Machine Learning-Aided Real-Time Optimized Multibeam for 6G Integrated Satellite-Terrestrial Networks: Global Coverage for Mobile Services

Trung Q. Duong, Long D. Nguyen, Tinh T. Bui, Khanh D. Pham, and George K. Karagiannidis

Abstract

Future wireless networks beyond the fifth generation (5G) have been envisioned to increase many folds, in terms of key performance metrics such as latency, data rate, reliability, mobility, and user's quality of experience. However, one of the biggest difference between the sixth generation (6G) and its predecessor is the ability to support high speed connectivity of mobile services for global coverage, especially focusing on under-connected areas (e.g., forests, oceans, deserts, and mountains). Integrated satellite-terrestrial networks (ISTNs) provide the best solution to unravel the unconnected issues of isolated areas not only on the ground but also in the air and on the sea. Despite this premise, the research in ISTNs is still in its infancy with many open problems, associated with long delay communications, large coverage for massive number of devices, and highly demanding real-time services. To alleviate these problems, this article introduces optimal multi-beam design empowered by machine learning techniques for 6G ISTNs, with respect to the real-time constraints of mission-critical services. First, we give an overview of the multibeam design for 6G ISTNs with user clustering approaches, energy-efficiency radio resource allocation, and distributed computing. Then, the frameworks for intelligent multibeam based on machine learning, real-time optimisation, and game theory, are proposed. As case studies, we investigate the performance of machine learning-aided real-time optimisation for 6G ISTNs in disaster relief and real-time optimal multibeam in satellite–terrestrial IoT networks. Potential research directions incorporating digital twin and quantum-inspired optimisation are presented to further support optimal multibeam design in 6G ISTNs.

Introduction to Integrated Satellite and Terrestrial Networks in 6G

The current fifth generation (5G) wireless networks are designed to extensively focus on three distinct components: enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable and low-latency communications (URLLC). The next-generation wireless networks, that is, the sixth generation (6G), will depart from these general beliefs by delivering seamless connectivity for global coverage of mobile services anywhere and anytime. Although researching and employing 6G is still in its early stage, several 6G use cases and applications have been addressed including ubiquitous mobile ultra-broadband (uMUB) and ultra-high speed ultra-reliable and low-latency communications (uHURLLC). It should be noted that one of the most distinct features of 6G is the ability to offer seamless coverage for under-connected areas spanning from land, sea, and sky [1].

Recently, integrated non-terrestrial and terrestrial networks have been considered as a promising future technology for 6G, to provide wireless connectivity in isolated areas with under-equipped network infrastructures, including under-developed rural regions, remote mountains, onboard cruise ships, and airplanes. An overview of integrated space and terrestrial networks is shown in Fig. 1, where satellites, unmanned aerial vehicles (UAVs) a.k.a. drones, high attitude platforms (HAPs), aeronautical ad-hoc networks (AANETs), and cellular networks jointly create a global integrated communication network that offers seamless coverage on the land, on the sea, and in the sky. With this futuristic vision, 6G is able to accommodate the expansion of new usage scenarios such as high-precision satellite-ground positioning and real-time imaging as well as facilitate new classes of immersive time-sensitive and computation-insensitive data for a large number of Internet-of-Things (IoT) devices (IoD) [2].

Within this comprehensive network infrastructure, satellite communications can serve as a complementary platform to terrestrial networks and other air networks (e.g., UAV and AANET) with the rapid development of high speed satellites. As such, we support that integrated satellite and terrestrial networks (ISTNs), including low/medium/geostationary earth orbit (LEO/MEO/GEO) satellites, will be a key component in 6G. Due to high altitude of the satellite, for example, 500-2000 km attitude for LEO, 8000-20000 km attitude for MEO, and 36000 km attitude for GEO, many challenges in terms of mobility management, radio resource management,

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Digital Object Identifier: 10.1109/MNET.003.2200275

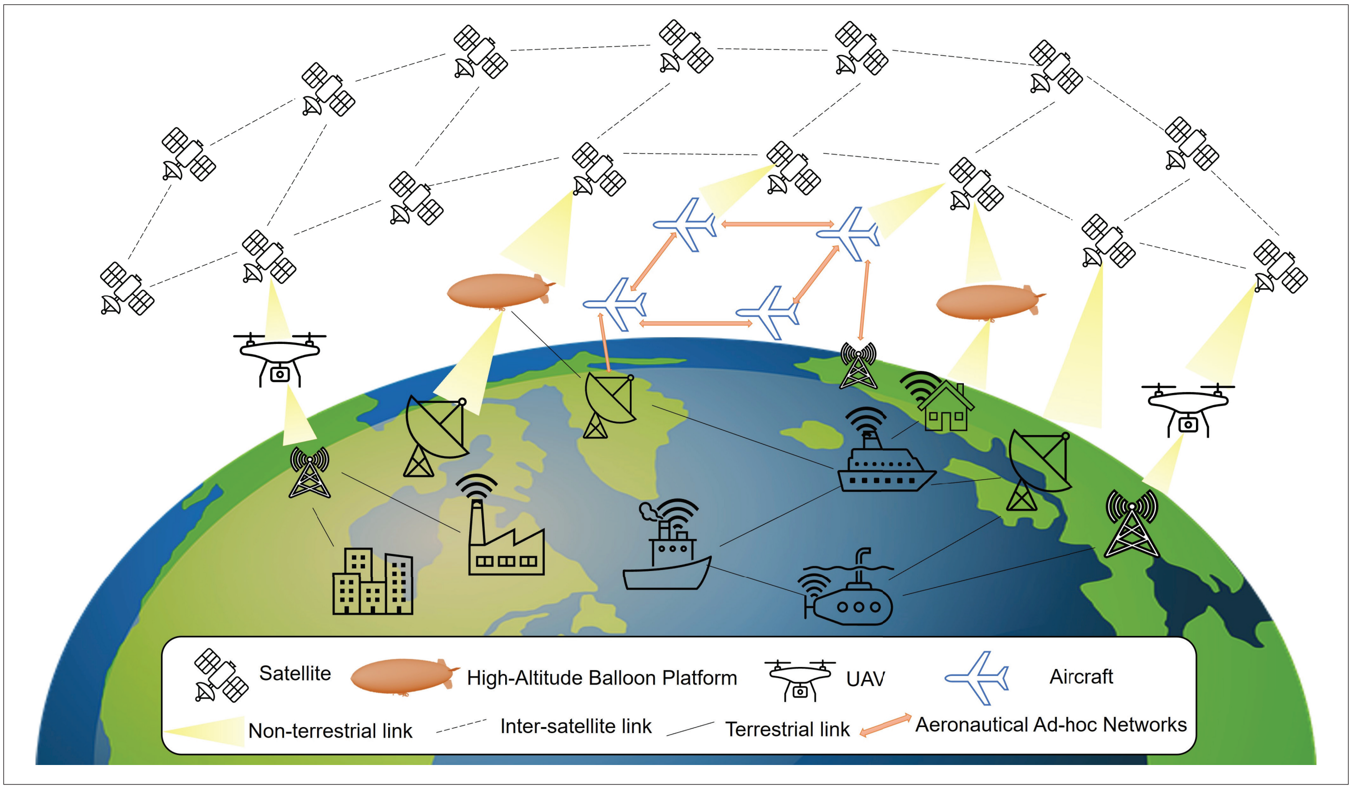


FIGURE 1. An overview of integrated non-terrestrial and terrestrial networks to provide global coverage for mobile services.

routing, and networking need to be solved along with the development of ISTN in 6G. Of utmost concern is the radio resource management for ISTN to target a massive number of users with diverse traffic demands spanning from eMBB, to eMTC, and URLLC. Unlike in terrestrial networks where satisfying these high demands in traffic classes is not a trivial task, it is even more problematic for ISTN with the inherent nature of satellite communications, that is, long distance communications.

There are several major challenges, for example, spectrum-sharing and large coverage, from the physical layer perspective to realize the full potential of ISTN to support massive number of IoDs. To elaborate further, the overlapping of multi-layer UAV/HAP/LEO communications results in inevitably high interference, due to limited frequency as well as inter-beam and intra-beam interference. As such, it is vital for efficient optimal design of interference management not only for the satellite in the space but also for the devices on the ground. Optimal radio resource management is crucial but fundamentally different from satellite and terrestrial devices, which leads to the fact that the joint optimal design for ISTN become a complicated problem and need carefully to be addressed. Specifically, due to the movement of satellites and long distance, the high latency exhibits the rapidly changed network coverage. As such the resource allocation needs to be smartly and dynamically designed to cope with this significant feature of satellite communications compared with terrestrial scenarios. In addition, to offer a high quality-of-service (QoS) for a large number of users on the ground with real-time application, the multibeam design for ISTN is a nontrivial task. This article provides the overall technical framework of the aforementioned interference management and multibeam design for ISTN by taking into account the real-time applications. Finally, this article will shed light on the main research challenges and opportunities of multibeam design for ISTN with respect to spectrum sharing, energy efficiency, and low latency.

Multibeam Design for 6G Integrated Satellite and Terrestrial Networks

The most important advantage of using satellites in communications is the large coverage, which fills almost all the gaps in cellular networks to reach global coverage. However, due to the far distance between satellite transponders and 6G devices, the propagation time of the signal is really high. In addition, the path-loss is extremely high, and the channel gets harmful effects from the environment. Thus, the data rate at the 6G devices is not high enough to alleviate the problem of high propagation time since higher amount of data is received by the devices with the same propagation time. Nowadays, satellite communications are mostly commercially used for broadcast services (e.g., television and radio) which do not have the strict requirement of latency. However, with the incredible progress of massive multiple-input multiple-output (mMIMO) technology in 5G and even in 6G, we can create multiple narrow pencil beams which converge the energy of each beam at nearly one point toward one ground user. Therefore, the higher power received by users helps to achieve a higher data rate with lower latency that meets the constraint of time-sensitive services such as video calls, online meetings, among many others.

Compared with GEO/MEO satellites, LEO satellites have more dominant advantages such as lower distance to the Earth, lower power consumption, and lower cost. Thus, using LEO satellites can support ISTNs in serving a huge number of ground users with low cost, low latency, flexible access, and high data rate.

A Design of Multibeam for 6G ISTN

According to [3], there are three main categories of approaches to designing multibeam antennas, namely passive multibeam antennas (PMBA), multibeam phased-array antennas (MBPAA), and digital multibeam antennas (DMBA). While PMBAs and MBPAAs use analog beamforming components such as reflectors, lenses, beamforming circuits, or phase-shifting networks, DMBAs use a combining weighting matrix to control a uniform linear array of antennas for steering beams. Due to the disadvantages of fixed directions of PMBAs and the requirement of a number of phase shifters of MBPAAs, DMBAs are more powerful in generating multiple agile and flexible beams. However, the complexity of calibrating parameters in the weighting matrix is very high since the channel change rapidly over time. Fortunately, with the strong development of semiconductor technology, digital signal processing (DSP) chips with a high amount of computational resource are used for solving this problem. Besides the analog and digital architectures, there is also an attractive option of using hybrid beamforming scheme for the ISTN [4].

In 6G, technologies with ultra-high frequency such as millimeter wave (mmWave), terahertz technology, and lightwave technology will be used. In addition, in 6G ISTNs, using signals with short wavelengths that are less absorbed by the ionosphere facilitates the integration of large-array antenna platforms in a small physical area. Despite the advantage of being able to generate high-gain and narrow beams which concentrate the signal energy in a small space as a laser, the complexity of controlling many coefficients in weighting matrices is a challenge. To overcome this problem, a design of multi-massive multiple-input multiple-output (MM-MIMO) where an array of ultra-massive number of antennas is divided into multiple sub-arrays by software with the constraint of mMIMO. Each sub-array is used for generating one independent beam toward one ground user, and the number of antennas in each sub-array is determined by the distance and channel state. In detail, if we use one weighting matrix for generating N beams from an array of M antennas, then the number of coefficients that need to calibrate for steering beams equals to $N \times M$. This number is proportional to the complexity of beamforming design. On the other hand, when using MM-MIMO, the number of coefficients equals to $\sum_{i=1}^{N} M_i$ where M_i represents the optimal number of antennas used for the ith beam. Because we optimise the number of antennas, Mi is always less or equal to M, leading to less complex computation.

Clustering Approaches for Terrestrial and Non-Terrestrial Networks

Compared with GEO/MEO satellites, LEO satellites have more dominant advantages such as lower distance to the Earth, lower power consumption, and lower cost. Thus, using LEO satellites can support ISTNs in serving a huge number of ground users with low cost, low latency, flexible access, and high data rate. The number of LEO satellites in total reaches about 5000 as of 30 March 2021 [5], and it is expected to increase incredibly. Nowadays, many large companies show the ambition to build a mega constellation of LEO satellites that can provide 6G communications with global coverage such as SpaceX with the Starlink project, OneWeb, Amazon, Telesat, GW [5]. Controlling and designing beams for thousands of satellites in ISTNs are challenging problems in terms of computing, interference management, and data exchange.

To tackle with aforementioned problems, efficient clustering methods for satellites play a key role in 6G ISTNs. The orbit of LEO satellites changes rapidly over time while serving a huge number of users. This requires a processor with ultra-high computing capacity if using centralized approach.

Therefore, dividing large-scale terrestrial networks into multiple clusters of satellites helps to reduce the complexity of multibeam design. On the other hand, the overlapping areas of the coverage of adjacent satellites are usually large. Despite using mMIMO, the users in these areas still face high inter-beam interference in many cases. Thus, if the adjacent satellites are in the same cluster and communicate through inter-satellite links to cooperatively transmit the signal to their users, the interference is mitigated. Moreover, multiple satellites in each cluster can serve one ground user to reduce the number of handovers when moving along their orbits.

When there is a lack of an efficient method for steering beams from satellites, ground users may face extremely high interference by other beams from both the same satellite and others. In particular, to serve one user, a satellite calibrates the coefficients to steer the main lobe of one beam toward the user. Due to the pattern of the lobe and the far distance between the transmitter and the receiver, other undesired users which are adjacent to the desired user receive a high power of interference from that beam. Therefore, apart from non-terrestrial networks, clustering is also necessary for grouping users before multibeam design.

On the other hand, with a finite number of antennas, each satellite can generate a maximum number of given beams toward users. To allocate efficiently beams toward massive users, ground users need to be clustered with the constraints of either latency, channel gain or fairness quality of experience (QoE), or even both of them. As such, each cluster of users is guaranteed to be served by one or more appropriate satellites.

Radio Resource Allocation for ISTN

Unlike terrestrial networks where the source of interference mainly comes from the frequency reuse of spectrum, the radio resource allocation in ISTN needs to carefully address the different kinds of interference, for example, intra-beam interference (the interference between the adjacent beams of the satellite), inter-beam interference (the interference among multiple satellites), cross interference between satellites and terrestrial networks [6]. As such, radio resource allocation to achieve highly efficient interference management is a key aspect in ISTNs [7].

Similarly as in traditional terrestrial networks, precoding and beamforming strategies have been employed to mitigate the inter-beam interference. Several other well-known techniques have been considered to maximise the system throughput including multicast precoding and multicast multigroup beamforming. One of the unique features of ISTN in dealing with radio resource management is the very heterogeneous user density. As such, user clustering algorithms must be also taken into account while designing the optimal multibeam for ISTN. Extensive efforts in the research community should be dedicated to efficiently suppress the inter- and intra-beam interference as well as cross interference by taking into account the users scheduling in designing the optimal multibeam ISTN. It is important to note that conventional precoding and beamforming design for terrestrial networks cannot be directly applied to ISTNs. Novel radio resource allocations frameworks should be developed to handle different levels of interference in hybrid space and terrestrial scenarios.

Distributed Computing for Ultra-Low Latency ISTN

LEO satellites are promising to 6G ISTNs since their power consumption and propagation time are much less than the counterparts (GEO/MEO satellites). However, the speed of LEO satellites is very high since it only takes each LEO satellite from 90 to 120 minutes to complete its orbit. This causes the channel and locations of ground users to change rapidly relative to LEO satellites. In addition, different from conventional terrestrial networks, the propagation time to transmit the signal from satellites to ground users and vice versa is extremely high and cannot be reduced if access links are optimized. Thus, the requirement of designing multiple beams in real-time scenarios in large-scale ISTNs is crucial and also challenging. Distributed computing, which is efficient in dealing with large-scale problems in terrestrial networks, is also appropriate to be applied for multibeam design in ISTNs.

Distributed computing can be applied in many different forms in ISTNs. Distributed optimisation algorithms can be used to divide a complex multibeam-design problem into multiple sub-problems which are solved in parallel to take advantage of the capacity of multi-core chips. On the other hand, after clustering the satellites, ground computing stations, which are placed in the same or different geographic locations, can be used for processing independently the information from clusters. However, the propagation time of the signal on feed links is really high, which causes high total latency. Another option is using independent satellites as processing units that are connected to satellites of clusters through inter-satellite links (i.e., laser links). Although high-speed data delivery offered by laser links supports in overcoming the latency of propagation, the computing capacity of computing satellites is lower than the one of ground computing stations. Therefore, the trade-off between these two should be evaluated depending on the specific situations.

In ISTN, it is expected that ML-aided multibeam gives the benefits of improving both computing time and accuracy. For example, depending on the trajectory of mobile users, ML algorithms are used for predicting both new locations and channel state information of users.

Methodology

Intelligent Multibeam 6G ISTNs Based on Machine Learning Algorithms

With the support of the high computational capacity of recent computers, machine learning (ML) has been taking off in a wide range of fields such as computer vision, health care, finance, and many others. ML is especially useful in the cases which have already occurred multiple times in the past (i.e., training data) and probably happen in the future.

In ISTN, it is expected that ML-aided multibeam gives the benefits of improving both computing time and accuracy. For example, depending on the trajectory of mobile users, ML algorithms are used for predicting both new locations and channel state information of users. Then, satellites can pre-calibrate parameters in precoding matrices. Another example is that due to the large coverage of satellites, areas within the coverage may have different weather conditions. Depending on the information on meteorology, ML algorithms can be used for predicting the weather (cloudy, rainy, snowy) and then changing the beamforming strategy. Furthermore, elements in the ISTNs are clustered efficiently using ML algorithms with different objectives.

In spite of its outstanding benefits, applying ML for multibeam ISTN is still in its early stage. There are some promising ML algorithms (e.g., deep learning — DL, reinforcement learning — RL, federated learning — FL) which are expected to play an important role to achieve intelligent multibeam 6G ISTN. Overall, these algorithms need a high amount of data for training to optimise a loss function or a reward function that is designed depending on the given objectives. While DL tries to mimic the actions in scenarios of training data, RL can learn not only from given data but also from data generated by itself to obtain a better solution. With this characteristic, RL is suitable to use for intelligent multibeam ISTN with time-varying channels, especially along with digital twin. A digital twin which is used as an emulated model of ISTN generates the data for the training phase in RL. Therefore, multibeam systems based RL must be robust to risks in the future since these risks are expected in the training phase using the digital twin. Both DL and RL need all essential data in the entire networks since they are centralized algorithms. This causes issues on high data exchange, high complexity, and even privacy of users. Therefore, a better alternative option is FL, which is training in multiple packages of local data and then aggregating at the central processor without any local data exchanging. On the other hand, ML clustering algorithms also improve the network performance of ISTNs without any training process. For example, if adjacent users are served by two beams from one satellite or two different satellites, the intra-beam or inter-beam interference is extremely high. To overcome this

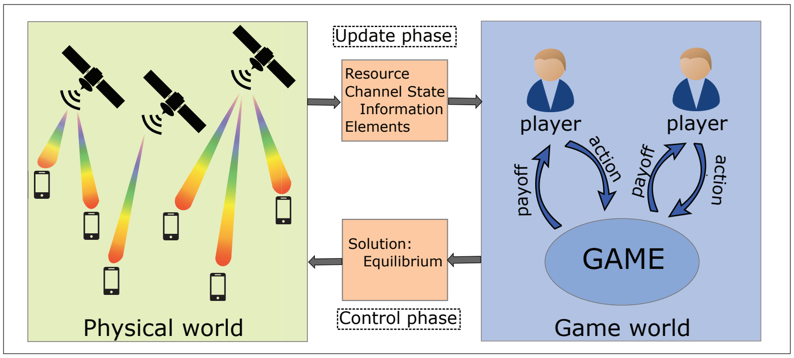


FIGURE 2. A flowchart for game theory in ISTNs.

problem, the K-means clustering algorithm which is unsupervised learning is used for clustering ground users. Adjacent users are in a cluster and are served by one beam only. Therefore, the interference is efficiently mitigated by using a ML clustering method.

Ultra-Low Latency Multibeam 6G ISTN Based on Real-Time Optimization Framework

Real-time optimization, where the execution time for obtaining the solution of an optimisation problem (OP) is stringently limited, is applied in sensitive-time systems. In 6G, real-time is expected to be a mandatory requirement in almost all OPs. There are three factors influencing execution time: the complexity of the OPs, the complexity of the solving algorithms, and the computing capacity of processors. Firstly, to deal with the high complexity of the original OP which is usually non-convex in ISTN, methods of alternative convex functions (minimisation problems) or alternative concave functions (maximisation problems) are investigated in many studies. All non-convex functions in the OP are converted into convex functions to form a convex OP that can be solved effectively by programming tools. If only one iteration takes place in approximation, the gap between original functions and alternative functions is very high. Therefore, an iterative algorithm is used with each loop being one approximating time. Secondly, distributed methods are proposed to reduce the complexity of solving algorithms. Using distributed methods supports dividing a large-scale OP into multiple sub-OPs of low-complexity which can be simultaneously solved by multiple concurrent threads. However, distributed methods face challenges in accuracy and synchronisation. The third factor to achieve real-time optimisation is the computing capacity of processors. Computing operations can be executed at ground stations or in the cloud. However, the latency witnesses a considerable increase by adding more propagation time. Another option to tackle this problem is using distributed satellites as units that are only used for processing and storage.

Multibeam design for ISTNs can be expressed by optimisation problems with the variables being radio resources such as power, bandwidth, time, or coefficients in precoding matrices. The OPs are usually non-convex since the objective functions and constraints are non-convex. Moreover, due to a huge number of ground users and large-array antenna platforms, the complexity of these problems is so high that processing in ultra-low latency is impossible if the problems are solved directly. Thus, the combination of considering the three aforementioned factors to reduce the solving time for multibeam design problems should be studied in order to design multiple beams to serve a massive number of users in real-time scenarios of ISTNs in 6G.

QoE Fairness for 6G ISTN Based on Game Theory Models

In ISTNs, the QoE fairness is essential. Due to the large coverage of satellites, an ISTN usually serves so many different ground user devices with different applications or services. In addition, users using one service require different technical constraints from the others, and their satisfaction may come from subjective factors. QoE which is defined in different ways is a metric to evaluate the satisfaction of users. The optimal solution of OPs such as energy efficiency (EE) maximisation, throughput maximisation, power minimisation, and interference minimisation, yet without considering QoE, could give a very good experience to some users while some others only receive the minimum quality of service with the strict constraints. Therefore, fairness is not guaranteed, which can not keep users satisfied.

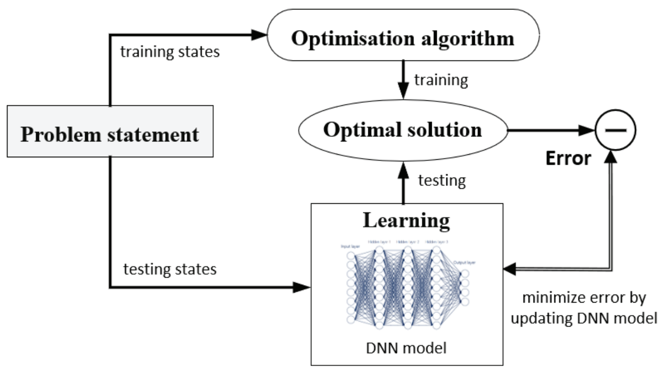
Game theory (GT) is a powerful tool to improve QoE while maintaining fair QoE for multibeams in 6G ISTNs. Figure 2 describes the way GT is used for solving problems of multibeam design in 6G ISTNs. According to the changes in channel gain or locations in the physical world of ISTNs, the parameters of the game are updated. Then, techniques or optimisation methods are used for the game to achieve the equilibrium in which optimal beams are steered toward appropriate users. The solution at this state is used for controlling the coefficients in precoding matrices of satellites. In contrast with the approach of multi-agent reinforcement learning in the design of multibeams in the ISTN [8], game theory does not require data for training, and distributed optimisation techniques can be employed easily to obtain the equilibrium more quickly.

Integrated Satellite and Terrestrial Networks: Case Studies

Machine Learning Real-Time Optimisation for Clustering in ISTNs Aided Disaster Relief

In this section, we apply the interplay of practical optimisation and deep neural network (DNN) model to design a cluster deployment of ISTN overlay with UAVs in real-time context of disaster relief. When we consider real network models with large-scale scenarios, conventional optimisation (Conv. OP) methods are implemented with an enormous amount of time and computing resource. To overcome this drawback, a learning-aided optimisation approach (DNN-OP) based on DNN models completely offers the real-time deployment of UAV-enabled cognitive radio networks [9, 10].

Similarly as in our previous works [11, 12], our simulation is performed using a PC having a AMD Ryzen 7 2700X, CPU @3.7GHz and 32GB memory. A network model consisting of one LEO satellite is a circle coverage with a radius of up to 2000m, K IoDs randomly distributed within the coverage area, the UAV's altitude of up to 150m, the carrier frequency/bandwidth at f_c = 2 GHz/B = 10 MHz (see more in



Scenarios $\{M, K\}$	Conv. OP	DNN-OP	Accuracy (%)
$\{2, 15\}$	0.15s	0.027s	93.1
$\{4, 30\}$	0.80s	0.028s	92.4
$\{8, 50\}$	4.27s	0.028s	90.8

FIGURE 3. A learning-based optimization model by amalgamating DNN and the execution time of clustering&deployment scheme under Conv. OP and DNN-OP approaches.

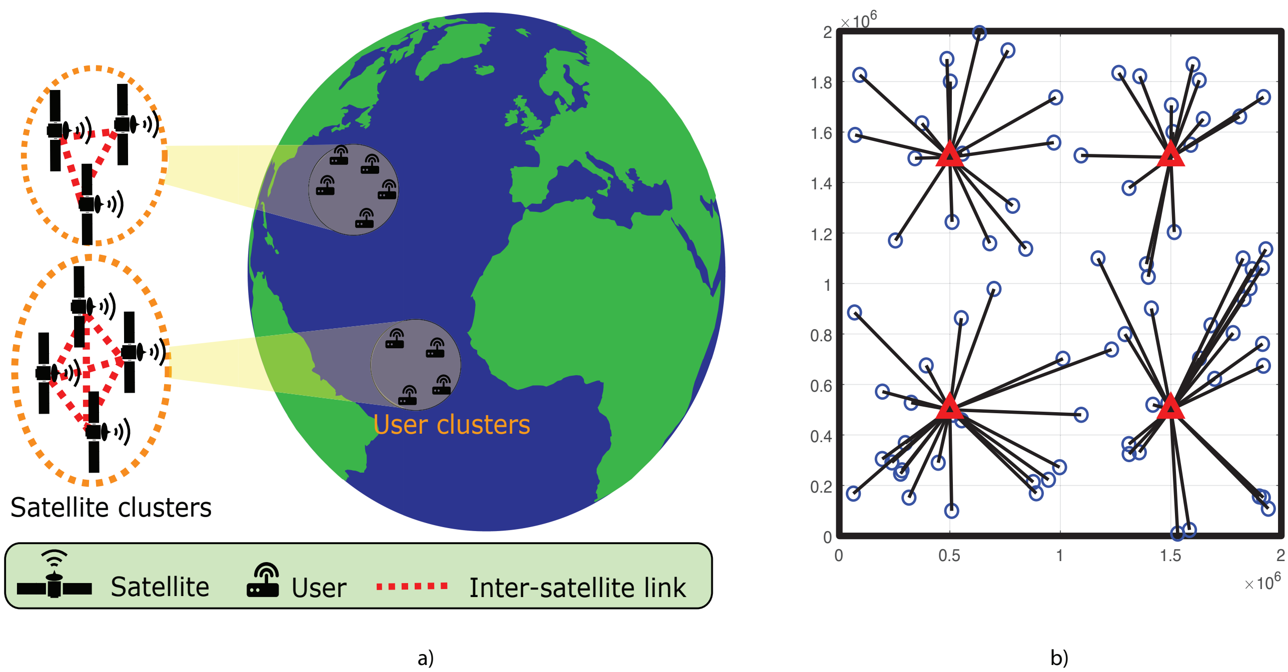


FIGURE 4. Typical clustering models in ISTNs. In 4b, red triangles represent satellites while blue circles are ground users, and multibeams from satellites to users are denoted by black lines: a) A theoretical clustering model; b) A practical game-based clustering model.

[12]). Figure 3 shows the model of learning-based optimisation by using the DNN and the execution time of the UAV deployment under different scenarios of the number of UAVs (M) and the number of IoDs (K). The results in Fig. 3 demonstrate that our proposed learning-aided optimisation based on DNN model offers a real-time deployment of UAVs even when large-scale networks are involved. Meanwhile, the accuracy metric, defined by the average similarity of the results between Conv. OP and DNN-OP approaches, is still very high.

Real-Time Optimized Multibeam and Power Allocation in ISTNs

Following the aforementioned statements, clustering for both satellites and ground users, which is illustrated in Fig. 4a, plays important role in ISTNs. In this case study, we investigate the efficiency of a joint optimisation framework for multibeam design by clustering only users and allocating power to satellites in ISTNs. Our system model consists of four LEO satellites and multiple ground users with the assumption that each user is only served by one satellite using full bandwidth. For clustering users, the objective is to simultaneously minimise transmission time and maximize the channel gain using a trade-off value with a constraint of minimum transmission time. Then, to allocate the optimal power for beams, a network EE maximisation problem is formulated subject to the constraints of the maximum transmit power of each satellite and minimum data rate each user requires. To obtain the solution, coalition game and bisection search algorithm are used for solving the clustering problem and power allocation.

For simulation, four satellites are uniformly located in a considered area of 2000 × 2000 km. Each satellite equipped with 100 antennas for generating a maximum of 25 beams has an altitude of 1000 km to the Earth. Additionally, the maximum transmit power of each satellite is 20 dBW while the circuit power is 10 dBW. In terms of communications, the channel model is

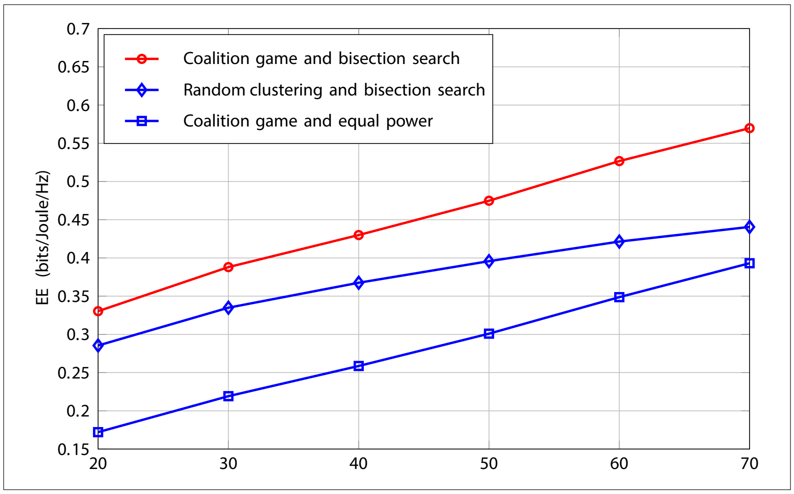


FIGURE 5. A comparison in the EE performance between the method using the combination of coalition game and bisection search, and the others consisting of random clustering and equal power.

designed with the Boltzmann constant of 1.38 × 10^{-23}, receiver noise temperature of 235.3 K, the total bandwidth of 500 MHz, and the normalisation of noise variance of 1. Other parameters are the minimum transmission time of 6.7 ms, the minimum data rate of 0.2 bits/Hz, and the tradeoff value of 0.5 between transmission time and channel gain. After clustering using the coalition game, the direction of beams toward 80 users from four satellites are shown in Fig. 4b.

To demonstrate the efficiency of multibeam design using the gaming clustering method and real-time power allocation, we introduce two more traditional methods as benchmarks. With a random clustering method, users are served by randomly chosen satellites. An equal power method divides the maximum power of each satellite by the number of its users and allocates it to each beam. Figure 5 reveals how the number of users in the range from 20 to 70 affects the network EE in our method and two traditional methods. Overall, the EE of the joint game theory and power allocation is always greatest in all cases with different numbers of users. The increase in EE by methods using coalition game for clustering is higher than the one of the method using random clustering. This proves that clustering users using the effective method improves considerably the network EE, especially with a high number of users. On the other hand, we further investigate the execution time of game theory based on clustering and power allocation, and the detailed results are shown in Table 1. A laptop with Intel Core i5-5200U CPU @2.2 GHz and 4 GB RAM memory is used for computing results. The execution time of these methods is low enough to achieve real-time optimized multibeam for given scenarios of ISTNs with the time constraint being less than tens milliseconds.

Open Research Directions and Challenges

Digital Twin-Aided Optimal Multibeam Design in 6G ISTNs

For joint optimal multibeam design between satellites and ground users, one of the main problems is that the latency of the link from satellites to users is much higher than those of the terrestrial links. As such the multibeam design must carefully address the frequent satellite handover which may cause the inconsistent multibeam on the ground. It is even more challenging for ISTN to support high-speed immersive services for a massive number of users. By offering a real-time two-way interaction between physical and virtual worlds, digital twin has been considered as a promising technology for many time-sensitive applications in manufacturing, aviation, healthcare, intelligent transport systems, and smart cities. As such, digital twin can be a key enabler to support robust and resilient multibeam design for ISTN. Recently, digital twin has been considered to solve the aforementioned challenge of satellite communications, for example, digital twin-assisted satellite routing scheme is introduced to enhance the reliability between satellites and ground users. In addition, the joint cache placement and beamforming design in ISTN networks has been considered in [13], which can lay some initial foundation on the joint optimal design of communications, computing, and caching for digital twin-assisted ISTN.

In spite of frequently moving, the satellites orbit can be predictable and therefore their parameters can be estimated. However, due to the fast movement of satellites and long-distance communication, it is really a major challenge to design the multibeam to match the real-time perspective between satellite and terrestrial networks. By incorporating digital twin framework into ISTNs, unknown information from satellite networks can be interpreted and reproduced, which can facilitate the joint multibeam design and radio resource management as well as prevent the inter-beam and intra-beam interference among multiple satellites.

Quantum-Inspired Optimization and Machine Learning for Optimal Multibeam Design in 6G ISTN

Another important issue involving in the dynamic topology and rapidly changing positions of satellites is the frequent satellite handover, which reduces the utilisation of multibeam design. Moreover, due to the fact the degradation of turbulent atmosphere of the Earth is higher than the noise, the unbalanced channel exists between the downlink (i.e., satellite-to-ground) and uplink (i.e., ground-to-satellite) of ISTN cannot be overlooked when designing the optimal radio resource allocation [14]. In other words, the impact of turbulent atmosphere is more severe in the uplink compared to the downlink, leading to the fact that the degradation of the ground-to-satellite is significantly comparable to that of satellite-to-ground. As a result, the large dissimilarity in the uplink makes its beam more random and render to higher loss in the uplink than the downlink. To overcome this obstacle, by exploiting the effective quantum-space impact in the noisy environment, quantum-based satellite communications with LEO has been considered as a key enabler in supporting global quantum Internet [15].

Another application of quantum computing in ISTN is to investigate the use of quantum computing in optimisation and machine learning that can alleviate the complex optimal resource allocation of ISTN in supporting the large-scale deployment of extremely immersive mission-critical services such as virtual reality, augmented reality, and tactile Internet.

To support these services with highly demanding constraints of high data rates, ultra-reliable, and low latency, quantum-inspired optimisation and machine learning solutions are urgently needed.

Conclusions and Future Works

In this article, inspired by the advances of satellites technology, we have investigated the optimal multibeam design and user clustering to improve the interference management of ISTN for supporting a massive number of users with diverse real-time services. We proposed a machine learning-aided real-time optimisation scheme for optimal multibeam and clustering for ISTN to efficiently suppress the interference coexisting between the satellites and terrestrial networks. Several important mathematical optimisation approaches empowering the optimal multibeam design and clustering algorithms have been introduced including real-time optimisation with machine learning and game theory. As case studies, we have demonstrated the advantages of our proposed schemes in several practical scenarios of ISTN including machine learning-assisted real-time optimisation for clustering and real-time optimal multibeam and power allocations. Finally, several potential topics in ISTNs with digital twin technology and quantum computing have been introduced as future research direction. Although there are still persistent challenges, research efforts have been extensively made to fully realize this promising ISTN candidate for 6G networks.

Number of IoDs	20	30	40	50	60	70
Game theory based clustering (ms)	1.14	1.77	2.27	3.50	6.26	10.10
Power allocation (ms)	1.01	1.13	1.14	1.25	1.31	1.38

TABLE 1. The average execution time spent for clustering and PA when the number of ground users changes.

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