data-driven applications. From immersive augmented reality (AR) and virtual reality (VR) experiences to autonomous driving and the widespread reach of Internet of Things (IoT), we are witnessing a significant shift in how we interact with the world. These advancements, however, bring a growing demand for computational power that pushes the boundaries of traditional computing paradigms.

Applications like AR/VR demand high-resolution graphics and real-time processing for seamless user experiences. Autonomous vehicles rely on continuous data analysis for navigation and safety. IoT connects billions of devices globally, generating vast quantities of data that require efficient processing and management to derive meaningful insights for applications such as smart cities, healthcare, and industrial automation [1, 2, 3, 4, 5]. Such computationally intensive applications necessitate robust and responsive networks that can handle large data volumes with minimal latency.

Existing terrestrial networks often struggle to meet these increasing demands. Their reliance on ground-based infrastructure, like cellular networks and fiber optics, inherently limits their capabilities, resulting in coverage gaps, capacity limits in densely populated zones, and insufficient latency for real-time applications. These limitations are particularly pronounced for applications that require high bandwidth and ultra-low latency, especially those driving the evolution towards 6G [6, 7, 8, 9, 10, 11, 12].

Non-terrestrial networks (NTNs) have emerged as a promising solution to complement terrestrial networks. Aerial platforms, such as high-altitude platforms (HAPs) and unmanned aerial vehicles (UAVs), along with space-based infrastructure like low-earth orbit (LEO) satellites, can overcome geographic limitations and serve remote regions [7, 13, 14, 15]. Integrating these platforms is widely recognized as a key enabler for 6G networks, with the potential to reshape communication paradigms [6, 16]. The integration of aerial platforms for computation offloading has also become a crucial strategy to address the resource limitations of mobile devices and utilize distributed computing capabilities. Offloading computationally intensive tasks from resource-constrained devices to dedicated remote servers or edge nodes located on these platforms can significantly reduce latency, enhance energy efficiency, and improve the overall quality of service (QoS) [17, 18, 2].

This document explores various computation offloading strategies within integrated terrestrial and non-terrestrial networks (IT-NTNs). We provide a comprehensive analysis of how these networks manage computational workloads, allocate resources, and ensure efficient and reliable service delivery. We explore the key technologies and algorithms that underpin these strategies and discuss their strengths and limitations. We also examine potential use cases of computation offloading across diverse applications and present future research opportunities. By examining the complexities and possibilities of this technology, we aim to provide a roadmap for realizing the full potential of IT-NTNs in the next generation of communication networks.

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2. Enabling Tenchnologies and Algoritms

Cutting-edge technologies and algorithms are paving the way for computation offloading in IT-NTNs. These advancements are crucial for tackling various challenges and capitalizing on opportunities presented by combining terrestrial and non-terrestrial resources. This section explores key enabling technologies and algorithms that make efficient computation offloading possible.

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Key Enabling Technologies

Several technologies are instrumental in enabling efficient computation offloading in ITNTNs and are considered key enablers of beyond 5G and 6G networks. We discuss some of the most prominent ones below.

Novel Multiple Access Schemes

Efficient spectrum use is vital for supporting massive connectivity and enabling numerous devices to offload computation tasks simultaneously. Non-orthogonal multiple access (NOMA) boosts spectral efficiency by enabling multiple users to share the same radio resources, such as time and frequency [25]. Unlike orthogonal multiple access (OMA), which allocates orthogonal resources to avoid inter-user interference, NOMA uses superposition coding at the transmitter and successive interference cancellation (SIC) at the receiver. By leveraging power domain differences and varying channel conditions, NOMA can accommodate more users within the same resource block, significantly improving spectral efficiency. In IT-NTNs, NOMA can enable simultaneous offloading from multiple ground users to a cluster of UAVs acting as decode-and-forward relays in a satellite-aerial-terrestrial network [26]. These UAVs can use coordinated multi-point (CoMP) transmission to cooperatively serve users on the same resource block, further enhancing coverage and system throughput. Rate-splitting multiple access (RSMA) is another advanced multiple access scheme that builds on NOMA principles, offering a more generalized and flexible multiple access framework [27]. RSMA divides user messages into common and private parts, allowing for flexible interference management and a better balance between user fairness and overall system throughput. In downlink RSMA, all users decode the combined common parts of all user messages, while private parts are decoded individually using SIC. For uplink RSMA, each user's message is split into two sub-messages, and the receiver uses SIC to decode all submessages based on their respective power levels and channel conditions [28]. Compared to NOMA, RSMA offers several advantages, particularly in uplink scenarios where it can achieve the full capacity region of the multiple access channel [28]. By tuning rate-splitting parameters and the decoding order, RSMA effectively manages interference, enhances user fairness, and improves the overall computation offloading rate in RSMA-aided MEC (RSMA-MEC) systems. Notably, RSMA generalizes NOMA in uplink transmission, providing greater design flexibility and potential for superior performance [29].

Millimeter Wave (mmWave) and Terahertz (THz) Communications

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mmWave and THz communication technologies operate at extremely high frequencies, offering abundant bandwidth and enabling very high data rate communication [8]. This vast bandwidth is particularly advantageous for computation offloading, allowing rapid and efficient transmission of large data volumes, resulting in lower transmission latency, which is much needed for delay-sensitive applications. These technologies are especially well-suited for short-range, high-capacity links in ITNTNs. For example, mmWave links can connect terrestrial base stations with UAVs and facilitate high-speed data transfer for computation offloading. THz offers even higher bandwidth and data rates, making it ideal for ultra-high-definition video streaming, real-time gaming, and other data-intensive applications. Thus, by leveraging these communication technologies, IT-NTNs can provide high-speed, low latency connectivity for computation offloading, significantly enhancing the performance of resource-constrained devices. However, mmWave and THz signals are more susceptible to higher propagation losses and blockage by obstacles compared to lower frequency signals. This necessitates careful network planning and deployment, especially in IT-NTN scenarios where signal propagation can be affected by atmospheric conditions, terrain, and user mobility.

Reconfigurable Intelligent Surfaces (RIS)

RIS technology enhances wireless communication performance and coverage by intelligently controlling the propagation environment [30, 3]. RISs are thin, reconfigurable surfaces composed of numerous passive reflecting elements that can be dynamically adjusted to reflect, refract, or absorb incoming signals, effectively creating a controllable wireless environment. Strategic placement and configuration of RISs in IT-NTNs can significantly improve signal strength, mitigate interference, and enhance coverage. For instance, RIS mounted on a building can redirect signals from a HAP to a ground user in a dead zone where direct communication is blocked [31]. Similarly, UAV-deployed RISs, known as aerial RISs (ARIS), provide flexible and on-demand coverage enhancement for dynamic vehicular networks. Complementing these enabling technologies are intelligent algorithms that optimize resource allocation, guide task offloading decisions, and manage mobility effectively within the IT-NTN framework.

Offloading Algorithms

Efficient computation offloading in IT-NTNs relies on intelligent algorithms that address the unique challenges of heterogeneous resources, dynamic environments, and diverse service requirements. These algorithms focus on optimizing resource allocation, guiding task offloading decisions, and managing mobility effectively.

Resource Allocation

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Optimal resource allocation is crucial for maximizing the efficiency of computation offloading and meeting diverse QoS demands. It involves strategically distributing communication and computation resources among multiple users and tasks, considering factors such as channel conditions, task characteristics, and resource constraints. Resource allocation in IT-NTNs encompasses strategies for bandwidth allocation, power control, and server scheduling to ensure efficient resource use.

Consider a NOMA-MEC enabled aerial-terrestrial network, where multiple ground users offload computationally intensive tasks to a HAP equipped with an MEC server. This scenario utilizes both NOMA, a multiple access technique, and MEC, an edge computing paradigm, as previously discussed. To facilitate efficient offloading, users are grouped into clusters, with devices in each cluster offloading their data to the MEC server using the NOMA principle [32]. In this context, power and computational resources need to be allocated carefully to each user within the NOMA cluster to optimize performance.

Minimizing the execution delay difference between the paired NOMA users is crucial for enhancing spectral efficiency and resource utilization. A significant disparity in execution delay between users leads to wasted resources, as the system remains idle while waiting for the slower user to complete its task.

By allocating optimal power to each user, we can equalize their data transmission times, minimizing the execution delay difference and improving overall system throughput [32]. Optimizing the allocation of computation resources, such as the number of cores assigned to each user at the MEC server, can also reduce the delay difference via equalization of computation times. To address these complex optimization problems in IT-NTNs, various techniques can be employed. For example, the Lagrange multipliers method decouples the problem into independent sub problems with their own constraints. Additionally, data-aware NOMA clustering schemes, as proposed in [33], can further improve the effective throughput and spectral efficiency of the system.

Task Offloading Decision-Making

Another fundamental aspect of computation offloading in IT-NTNs is deciding which computation tasks to offload and to which computing resources. These decisions should be based on factors such as task complexity, latency requirements, energy constraints, available computing resources, and associated costs. Researchers have proposed multiple methodologies to address task offloading decision making. Optimization methods, including linear and convex optimization, model the problem by defining an objective function, like minimizing latency or energy, and corresponding constraints [24].

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While these techniques provide optimal solutions under given conditions, they often require complete system information and can be computationally demanding for large-scale networks.

Game theory offers an alternative approach, modeling strategic interactions among multiple rational decision-makers competing for shared resources [34]. The task-offloading problem can be framed as a non-cooperative game, with each user seeking to minimize their own costs, such as latency or energy [35]. Characterizing the equilibrium strategies within the game can provide valuable insights into the offloading choices made by rational users. Machine learning algorithms, particularly reinforcement learning (RL), have emerged as effective methods for making task offloading decisions in complex and unpredictable environments [4, 36]. RL algorithms learn optimal offloading policies through a trial-and-error approach, mapping system states (e.g., channel conditions, task queue lengths, resource availability) to actions (e.g., offloading decisions, resource allocation), and striving to maximize a cumulative reward (e.g., minimizing long-term cost or latency). For instance, Li et al. [18] proposed an asynchronous federated deep RL (FDRL)-based computation-offloading framework. The asynchronous model uploading in FDRL avoids network congestion and reduces the waiting delay for global model training. Similarly, Zhu et al. [2] proposed a deep RL-based task-offloading (DRTO) algorithm that accelerates the learning process by adjusting the number of candidate offloading locations.

In IT-NTNs, RL algorithms can be designed to adapt to the unique challenges posed by dynamic channel conditions, varying user mobility, and unpredictable traffic patterns. For example, in a satellite-terrestrial edge computing network, an RL agent can learn to make real-time offloading decisions based on channel conditions, satellite availability, and task urgency, enabling devices to efficiently utilize both satellite edge computing (SEC) and urban terrestrial cloud (TC) for computing [2].

Mobility Management

Efficient mobility management is essential for uninterrupted computation offloading in IT-NTNs, especially when users move between the coverage areas of different NTN nodes, such as terrestrial BSs, UAVs, HAPs, or satellites. Maintaining service continuity and enabling smooth handovers is necessary to ensure minimal performance degradation. Mobile users in NOMA-MEC enabled aerial-vehicular networks operating at mmWave can experience rapid variations in channel conditions due to mobility, affecting the performance of both task offloading and resource allocation [33]. For instance, as vehicles move, signal blockage from buildings can result in intermittent line-of-sight (LoS) and non-line-of-sight (NLoS) links with the serving HAP. This necessitates adaptive algorithms for both power control and core allocation to maintain stable offloading performance despite these fluctuations.

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To address mobility management challenges, predictive handover mechanisms based on user mobility patterns and network topology information can be employed. Anticipating potential handover events beforehand can help in pre-allocating resources at the target node, resulting in lower handover latency. Efficient handover protocols are also crucial for facilitating seamless transfer of offloaded tasks and data between different NTN nodes. These protocols should be designed to minimize data loss during handover, ensure secure authentication and authorization of users at the new node, and maintain the overall QoS of offloaded tasks.

3. Application and Use Cases

Computation offloading in IT-NTNs offers solutions to challenges that traditional terrestrial networks often struggle with. This section explores various applications and use cases, showcasing how these integrated networks can transform different domains.

Autonomous Driving

Autonomous vehicles require robust, low-latency communication networks for real-time data processing for critical functions like perception, path planning, and control. IT-NTNs address terrestrial network issues by providing ubiquitous coverage and reliable connectivity that are a must for ensuring safe and efficient autonomous driving, especially in complex urban environments.

Recent research has explored innovative approaches to support autonomous driving through integrated networks. For example, Yastrebova et al. [37] examined how aerial platforms like UAVs and HAPs can enhance terrestrial network infrastructure for autonomous vehicles, demonstrating that integrating these platforms can significantly expand coverage and reduce latency. Building on this, the authors in [38] investigated real-time HAP-assisted vehicular edge computing (VEC) for autonomous driving in remote areas. They showed that offloading computationally intensive tasks to HAPs allows autonomous vehicles to leverage superior processing capabilities while meeting strict latency requirements.

Remote Healthcare

Applications like telemedicine, remote diagnosis, and real-time patient monitoring demand reliable, low-latency communication networks for timely data transmission and analysis. IT-NTNs make these services possible in remote areas with limited or no terrestrial coverage, enhancing healthcare accessibility and quality for underserved regions.

The potential of edge computing in healthcare has been the focus of several recent studies. Hartmann et al. [19] conducted an extensive review of edge computing in smart healthcare systems, highlighting that processing patient data locally on edge devices or nearby edge servers can significantly reduce latency, facilitating real-time monitoring and diagnosis. Complementing this, a window-based rate control algorithm was proposed in

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[20] to improve QoS in mobile edge computing-based healthcare applications like telesurgery. This algorithm dynamically adjusts the data transmission rate based on network conditions and client buffer size, reducing latency and enhancing QoS for remote medical procedures.

Disaster Response

In disaster scenarios, where terrestrial networks are often damaged or destroyed, the rapid deployment capabilities of IT-NTNs are invaluable. These networks provide a resilie communication infrastructure for emergency response teams, enabling them to coordinate rescue efforts, gather situational awareness, and deliver critical services to affected areas.

Researchers have proposed innovative architectures to leverage integrated networks in disaster response. Sun et al. [17] presented a three-layer post-disaster rescue computing architecture that leverages MEC and vehicular fog computing (VFC) in an aerial-terrestrial UAV network. This architecture supports collaborative processing of computation tasks by ground rescue vehicles and UAVs, ensuring efficient resource utilization and minimizing latency for crucial rescue operations. Further exploring the potential of HAPs, Nauman et al. [13] investigated high-altitude edge computing (HAEC) enabled IT-NTNs for 6G co munications, highlighting the benefits of HAPs as quasi-static platforms that can guarantee higher endurance compared to low-altitude platforms, making them ideal for disaster relief and network offloading in emergency situations.

Smart Agriculture

IT-NTNs combined with computation offloading enhance smart agriculture practices. They provide farmers and analysts with timely and accurate data about crop health, soil conditions, and environmental factors, enabling informed decision-making, which in turn improves crop yields. The application of UAVs and edge computing in agriculture has garnered significant attention. The authors in [39] explored in-depth the use of airborne remote sensing (RS) and edge intelligence for precision agriculture, highlighting the benefits of edge intelligence for data processing on resource-constrained UAV platforms. This reduces latency and enables real-time insights for efficient crop management. Similarly, the study in [40] proposed a cloud-edge-fog architecture for smart agriculture, where UAVs collect data from IoT sensors in the field and offload it to edge servers for processing. This architecture ensures low-latency data analysis and decision-making, enhancing crop monitoring and management.

Industrial IoT (IIoT)

The IIoT generates vast amounts of data from interconnected sensors and devices within industrial settings. IT-NTNs with computation offloading capabilities facilitate efficient data processing, analysis, and control, particularly in scenarios with limited terrestrial infrastructure coverage.

Recent research has explored innovative solutions for IIoT using integrated networks. Miao et al. [41] investigated drone swarm path planning for MEC in IIoT, proposing a multi-UAVs assisted MEC offloading algorithm to address the limitations of traditional fixed base

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stations in complex terrains. This leverages the flexibility and maneuverability of UAVs to provide cost-effective and efficient computation offloading services. In a related study [5], a joint design of trajectory and offloading was proposed for energy-efficient UAV edge computing in the IIoT. Their work focused on minimizing energy consumption while considering the practical issue of UAV jittering, which induces uncertainties associated with flying waypoints.

These diverse applications demonstrate the potential of IT-NTNs across various sectors and highlight their ability to address challenges and enable new possibilities.

5. Conclusion

The preliminary version of this document explore computation offloading alternatives within IT-NTNs, revealing their potential to revolutionize data processing. We examined the rationale behind this integration, highlighting how non-terrestrial elements like UAVs, HAPs, and LEO satellites can overcome the limitations of traditional terrestrial networks. While challenges such as resource management, mobility, security, and standardization remain, ongoing research actively addresses these issues. As our future becomes increasingly data-intensive and resource-constrained devices proliferate, computation offloading in IT-NTNs offer a compelling solution for real-time data processing and analysis. Continued development and deployment with collaborative efforts between industry and research communities will develop networks where communication and computation commonly intertwine. This integration will enable innovative applications, paving the way for a more connected and intelligent world.

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