Artificial Intelligence Empowered Multiple Access for Beyond 5G Networks*

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Abstract

As the wireless world moves towards the B5G era, the need of additional bandwidth to satisfy the data rate requirement of killer applications, turned the attention of both industry and academia towards higher frequency bands, such as the terahertz (THz), creating the vision of THz networking. This shift to THz wireless networks comes with several challenges; especially, in the physical and medium access control (MAC) layers design, as a result of the directional nature, line-of-sight requirement, and ultra-dense deployment of THz networks. From several studies, it became clear that user association and resource allocation tactics need to be rethought to incorporate artificial intelligence (AI), which can offer "real-time" answers in challenging contexts that change often. Novel mobility management technologies are also necessary to meet the requirements for ultra-reliability and low latency of some B5G applications.

This white paper presents a comprehensive MAC layer strategy that enables intelligent user association, resource allocation, flexible mobility management, and blockage minimization, while maximizing system reliability. Specifically, a novel metaheuristic-machine learning (ML) framework is proposed, which enables quick and centralized joint user association, radio resource allocation, and blockage avoidance. This framework improves the performance of THz networks, while reducing association latency by roughly three orders of magnitude. A deep reinforcement learning (DRL) strategy for beam-selection is explored to assist mobility management and blockage avoidance inside the access point (AP) coverage region. Finally, a proactive hand-over system based on quick channel prediction with AI assistance is provided to allow user movement across the coverage zones of neighboring APs.

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* This white paper is a high-level summary of publication [9].

Introduction

A key promise of beyond fifth generation (B5G) networks is to bring the fiber quality of experience (QoE) to the wireless world [1]. An important goal in this direction is the development of terahertz (THz) wireless networks that can handle applications that require large amounts of bandwidth, such as holographic reality, collaborative robotics, self-driving cars, etc., without sacrificing reliability or adding latency [2]. Unfortunately, THz wireless links are sensitive to line-of-sight (LoS) obstruction [3], [4]. Likewise, THz wireless network deployments will be ultra-dense to countermeasure the high path-losses in this band [5]. As a consequence, the congestion of static or dynamic objects/users would unavoidably lead to blockages [6], [7]. This presents several significant challenges, including those related to mobility management (MM), radio resource (RR) allocation, and user equipment (UE) to access point (AP) association, which THz wireless systems medium access control (MAC) needs to face [8]. It is necessary to develop an adaptable joint UE-AP association and RR allocation approach that maximize network performance in terms of throughput, while avoiding LoS obstruction under conditions of extremely low latency [3]. This served as inspiration for the development of joint UE-AP association and RR allocation strategies using machine learning (ML) or metaheuristic methods.

Two MAC-related research approaches, namely beam selection and pro-active hand-over, have been pursued from the MM perspective [8]. For further information, see [9], which describes a random forest (RF) classification-based beam-selection method that improves data-rate maximization performance while reducing the computational burden of traditional approaches. A proactive hand-over and beam-selection technique for THz drone communications based on deep learning (DL) was reported in [10]. Both of the aforementioned methodologies need a large enough number of training samples and are unable to adapt to wireless environments that are constantly changing. By design, a MAC protocol for ultra-reliable and low-latency (URLL) THz wireless networks should mitigate the impacts of blockage, offer fast environment adaptability, and support mobile UE (MUE). However, no all-encompassing strategies that tackle these issues simultaneously have been put forth. Inspired by this**, this investigation** (presented in detail in [9]) **aims to set the stage for the development of an intelligent MAC protocol that allows centralized UE-AP association, local** w.r.t. individual APs**, and adaptable beam-selection as well as pro-active hand-over**.

AI-assisted Joint User Association and RR Allocation for Blockage Avoidance

By swiftly associating UEs with APs while satisfying a number of hard and soft restrictions, the association and blockage minimization problem attempts to provide URLL connectivity. Hard restrictions dictate the viability of the solution, whereas soft constraints affect the quality of the solution. Three hard constraints have been considered, namely:

i. Unique assignment: This guarantees that every UE is connected to exactly one AP. Note that the association process requires that the AP has enough available RR to cover the UE data-rate demands.
ii. Grouped allocation allows numerous UEs to be connected to a single AP; and
iii. Maximizing RR allocation efficiency while using the least amount of APs attempts to increase RR consumption at APs without going beyond their resource capacity.

On the other side, one soft constraint must be satisfied, namely LoS maintenance, that is equivalent to avoiding or minimizing LoS blockages.

To manage RR optimally and offer high QoE, the aforementioned issue must be effectively solved in complex and dynamic contexts. Given the scale, density, coverage, and RR management requirements, standard methodologies based on constraint resolution and combinatorial optimization techniques are unable to achieve the latency criteria for connection formation. For instance, LoS obstruction avoidance/minimization is required by the association approach in THz wireless networks. Due to the combinatorial explosion in the universe of alternative assignments, this problem quickly becomes insoluble for traditional constraint resolution methods, even in networks of moderate size. An approach is to train models that can roughly handle such optimization issues using ML-based techniques.

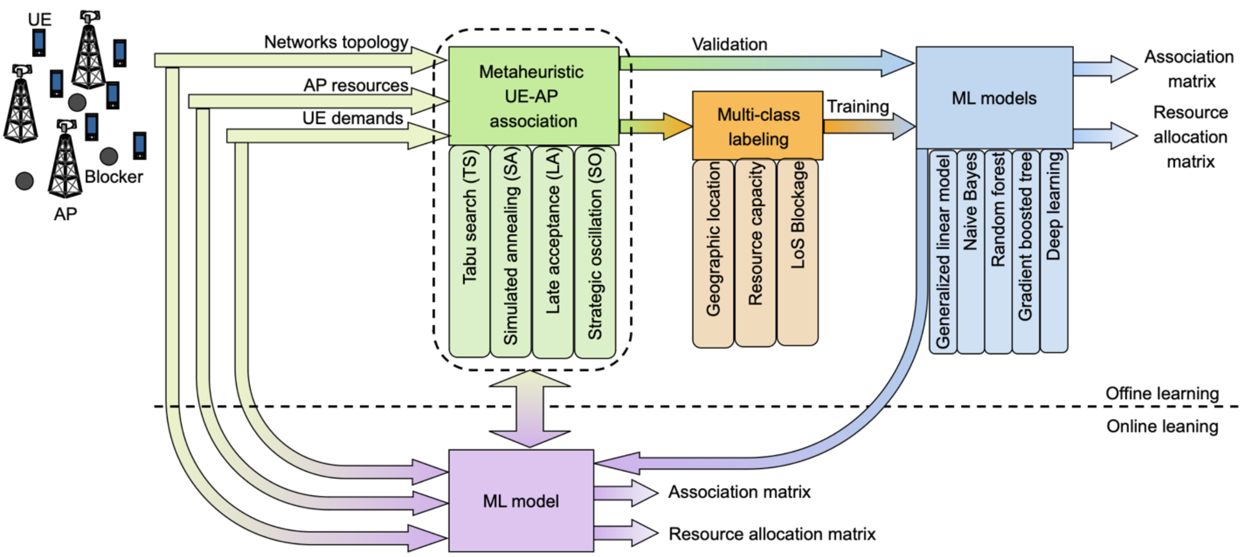

Figure 1: The hybrid metaheuristic-ML framework for UE-AP association with joint resource allocation and blockage avoidance.

As illustrated in Fig. 1, the UE-AP association problem is proposed to be solved using a hybrid metaheuristic-ML architecture that blends traditional search with ML. Classical constraint solving techniques are used to derive the best solutions to these snapshots after formalizing the problem as a constraint satisfaction problem and being given a variety of instances of it (snapshots). Metaheuristics are used to select from a large library of sophisticated search algorithms. These answers are then used to train and test a classifier that learns to generalize from the training snapshots to approximate answers to problems that have not yet been seen. The method is sufficiently general to be used for any sort of optimization issue, however despite its ability to adapt to change by retraining the model as needed on new snapshots, it performs poorly in terms of prediction.

The performance of the method has been illustrated using the following scenario, which also highlights some of the design choices made:

- A wireless network with 741 UEs and 125 APs spread throughout a 1 km^2 disk-shaped area, operating in the 100 GHz band. Independent Poisson point processes define the positions of UEs and APs.
- Both the required data rates from the UEs and the available RR at each AP are treated as independent uniformly distributed random variables.
- A tuple that defines an initial minimum-distance-based UE-AP clustering is the model's third component. Without taking the LoS barrier into account, the cluster is obtained. This clustering identifies UEs that might interfere with each other's LoS while they are facing a specific AP.

We do a 95-5 split, where 95% of the data is split for training and 5% is preserved for validation, after labeling the optimizer's outputs. We then examine the performance of GLM (generalized linear models), NB (naive Bayes), RF (random forests), GBT (gradient boosted trees), and DL (deep learning). The outcomes of GBT are better all around. The model's accuracy is 99.41%, its precision and recall are above 98% for all classes, and its standard deviation is in the range of 0.15%, demonstrating the stability of the model's performance. The model's accuracy after validation was 99.29%, demonstrating that it performs well under hypothetical but comparable network snapshots. The results reveal that both metaheuristic and ML were able to assign APs to all 741 UEs, so that both methods have a good capability to provide network coverage. We can see that the ML solution uses 98 APs to satisfy the resource needs of all the UEs, whereas the metaheuristic approach uses 95 APs. Furthermore, we can see that the metaheuristic approach has, on average, slightly overloaded 4.4% of the total capacity of 25 APs. Only 20 APs have been overloaded by the ML approach, however, there has been an average 14.5% capacity overload. This demonstrates that even while the ML model demonstrates that it has learned to respect the resource satisfaction constraint, more training is still required. Additionally, the metaheuristic optimizer found APs for each of the 741 UEs so that there were no partial blocks in the direct LoS link connecting them. In the instance of the ML, 643 UEs were mostly connected to APs without LoS blockers, while 98 UEs were connected to APs with a maximum of one LoS blocker. This outcome further demonstrates that the model learned the pattern to prevent or minimize LoS blockages. In regard to the proposed solution's latency consideration, it can be concluded that while predicting UE-AP associations for all APs, the calculations took 94.5ms, the associations can be predicted within 2.26ms if the nearest three APs are taken into account. Both values correspond to the related B5G network requirements.

DRL for Adaptive Beam Allocation

We examine a dynamic wireless network, where UEs and blockers are permitted to alter places, inside each AP service area. A smart mechanism must be installed in an AP to address RR management and allocation issues. This encourages the concept of applying deep reinforcement learning to enable the AP to interact with the environment (DRL). The DRL receives feedback in the form of a reward rather than learning from a labeled dataset. The agent performs better by altering its behavior to maximize the total reward over several steps [13]. Until the agent reaches a specified end state or until another stopping requirement (such as a set maximum number of repetitions) is satisfied, this process continues. The signal-to-interference-plus-noise-ratio (SINR) of the UEs and the UEs' positions over time are used to describe the environment (observation space). Figure 2 presents the strategy, and [0] provides a detailed explanation of it. The cutting-edge PPO (Proximal Policy Gradient) architecture was used to create the DLR [14].

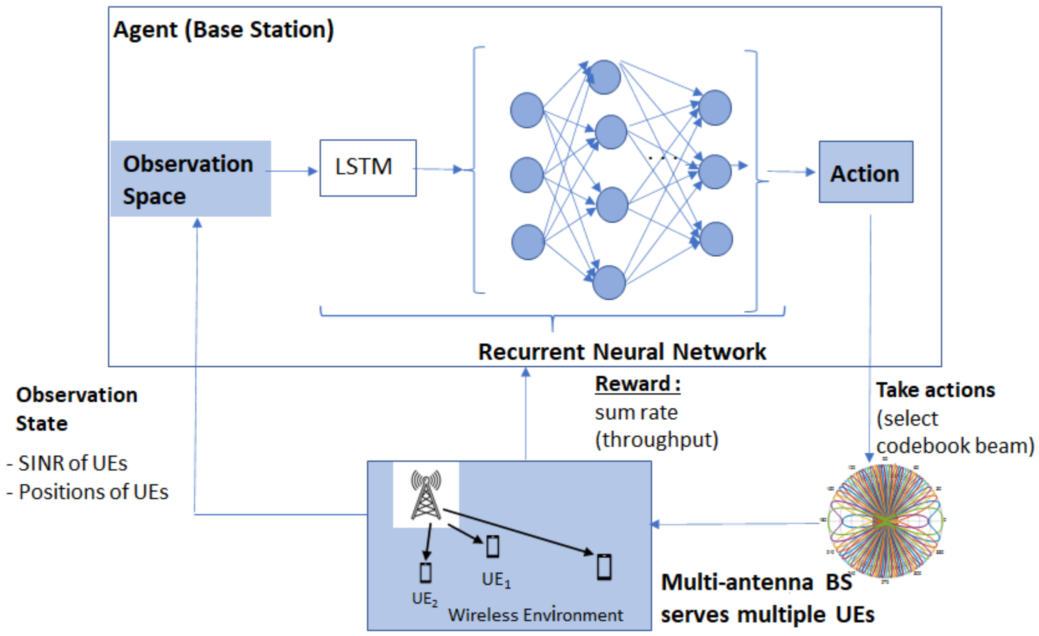

Figure 2: Information flow between agent and environment with action space and observation space.

There have been two main scenarios considered: (i) when the agent (AP) chooses a different codebook beam to serve each UE, and (ii) when the AP permits several UEs to share a beam. The inquiry setup takes into account the fact that the AP assigns codebook beam to serve 5 and 10 UEs simultaneously. In one configuration, the AP is thought to deploy 8 antennas with 16 predefined beams, whereas in the other, the AP would deploy 16 antennas with 32 predefined beams. The UEs are placed nearby the AP at random, i.e., within 100 meters, and they are close to one another. We can observe that the reward is bigger when some UEs can use the same beam than when the AP assigns a new beam to each UE. The reason is that certain UEs positioned next to each other desire to use the same beam; consequently, this leads to larger reward.

AI-assisted Pro-active Hand-over

To increase the system's dependability, effectiveness, and throughput in an ultra-dense wireless network, when multiple APs are capable of servicing the same mobile UE, it's crucial to provide proactive hand-over based on precise channel characteristic predictions. The following features have been identified as key inputs of most hand-over policies in the THz band:

i. signal strength,
ii. directionality, and
iii. existence of LoS path.

The inherent complexity of massive multiple-input multiple-output (MIMO) systems, which results from their huge degree of freedom, makes it impossible to use conventional methods that have been widely used in lower frequency bands. ML-based models that extract the connection between the environment and the aforementioned channel characteristics are thus anticipated to become crucial enablers of URLL proactive hand-over approaches to overcome this hurdle. Obtaining training and testing data, such as baseband channel coefficients, delays, azimuth angle of departure (AAoD), elevation angle of departure (EAoD), azimuth angle of arrival (AAoA), elevation angle of arrival (EAoA), delay spread angle (DSA), and azimuth angle (AA), as well as the transmitter and receiver characteristics of a UE that performed a variety of routes, is the first step in the creation of such an ML model.

The channel prediction problem has been split into two sub-problems. The first examines the behavior of individual path data in its raw or fine-grained form, while the second tries to aggregate (coarse-grained) data that has undergone feature engineering. The former can be used to foretell if a LOS or non-LOS path will be present, as well as path-loss for higher gain or higher power, delay spread, etc. The latter is able to forecast link-level behaviors, such as a link's characteristics that are proportionate to the received power at a specific point.

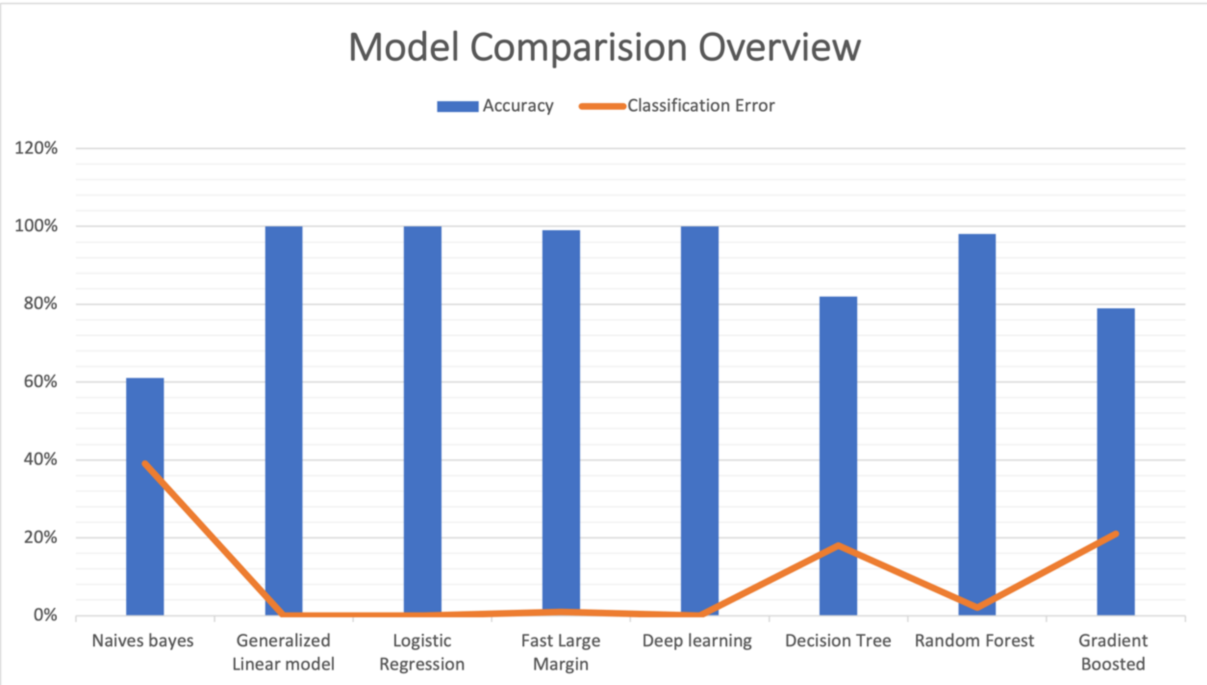

Figure 3: Model comparison.

Conclusions

Through a joint UE-AP association and RR allocation with blockage avoidance mechanism, a metaheuristic-ML based joint UE-AP association and blockage avoidance mechanism, and support for UE mobility and blockage avoidance within the AP coverage area through a DRL beam selection scheme, a comprehensive and intelligent MAC layer approach has been proposed. Through AI-assisted quick channel prediction, it provides ultra-reliable and proactive hand-over. The findings highlighted the critical function of ML in these networks and offered helpful guidance for the design of intelligent MAC for URLL THz wireless systems.

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