Machine Learning-Based User Scheduling in Integrated Satellite-HAPS-Ground Networks

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Abstract
Integrated space-air-ground networks promise to offer a valuable solution space for empowering the sixth generation of communication networks (6G), particularly in the context of connecting the unconnected and ultraconnecting the connected. Such digital inclusion thrives on solving management problems, especially those accounting for load-balancing considerations, of particular interest. The conventional model-based optimization methods, however, often fail to meet the real-time processing and quality-of-service needs, due to the high heterogeneity of the space-air-ground networks, and the typical complexity of the classical algorithms. Given the premises of artificial intelligence at automating wireless networks design and the large-scale heterogeneity of non-terrestrial networks, this article focuses on showcasing the prospects of machine learning in the context of user scheduling in integrated space-air-ground communications. The article first overviews the most relevant state-of-the-art in the context of machine learning applications to the resource allocation problems, with a dedicated attention to space-air-ground networks. The article then proposes, and shows the benefit of, one specific use case that uses ensembling deep neural networks for optimizing the user scheduling policies in integrated space-high altitude platform station (HAPS)-ground networks. Finally, the article sheds light on the challenges and open issues that promise to spur the integration of machine learning in space-air-ground networks, namely, online HAPS power adaptation, learning-based channel sensing, data-driven multi-HAPSs resource management, and intelligent flying taxi-empowered systems.

Introduction
Motivation
Due to their inherent limitations, the existing 5G cellular networks cannot achieve the full power of its initial premises (i.e., Internet of Everything applications (IoE)), which motivates researchers to explore innovative techniques to further empower the sixth generation of communication networks (6G) [1]. In fact, existing communications infrastructures mandate major restructuring to meet the deluge in data demand, so as to face the rapid growth of mobile devices and wireless traffic [2, 3]. 6G systems, therefore, aspire to achieve high reliability, low latency, and high data rate to provide mobile broadband reliable low latency communication (MBRLLC), massive ultra-reliable low latency communications (mURLLC), and human-centric services (HCS) [1].

While terrestrial densified networks have their own merits at increasing system throughput [31], areas such as isolated mountains, oceans, glaciers, and disasters surfaces, may not be suitable for the excessive deployment of base-stations. Further, ultra-dense networks often prove to be interference-exacerbated, all of which motivate the need to augment the ground communication systems with connectivity from the sky. Current satellite-ground networks provide a degree of seamless connectivity to extreme areas; however, the incurring transmission delay becomes substantial in large-scale network deployment. Embedding additional layers in between the satellite and ground platforms, also known as integrated space-air-ground networks, emerges therefore as a strong enabler to jointly improve the data throughput and achieve the global digital inclusion needed in 6G systems [4, 5]. This article, therefore, focuses on one particular space-air-ground system model, and showcases how machine learning plays a vital role in optimizing the user scheduling policy of the considered network through ensembling deep neural networks.

The projected performance of integrated terrestrial and non-terrestrial networks (TNTNs), often referred to as vertical heterogeneous networks (VHetNets), strongly depends on the nature of the interconnecting segments (i.e., satellite segment, air segment, and ground segment). The joint resource allocation problem across such heterogenous systems becomes, therefore, of considerable complexity, for example, see [4–6] and references therein, especially when accounting for practical system design constraints and the different modes of intra-layer and inter-layer interference. For instance, traditional model-based optimization algorithms usually require an accurate communication model, which is impossible to obtain in reality. In addition, thanks to the intricacy of most of the recent works on resource allocation in VHetNets [4–6], existing solutions remain of heuristic nature, and often exhibit high computational complexity that is incompatible with real-time processing of practical networks. Given the recent advances of machine learning, especially with regard to nonlinear mapping and powerful data mining capabilities, machine learn-
The machine learning framework illustrated in this article is related to the general resource allocation problem of wireless networks, its applications to space-air-ground communications, and the recently emerging learning-based optimization techniques in wireless systems. We next present a concise overview of such works, and motivate for one specific new application that uses ensembling deep neural networks for optimizing the user scheduling policies in integrated space-high altitude platform station (HAPS)-ground networks.

**Related Work**

The machine learning framework illustrated in this article is related to the general resource allocation problem of wireless networks, its applications to space-air-ground communications, and the recently emerging learning-based optimization techniques in wireless systems. We next classify the state-of-the-art of such topics in a systematic fashion, and motivate for the use-case adopted in this article.

The general framework of resource allocation includes optimizing resources (e.g., channels and bandwidth) and computing resources (e.g., power and memory) so as to optimize specific network utilities. Other dimensionality-dependent resources also include beamforming in multi-input multiple-output (MIMO) systems, time-slot allocations in time-division multiple-access system (TDMA), frequency-bin allocations in frequency-division multiple-access system (FDMA), and so on. The conventional approach to solve such resource allocation problems is to tackle well-modelled optimization problems using mathematical programming techniques, for example, [4–6]. Such optimization problems, typically concerned with throughput maximization, transmit power minimization, energy-efficiency maximization, and so on, often aim at optimizing the network resources, for example, user scheduling, power, spectrum optimization, and so on. For example, in the particular context of resource allocation in space-air-ground communications, existing works that solve the user scheduling problem mostly focus on throughput maximization, transmit power minimization, energy-efficiency maximization, and so on, often aim at optimizing the network resources, for example, user scheduling, power, spectrum optimization, and so on. For example, the recursive shrink-and-realign process in [8], and the joint integer linear programming, generalized assignment problem, and weighted-minimum mean squared error (WMMSE) in [5].

Despite the numerical prospects of the above classical techniques, recent references, for example, [6, 9–13], show that machine learning techniques can indeed outperform conventional algorithms. This is especially the case for non-terrestrial networks, where classical optimization becomes obsolete.

The rationale behind the non-practicality of the use of conventional algorithms in VHetNets is twofold. Firstly, VHetNets are often quite complex from an optimization algorithmic perspective [5], which particularly stems from the multiples modes of coupled cross-layer interference (i.e., intra-layer interference, intra-layer interference, inter-base-station interference, and intra-base-station interference). Secondly, the stochasticity of VHetNets underlying channels renders the problem modelling a daunting task, especially given the ever-changing nature of the space-air-ground channels. Strictly speaking, utilizing classical optimization algorithms would imply solving the problems in an offline fashion, and repeating the solution process whenever the cascaded multi-layered channel changes. Such a process is clearly unfeasible for any reasonably sized VHetNet. For instance, paper [9] points out that machine learning can be used to solve four main problems in integrated air-space-ground networks (i.e., resource management, security authentication, attack detection, and target recognition and location). Reference [6] further studies the difficulties of resource optimization due to the heterogeneity of space-air-ground networks and proposes adopting machine learning to improve traffic control performance in one particular system model.

References [9, 6], however, do not consider the user scheduling issues, which the current article tackles via ensembling deep neural network in a space-HAPS-ground system.

From methodologies perspectives, references [10, 11] adopt deep learning to optimize power control in general wireless networks setups. Particularly, [10] illustrates how a class of signal processing algorithms can be approximated by deep neural network. Reference [11], on the other hand, proposes using ensemble learning to improve the system performance as compared to a single deep neural network. Similarly, device-to-device (D2D) scheduling problem is solved in [12] using spatial deep learning, whereby spatial convolutional filters are adopted to estimate the interference and channel strength of each link from geographic location information as feature vectors of the subsequent fully connected network. Further, reference [13] employs scalable reinforcement learning (i.e., deep Q-learning) to jointly optimize the routing and spectrum allocation, where a multi-agent distributed method is adopted to optimize its own flow and deep learning is used to predict the Q-value.

**Contributions**

Unlike the aforementioned references, the current article focuses on one particular VHetNet system model, where one geo-satellite connects to one HAPS platform so as to improve the throughput of the ground-level communications. The performance of the considered network, hereafter denoted by space-HAPS-ground network, becomes a strong function of the ground users’ scheduling policy, that is, user-to-HAPS or user-to-ground base-station association protocols. The article then proposes, and shows the benefit of, using ensembling deep neural network for optimizing the user scheduling policies in the underlying space-HAPS-ground networks, so as to determine the user-association strategy in an online fashion and highlight how such proposed method outperforms the traditional optimization approach. In light of the numerical prospects of the artificial-intelligence (AI)-based proposed solution, the article also sheds light on the challenges and open issues that promise to spur the integration of machine learning.
When supervised learning is applied to wireless networks resource allocation problems, labeled data hinges upon deriving specific optimization algorithms, and then learning (approximating) the underlying function of the optimization algorithm in space-air-ground networks, namely, online HAPS power adaptation, learning-based channel sensing, data-driven multi-HAPSs resource management, and intelligent flying taxi-empowered systems. In light of the related works section above, the contributions of the current article can be summarized as follows:

- The article presents a concise overview of the existing machine learning-based methods that aim to solve the general resource allocation problems in existing wireless networks.
- The article addresses the problem of user scheduling in space-HAPS-ground networks subject to user-connectivity, backhaul, and power constraints, by maximizing the network throughput at the ground-level users.
- The article determines the user scheduling policy (i.e., user-to-HAPS or user-to-ground base-station) by using ensembling deep neural network for optimizing the user scheduling policies in an online fashion.
- The article simulations results show how the proposed ensembling deep neural network approach always outperforms the other classical offline optimized schemes, especially those recently developed in [5]. The proposed solution particularly outperforms all other offline optimization solutions when the ensemble size increases, which illustrates the promising role of the proposed solution in optimizing future integrated space-air-ground networks.
- The article proposes a handful of timely open issues, which promise to spur the integration of machine learning in future space-air-ground networks. For example, see [13] and references therein.

### Organization

The rest of the article is organized as follows. We next present the applications of machine learning in the context of general resource allocation problems, and illustrates the prospects of using ensembling deep neural networks in optimizing the user scheduling in space-HAPS-ground systems. Following that, we highlight the major challenges and open issues of using machine learning in future space-air-ground networks. The article conclusions are finally presented in the last section.

### Machine Learning for Resource Allocation: The Case of Space-HAPS-Ground Networks

Machine learning has recently emerged as a powerful solver for optimizing wireless communications [7, 9]. Thanks to its inherent characteristics in terms of data driven, automating analytical modeling, and online processing, machine learning proves to be useful at solving complex communication optimization problems with random, dynamic channel and unpredictable users demands in time and space [7]. For the sake of completeness, we next briefly present how supervised, unsupervised, and reinforcement learning methods tackle the resource allocation problems in wireless systems.

#### Supervised Learning

When supervised learning is applied to wireless networks resource allocation problems, labeled data hinges upon deriving specific optimization algorithms, and then learning (approximating) the underlying function of the optimization algorithm. Such approach uses the fact that specific machine learning techniques, for example, deep learning, can act as a universal function approximator; see [7] and [10] and references therein.

#### Unsupervised Learning

Unlike supervised learning which produces an approximate solution that is at best on the same par with the original algorithm, unsupervised learning directly uses the objective function as the loss function of the underlying wireless communication optimization problems, the objective functions and constraints of which are typically complex and non-convex. By further using specific penalty terms to account for the constraints, ensembling learning can also improve the system performance [11], which is adopted in this article in the context of user scheduling in VHetNets.

#### Reinforcement Learning

Reinforcement learning is an alternative approach that maximizes cumulative rewards. More specifically, reinforcement learning consists of agent, environment, state, action and reward. After the agent takes an action, the environment transitions to a new state and evaluates the reward. Subsequently, according to the new state and reward, the agent takes a new action and policy, in an effort to eventually maximize the long-term cumulative reward. Such approach is particularly useful in resource management problems that can be formulated as Markov decision processes, for example, see [13] and references therein.

#### Adopted Approach

As mentioned earlier, the current article adopts an unsupervised ensembling deep neural network approach to solve the user scheduling in VHetNets. The rationale behind adopting such an unsupervised learning algorithm as opposed to other machine learning types is that supervised learning is a rather suboptimal solution that can yield a solution which is at best as good as the known heuristics. The setup of the problem under study also does not fit the general framework of reinforcement learning, since the optimization problem under study does not assume a cumulative reward-based objective. Given how complex the discrete scheduling problem under study is — which makes finding the global optimal solution of exponential complexity — and given the stochasticity of the VHetNets underlying channel, the article uses ensembling deep learning approach to solve the problem. The compelling feature of the proposed approach is that it combines the capabilities of the deep learning algorithm with the enhanced search space obtained through the ensembling approach.
User Association in Satellite-HAPS-Ground Systems Using Ensembling Deep Neural Networks (EDNN)

This section considers a specific satellite-HAPS-ground network, and illustrates its potential at augmenting the ground-level communication, especially for connecting the unconnected and ultraconnecting the connected. In an effort to boost the digital inclusion index, the article considers solving the user scheduling problem (i.e., user to geo-satellite via the HAPS, or user to BS) by imposing a specific user connectivity constraint. In fact, compared to conventional standalone terrestrial networks, scheduling problems in space-HAPS-ground networks are more complex. This mainly stems from the several modes of cross-layer interference of the considered system (i.e., intra-HAPS interference, intra-BS interference, and HAPS-BS interference), in addition to the stochasticity of their underlying channels. Given the random nature of the underlying space-air-ground channels, the article, therefore, adopts an artificial-intelligence based technique to maximize the network sum-rate subject to specific connectivity and power constraints. Ensembling deep neural networks are particularly adopted to solve such the user scheduling problem in an online fashion. The simulation results then illustrate how the proposed solution acts a powerful enabler to improve the performance of the considered integrated satellite-HAPS-ground network.

The Considered System Model

Consider an integrated satellite-HAPS-ground network, which consists of one geo-satellite, one HAPS and several ground base-stations (BSs), where the geo-satellite is connected to the HAPS via a free-space optical (FSO) link. The HAPS then transmits data to the ground users via radio-frequency (RF) links. On the ground level, the BSs which are equipped with multiple antennas serve users through spatial multiplexing, that is, beamforming. In addition, the gateway and satellite transmit data at different time intervals, and so we do not consider the interference between uplink and downlink. An example of the considered network is illustrated in Fig. 1. In fact, such networks have recently attracted attention in the context of 6G research directions. From a link level analysis perspective, reference [2] investigates the point to point (P2P) links between the different entities of the three-layer network, that is, space-air-ground networks. The characteristics, feasibility, advantages, and challenges of HAPS as air-based networks are also analyzed in [3], which highlights how HAPS quasi-stationarity makes it suitable for augmenting ground-level communications infrastructures. More recently, the results in [5] prove that the integrated satellite-HAPS-ground network can majorally help mitigating the digital divide problem through joint user scheduling and beamforming. The discrete user scheduling solution provided in [5], however, relies on traditional optimization heuristics. To this end, the current article goes one step forward toward developing machine-learning based-resource allocation solutions, and illustrates how ensembling deep neural networks-based solution outperforms the conventional systematic approach.

System Objective and Constraints

This article focuses on maximizing the network sum-rate subject to user-connectivity, backhaul, and power constraints, so as to determine the user scheduling variables (i.e., user to geo-satellite via the HAPS, or user to BS). The mathematical details of the problem formulation and adopted symbols can be found in our technical report available on archive [14]. The article particularly imposes the relevant constraint that the network needs to serve K users at least, so as to guarantee a K-user inclusion within the integrated system. The article further imposes that each user can only be served by at most one BS or by the HAPS, and that the number of users served by HAPS or BSs cannot exceed their respective payloads. The transmissions from the HAPS to users and BSs to users use the same RF bands, but adopt beamforming to serve multiple users simultaneously. The transmit powers of BSs and HAPS are limited by their respective nominal maximum powers. Due to the backhaul capacity, the achievable rate of users served by HAPS is subject to FSO rate and RF rate, as mathematically illustrated in our technical report available on archive [14].

It is worthwhile to note that the classical approach to solve the above complex problem often relies on solving a snapshot of the problem for fixed channel values, and repetitively execute the process whenever the channel changes. Such approach, however, requires the algorithmic processing time to be less than the time of channel changes. Obviously, this is not always possible with model-based traditional algorithms. Therefore, our article next proposes using ensembling neural networks to achieve real-time processing and gain better performance.

Ensembling Deep Neural Networks Approach

As mentioned earlier, since supervised learning is akin to a redesign of existing traditional methods (through approximating complex algorithms),
This article rather adopts unsupervised learning to address the user scheduling dilemma. The article particularly uses ensembling deep neural networks (EDNN) to solve the problem described above, due to EDNN promising numerical prospects in solving complex non-convex optimization problems; see [11] and references therein. Using an online optimization approach, the maximization of the network throughput can be recast as a minimization of the loss function which accounts for the original objective and constraints. More details of the associated loss function can be found in our technical report posted on archive [14].

More specifically, minimizing the loss function takes the channel values and beamforming vectors as inputs, and outputs the user association variables. Our article proposes a fully connected deep neural network to solve the user scheduling problem. More specifically, the neural network consists of 2 hidden layers which have ReLU activation functions and adopts batch normalization. Because the value of $a_{ij}$, that is, the user association binary variable of user $j$ and transmitter $i$, is between 0 and 1, the output layer has a sigmoid activation function. The structure of the deep neural network is shown in Fig. 2. It is worth mentioning that in order to satisfy the constraints of the problem, we use the Lagrangian dual ascent to update the regularization parameters for each of the constructed deep neural network of the overall ensemble. The overall algorithm technical steps can be found in our detailed report posted on archive [14].

To assess the numerical prospects of the above solution, the article also simulates some classical discrete optimization methods, namely, the integer linear programming and generalized assignment problem (ILP-GAP), the channel dependent (CD), and distance dependent (DD) methods as baselines, the details of which can be found in [5].

SIMULATIONS

This section illustrates the performance of the proposed EDNN-based solution versus the maximum power of HAPS, the $K$-value (i.e., the minimum number of users to be served.), the ensembling size and the running time, so as to highlight the numerical prospect of the above solution. We consider an integrated satellite-HAPS-ground network, wherein 20 users are distributed in three different subareas: Subarea 1 contains 6 BSs and 12 users. Subarea 2 contains 3 BSs and 6 users. The remaining area is Subarea 3 and contains 2 users, with 1 BS. The HAPS is equipped with 10 antennas. For brevity, we refer the readers to reference [5] for the details of the adopted system parameters of the simulated integrated satellite-HAPS-ground network. Further, the details of the hyper-parameters including the minibatch size, the learning rate, and the number of epochs can be found in our detailed report available on archive [14].

Firstly, Fig. 3 shows the sum-rate versus the maximum power of HAPS when $K$ is 15. It is clear that, as the maximum power of HAPS increases, all highlighted solutions decrease, due to the increased interference levels. The figure particularly shows how the proposed (online) deep learning approach always outperforms the other classical offline optimized schemes developed in [5]. The EDNN-based solution particularly outperforms all other simulated solutions for all values of the HAPS power, which highlights the numerical prospect of advanced machine learning techniques in solving sophisticated resource allocation problems.

To illustrate the impact of the proposed solution in connecting the unconnected and ultraconnecting the connected, Fig. 4 shows a comparison of ILP-GAP versus the deep neural network (DNN)-based algorithms for different values of $K$ when the maximum power of HAPS is 200 Watts. The figure shows that, as the value of $K$ increases, the sum-rate of the proposed DNN approach decreases, due to more users served by the system, which introduces more interference. The figure, however, shows that the proposed EDNN approach always has a superior performance as compared to the offline optimization approach.
Figure 5 represents the added value for using ensembling learning when the maximum power of HAPS is set to 200Watts and K is set to 15. Figure 5 shows that, with the ensembling size increasing, the sum-rate also increases. This is because the considered user scheduling problem is a discrete non-convex problem, which typically has several local optima. Therefore, DNN with different training data and initialization methods improves the local optima search, and can reach up to 26 percent in terms of sum-rate as compared to the classical offline optimized schemes developed in [5]. Figure 5 further reemphasizes how the proposed machine learning-based techniques always outperform all the offline optimized methods for all values of the ensembling size.

Finally, to illustrate the computational complexity and sum-rate performance of the different association methods, Table 1 depicts the sum-rate performance, time complexity, and training time, when K is 15 and the maximum power of HAPS is 200Watts. In this part of the simulations, DNN and EDNN are implemented in python 3.8.0 with Torch 1.8.0 on one computer (Intel Core-i5 processor). Table 1 illustrates that the machine learning-based approaches (i.e., DNN and EDNN) achieve higher sum-rate with substantially lower computational complexity than the traditional optimization algorithms (i.e., given that training occurs in an offline fashion). In particular, note that our proposed DNN and EDNN methods outperform the ILP-GAP solution by a significant margin of 1058.684ms and 1056.594ms, respectively, which provides an additional valuable testimony of the proposed solution prospects in optimizing future integrated space-air-ground networks.

Challenges and Open Issues

Despite the numerical advantages of artificial intelligence-based methods in integrated space-air-ground networks, their practical implementation remains a strong function of system challenges, such as spatio-temporal channel variations, scarcity of dataset, heterogeneity, and data collection hurdles. On the one hand, the current hardware, including batteries and on-system components, cannot meet the stringent requirements of integrated space-air-ground networks. On the other hand, despite its great potential, machine learning relies heavily on the data availability and is computationally demanding at the training stage. To this end, this section sheds light on some of the noticeable challenges and presents some promising open issues on this topic.

Online HAPS Power Adaptation

Flight control and communication payload are among the major aspects of HAPS energy consumption [3]. Specifically, HAPS flight control often imposes quasi-stationary constraints, which necessitates propulsion power. HAPS can also be often treated as a super-macro base-station, the energy consumption of which includes transmitting and processing information signals. Since the height of HAPS is generally in the order of 18–21km [3], the considerable path loss requires to be compensated with high transmit power. Unlike ground BSs which can be connected to the electrical grid, however, HAPS operation relies on the available on-board energy sources. So far, there are three types of energy sources that serve to empower HAPS (i.e., battery energy source, energy beams, and laser beams) [3]. While conventional battery energy cannot provide a long HAPS endurance, the other two energy sources cause high power irradiation risks. To this end, one considerable way to increase the energy of HAPS is to use solar or hydrogen fueled...
The integration of artificial intelligence into future communication networks is expected to spur a myriad of possible advantages in the context of space-air-ground communications.

Learning-Based Channel Sensing

Channel knowledge is a key factor in optimizing future integrated space-air-ground communications. Given the ever-changing spatio-temporal conditions of the surrounding environment, the problem of dynamically choosing the proper source to empower HAPS (i.e., battery energy source, energy beams, laser beams, solar or hydrogen) becomes intrinsically related to adopting the most appropriate learning-based approaches, which promises to be a timely topic for future investigation.

Data-Driven Resource Management in Multi-HAPSs Scenarios

Multi-HAPSs systems are expected to provide a distributed air-platform enabling to achieve global seamless connectivity [3]. Under such systems, however, several cross-layer interference modes are bound to coexist, namely, intra-HAPS interference, inter-HAPS interference, intra-BS interference, inter-BS interference, and HAPS-BS interference. The resource management problems in multi-HAPS scenarios become, therefore, more complex than its one-HAPS scenario counterpart. In essence, the approach proposed earlier assumes that decisions are made within a centralized processor, that is, through centralized learning which requires that all collected data need to be uploaded to the centralized processor; thereby raising a multitude of security and privacy concerns. To best handle resource allocation problems in multi-HAPS scenarios, federated learning, where each data owner does not need to share their own data set, promises to offer an efficient paradigm to enable a democratized distributed learning platform [7]. In fact, the marriage of ensemble deep learning with federated learning can play a major role in tackling the intricacy of security and privacy concerns through multi-HAPS data-driven resource management protocols, which promises to be an active area for future research.

Intelligent Flying Taxis-Empowered Systems

Flying vehicles (e.g., flying taxis, delivery systems, etc.) are regarded as the potential futuristic solution to handle the traffic congestion and the rapid expansion of the delivery industry [15]. Augmenting future intelligent transportation systems (ITS) with machine learning capabilities are expected, therefore, to spark major research fields for boosting flying taxis-empowered systems, especially under the framework of future smart cities. More specifically, flying vehicles require dynamic control signals to avoid collisions, overcrowding, and so on. Data transmission across vehicles, further, would guarantee voice and multimedia high quality-of-service. Given the height of future flying vehicles, providing the ground-based platforms can help enhancing both their control signals and their quality-of-service targets. Considering the contextual mobility across the flying cars, in addition to the handover and channel variations, investigating data-driven resource allocation schemes in integrated HAPS-flying taxi systems becomes essential in the context of next generation ITS design. Such emerging AI-empowered interdisciplinary research direction that falls at the intersection of communication, transportation, and computation, promises to be a timely topic for future investigation.

Conclusion

The integration of artificial intelligence into future communication networks is expected to spur a myriad of possible advantages in the context of space-air-ground communications. To this end, this article goes one step forward toward developing machine-learning-based-resource allocation solutions in satellite-HAPS-ground networks. The article first overviewed the most relevant state-of-the art in the context of machine learning applications to the resource allocation problems in space-air-ground networks. The article then proposes, and shows the benefit of, one specific application that uses ensembling deep neural network for optimizing the user scheduling in integrated space-HAPS-ground networks. The proposed solution is particularly shown to outperform all other offline optimization solutions when the ensemble size increases (with up to 26 percent in sum-rate improvement), which illustrates the promising role of the proposed solution in optimizing future integrated space-air-ground networks. The article finally presents a handful of challenges and open issues that promise to spur the integration of machine learning in space-air-ground networks, for example, online HAPS power adaptation, learning-based channel sensing, data-driven multi-HAPS resource management, and intelligent flying taxis-empowered systems — topics that are soon expected to trigger the discussion on beyond 6G systems.

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