ProSky: NEAT Meets NOMA-mmWave in the Sky of 6G

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Abstract—Rendering to their abilities to provide ubiquitous connectivity, flexibly and cost effectively, unmanned aerial vehicles (UAVs) have been getting more and more research attention. To take the UAVs' performance to the next level, however, they need to be merged with some other technologies like non-orthogonal multiple access (NOMA) and millimeter wave (mmWave), which both promise high spectral efficiency (SE). As managing UAVs efficiently may not be possible using model-based techniques, another key innovative technology that UAVs will inevitably need to leverage is artificial intelligence (AI). Designing an AI-based technique that adaptively allocates radio resources and places UAVs in 3D space to meet certain communication objectives, however, is a tough row to hoe. In this paper, we propose a neuroevolution of augmenting topologies NEAT framework, referred to as ProSky, to manage NOMA-mmWave-UAV networks. ProSky exhibits a remarkable performance improvement over a model-based method. Moreover, ProSky learns 5.3 times faster than and outperforms, in both SE and energy efficiency, both b better than a deep reinforcement learning DRL based scheme. The ProSky source code is accessible to use here: https://github.com/Fouzibenfaid/ProSky

Index Terms—Deep reinforcement learning (DRL), millimeter wave (mmWave), neuroevolution of augmenting topologies (NEAT), non-orthogonal multiple access (NOMA), unmanned aerial vehicle (UAV).

I. INTRODUCTION

Despite the unprecedented advancements in telecommunication technologies in recent years, around half of the world's population, mostly living in rural and developing areas, still has limited or no access to cellular communication services [1]. Providing connectivity to those underprivileged areas could unequivocally enhance the quality of their lives. One of the envisioned, must-be-met, requirements of 6G is enabling ubiquitous geographical coverage anywhere, anytime. Due to the lack of essential cellular infrastructures in rural areas and the high cost of establishing them, along with the incapability of terrestrial base stations (BSs) to cover hotspot areas during special events or disaster scenarios, unmanned aerial vehicles (UAVs), thanks to their flexible 3 D mobility and ease of deployment, are envisioned to be a major part of the 6G wireless networks, acting as flying BSs [2]. Allowing sharing same spectrum resources among multiple wireless nodes simultaneously, non-orthogonal multiple access (NOMA) is emerging as another 6G enabler offering massive device connectivity without exhausting spectrum resources [2]. The emergence of NOMA-aided UAV networks necessitates a careful investigation of optimal UAV 3D deployment, and power allocation (PA) management [2]. Due to the high complexity of such an optimization problem, authors in [3], for example, approached the UAV placement and PA problems disjointly, whereas the number of served users was limited to two in [4], [5], and the UAV mobility was restricted to a 2D plane in [3]–[5]. There have been some attempts to address the UAV 3D placement problem, but these have primarily been accomplished by disjoining the UAV placement and PA problems, as done in [6].

Furthermore, due to the high probability of line-of-sight (LoS) links UAVs offer, the vast millimeter wave (mmWave) and terahertz spectrum can be utilized to satisfy the major 6G data rate enhancement requirement [2]. Nevertheless, managing NOMA-mmWave-UAV network resources to satisfy dynamic, heterogeneous, and massive needs adaptively yet fairly and efficiently is a complicated challenge, which conventional and even machine learning methods fail to handle. The good news, however, is that deep learning and, more generally, artificial intelligence (AI) technologies have the strong potential to handle multi-state network statuses and demands. After proving their effectiveness in solving problems with a large degree of freedom in various fields, AI techniques are proposed to be a key enabler for self-organizing, self-optimized networks in the 6G era [2].

Inspired by the remarkable successes of incorporating deep reinforcement learning (DRL) into different fields, a DRL model has been used to solve the placement problem of UAVs that fly at a fixed height [7]. More interestingly, our previous work, AdaptSky [8], unlike any other work, jointly solved the non-convex optimization problem of the 3D deployment and the PA of a NOMA-equipped UAV BS in the mmWave spectrum. Another AI tool that has recently shown outstanding performance in a variety of applications, including robotics and gaming [9], is neuroevolution of augmenting topologies (NEAT) [10]. Furthermore, although fairly limited, NEAT has been recently used in the area of communications, for example, in [11] to improve beam management in vehicle-to-vehicle communications. To the best of our knowledge, no work has studied the use of NEAT to manage UAV-based communications. In this work, we propose ProSky, a novel NEAT-based framework that jointly optimizes 3D deployment and PA for NOMA-aided UAV BSs operating in the mmWave spectrum. The main contributions of this work,
and advancements over [8], are summarized as follows:

(i) ProSky incorporates and demonstrates the effectiveness of NEAT, for the first time, to manage NOMA-mmWave-UAV networks. We set the NEAT environment that leads to the optimal UAV placement and NOMA PA such that, without sacrificing fairness, the total network data rate is maximized.

(ii) Although DRL based algorithms show tremendous improvements over a state-of-art in managing 3D networks while exhibiting high generalization capabilities [8], they have two drawbacks: i) specifying their neural network (NN) structure beforehand and tuning it using trials and errors does not only lead to degradation in efficiency but also sometimes in performance, ii) they train, relatively, slow and run into local minima issues. As NEAT optimally determines the NN structure, ProSky, however, demonstrates, while being reasonably fair, 5.8% improvements in SE and 21.9% in EE over a DRL based benchmark. More interestingly, as NEAT simultaneously trains multiple NNs to evolve based on a genetic algorithm (GA), ProSky exhibits more than 400% improvement in learning rate.

II. SYSTEM MODEL

A. Network Model

Embracing the 3D coverage capability of UAVs, and similar to our work in [8], we consider a 3D downlink cellular network that covers an area $A$ of $L \times L$ units in which a UAV serves a total of $2N$, for some integer number $N$, uniformly distributed ground users, $\mathbb{U}_g$. The UAV and ground users are assumed to be equipped with $N_{UAV}$ and $N_{UG}$ antennas, respectively. Throughout the paper, user $i$ is denoted by $\mathbb{U}_i$, where $i \in \{1, 2, ..., N_{UG}\}$. We assume that the users are grouped into clusters, as depicted in Fig. 1, in such a way that users $\mathbb{U}_i$ and $\mathbb{U}_{i+1}$ for $i \in \{1, 3, ..., N_{UG} - 1\}$ are associated with the same cluster and $\mathbb{U}_1$ has a stronger channel gain than $\mathbb{U}_{E_{i+1}}$, following the distance-based pairing strategy discussed in [12]. The assumption of having $2N$ users is set only for convenience and should not affect the model’s generality. In case there is an odd number of users, a cluster will encompass a single user and every thing else is still valid. The UAV serves each cluster over an orthogonal power resource with a total power $P_T$, distributed between the two corresponding users based on their channel conditions. The received power at the $\mathbb{U}_i$ at a given time step $\tau$ can be expressed as

$$P_{i,\tau} = P_T g^{\text{H}}_{i,\tau} (d_{i,\tau}) \alpha_{i,\tau},$$  \hspace{1cm} (1)

where $g^{\text{H}}_{i,\tau} (d_{i,\tau})$ is the gain between the UAV and $\mathbb{U}_i$ separated by a 3D distance of $d_{i,\tau}$, and $\alpha_{i,\tau}$ is the percentage of the $P_T$ assigned to $\mathbb{U}_i$. If we consider only a large scale fading and assume a slight difference between antenna pairs, the gain can be approximated as $g^{\text{H}}_{i,\tau} (d_{i,\tau}) = C d_{i,\tau}^{-\alpha}$, where $C$, equals $N_{UAV} \times N_{UG}$, is the gain resulting from applying multiple-input multiple-output (MIMO) antenna configurations at the UAV and $\mathbb{U}_i$. $g_{i,\tau}(d_{i,\tau})$ is the channel gain.

Based on the principle of NOMA, the superposition coding (SC) is used at the UAV to transmit signals to users located in the same cluster. SC encodes different signals into a single signal while assigning them different power values. The successive interference cancellation (SIC) is used at the receiver side for signal detection. The received signal to interference plus noise ratio at $\tau$ for $\mathbb{U}_i$, $\text{SINR}_{i,\tau}$, is expressed as

$$\text{SINR}_{i,\tau} = \frac{P_T g_{i,\tau}(d_{i,\tau}) \alpha_{i,\tau}}{P_T g_{i,\tau}(d_{i,\tau}) \beta_{i,\tau} + \sigma^2},$$  \hspace{1cm} (2)

where $\beta_{i,\tau} = \alpha_{i-1,\tau}$ if $i$ is even and zero otherwise, $\sigma^2$ is the noise power. The first term in the denominator of (2) represents the interference from the user with the stronger channel gain on the other user in the same cluster. Using the SIC technique, however, the interference from the user with the stronger channel gain gets removed. The data rate of $\mathbb{U}_i$ at $\tau$ is given by

$$R_{i,\tau} = W \log_2(1 + \text{SINR}_{i,\tau}),$$  \hspace{1cm} (3)

where $W$ is the communication bandwidth. The channel gain, $g_{i,\tau}(d_{i,\tau})$, between the UAV and $\mathbb{U}_i$, at the mmWave spectrum, in the presence of the LoS link [13], is expressed as

$$g_{i,\tau}(d_{i,\tau}) = C d_{i,\tau}^{-\alpha},$$  \hspace{1cm} (4)

where $a$ and $C$ are the path loss exponent and intercept, respectively. We assume that the UAV collects the channel state information at the beginning of each time step [15], in that a user can send a pilot signal prior to transmission to allow the UAV to estimate $g_{i,\tau}$.

B. UAV Mobility Model

The UAV is assumed to be located at $(x_{UAV,\tau}, y_{UAV,\tau}, h_{UAV,\tau})$ at time step $\tau$, and it is able to move, in the next time step, to $(x_{UAV,\tau} + \delta_x, y_{UAV,\tau} + \delta_y, h_{UAV,\tau} + \delta_h)$, where $\delta_x$, $\delta_y$, and $\delta_h$ are the magnitude of change in the $x$, $y$, and $z$ axes, respectively. $h_{UAV,\tau}$ is assumed to have a minimum value of $h_0$. 

Fig. 1: System model.
III. 3D UAV PLACEMENT AND POWER ALLOCATION FORMULATION

We propose to optimize the UAV placement and PA such that the total users' data rate is maximized subject to a fairness condition imposed through satisfying a minimum rate for each user, \( R_{\min} \). We define the total users' data rate at \( \tau \) as

\[
R_{\tau}^{\text{tot}} = \sum_{i=1}^{\#\text{UE}} W \log_2(1 + SINR_{i,\tau}).
\]  
(5)

The optimization problem is formulated as follows

\[
\max \quad x_{UAV,\tau} \cdot y_{UAV,\tau} \cdot h_{UAV,\tau} \cdot R_{\tau}^{\text{tot}},
\]

\[
a_{i,\tau} > 0, \forall i \in \{1, \ldots, \#\text{UE}\},
\]

\[
a_{i,\tau} + a_{i+1,\tau} = 1, \forall i \in \{1, 3, \ldots, \#\text{UE} - 1\},
\]

\[
R_{i,\tau} \geq R_{\min}, \forall i \in \{1, \ldots, \#\text{UE}\},
\]

\[
L/2 \geq x_{UAV,\tau} \geq -L/2,
\]

\[
L/2 \geq y_{UAV,\tau} \geq -L/2,
\]

\[
h_{UAV,\tau} \geq h_0.
\]

(6a) (6b) (6c) (6d) (6e) (6f) (6g)

Remark 1: The problem is feasible if, in addition to the previously stated constraints, for all \( i \in \{1, 3, \ldots, \#\text{UE} - 1\} \), \( a_{i,\tau} \) satisfies the following:

\[
a_{i,\tau} \geq \frac{2R_{\min}/W - 1}{SNR_{i,\tau}},
\]

(7)

where the received signal to noise ratio at \( \tau \) for \( \text{UE}_i \), \( SNR_{i,\tau} \), is expressed as \( PR \times g_{i,\tau}(d_{i,\tau}) \times G/\sigma^2 \). (7) follows from (2), (3), and (6d).

Solving the non-convex objective function presented in (6) is challenging. By imposing the condition in (6d), we are making sure that the problem's solution does not favor the sum rate over fairness, as improving the former may lead to sacrificing servicing some users.

To solve this problem, however, we propose AI based framework which trains the UAV to solve (6) efficiently and determine both the optimal PA and 3D UAV placement accordingly.

IV. ProSky: A NEAT-BASED FRAMEWORK FOR UAV NETWORK RESOURCE MANAGEMENT

Our proposed framework is designed to have a UAV environment learned and modeled using a NN, which as a consequence determines the UAV 3D deployment and NOMA PA decisions. In some AI techniques, DRL, for example, the NN topology needs to be defined before training, which is usually hard to select and tune for practical applications. The NN structure needs to be chosen such that the trained model learns the environment well but does not overfit it. During the training process, a NN's weights and biases are to be optimized to minimize a cost function. The performance of a NN is affected by the choice of the optimization method. The backpropagation method, for example, used in DRL, suffers from the local minima problem. To avoid the aforementioned issues, we design a novel framework that manages the NOMA-mmWave-UAV resources based on NEAT. Unlike many other AI methods, NEAT evolves and optimizes the parameters of a number of NNs or solutions simultaneously using GAs. In addition, NEAT optimizes and complexifies topologies of NNs to allow complex solutions to evolve. In this section, we provide the NEAT background and present how we implemented it to solve the problem on hand effectively.

A. NEAT

In NEAT, a large set of variant-topology NNs, or generations, are tested on a certain task and evaluated based on a certain reward function. Networks that perform well are chosen to contribute, through crossover and mutation, in making a new generation of NNs. Mutation occurs by randomly altering a connection parameters, or adding a node or connection to a NN to ensure diversity of solution and maturity of convergence. The evaluation and evolution processes continue until a certain criterion related to a maximum number of generations, or average reward is met. For the effectiveness of NEAT, though, three main concerns are to be taken into account i) disparities and similarities among NNs need to be well represented to crossover them meaningfully, ii) NNs need not to disappear prematurely as they could improve performance as they evolve, iii) an effective way that allows NNs to complexify but only as performance demands to avoid slowing down learning is required. To handle the aforementioned issues, NEAT utilizes some fundamental techniques. One of which is historical marking. Every NN in NEAT is encoded with two sets. One identifies all connections, their connecting node, weights, enablement status, and an innovation number (IN) assigned uniquely to a connection when created. In addition, every node is given a historical marking shared among all NNs with the same node. Hence, NNs can be tracked, allowing topologies crossover. Another idea of NEAT is speciation. To preserve solutions, NNs are separated into different species. This allows NNs to compete with their species and solve the issue of eliminating them prematurely. Complexifying is another key technique for NEAT. Topologies in NEAT develop incrementally, only as needed, starting from structures with no hidden layers, allowing for finding minimal optimal solutions. We will utilize these techniques to solve the problem stated in (6).

B. The ProSky Model

Our proposed framework is designed based on NEAT to make the UAV effectively learn its environment and efficiently take mobility and PA actions such that fairness and rate objectives are met. The main components of ProSky are described as follows.

Initialization. To train ProSky effectively, we initialize a generation of NNs of size \( G_s \) structured from input and output nodes randomly connected. Input and output represent
system state and UAV actions respectively, which need to be carefully designed to determine the most effective NN model. At any time $\tau$ through out the learning process, a state $s_\tau$ is defined as $s_\tau = \left[ s_{0,\tau}, s_{1,\tau}, ..., s_{N_{\text{UE}},\tau}, h_{UAV,\tau} \right]^T$, where $s_{i,\tau} = \left[ \Delta x_{i,\tau}, \Delta y_{i,\tau}, \alpha_{i,\tau}, g_{i,\tau}(d_{i,\tau}) \right]^T$, $\forall \ i \in \{1, ..., N_{\text{UE}}\}$. $\Delta x_{i,\tau}$ and $\Delta y_{i,\tau}$ are the x-axis and y-axis difference between the UAV and UE$_i$ locations respectively. The action $a_\tau$ is defined as $a_\tau = \left[ d_x, d_y, d_b, \delta_{i,\tau}, \delta_{i,\tau}^T \right]$ where $\delta_{i,\tau}$ is defined as $[\delta_{1,\tau}, \delta_{3,\tau}, ..., \delta_{N_{\text{UE}},\tau}]^T$, where $\delta_{i,\tau}$ is the change in the PA coefficient of the UE$_i$.

**Evaluation.** The learning process of ProSky occurs over $E$ episodes with $T$ time steps each. At every time step a system state is fed to a NN, or a UAV, which results in a corresponding action. Based on the resulted action, the UAV is given a reward $r_\tau$ defined as follows.

$$r_\tau = w_r \times \frac{P_{\text{tot}}}{W} \times \prod_{i=1}^{N_{\text{UE}}} \mathbb{I}(R_{i,\tau} \geq R_{\text{min}}) + w_u \times \sum_{i=1}^{N_{\text{UE}}} \mathbb{I}(R_{i,\tau} \geq R_{\text{min}}) + w_u \times \frac{R_{i,\tau}}{W} \times \mathbb{I}(R_{i,\tau} < R_{\text{min}}),$$

where $\mathbb{I}()$ is the indicator function. $w_r$, $w_u$, and $w_a$ are total rate, and satisfied and unsatisfied minimum rate weights respectively. The reward is designed, with some similarity to that proposed in [8] to facilitate comparison between our NEAT and DRL frameworks, carefully to make the UAV learn efficiently. The first term in (8) aims to increase the total sum rate only if all users meet the minimum rate constraint. A reward of $w_u$, with a relatively large value, contributes to $r_\tau$ to reinforce satisfying meeting the minimum rate requirement for every user. In addition, users which do not satisfy $R_{\text{min}}$ result in unsatisfied minimum rate reward which is directly proportional to the sum of their rates. In other words, the UAV gets rewarded for any improvements it makes for rates that are below $R_{\text{min}}$. The episode reward for every NN in a generation determines which NNs evolve to the next generation. The NNs with the highest reward are to be included for the next generation. For the rest of NNs, the higher the average reward, the more the probability it gets selected for the evolution process.

**Evolution through crossover.** Historical marking makes a meaningful crossover possible. To crossover two NNs, they get aligned based on their INs. Connections with identical IN, also referred to as matching connections, are randomly selected to appear in the composed NN. Connections that do not match are called disjoint if they are within the IN range of the other NN or excess otherwise. All excess or disjoint connections are included from the NN that achieved a higher average reward when crossing over.

**Evolution through mutation.** To diversify solutions, mutation, which either alters existing connections or contribute a new structure to a network, is implemented. When a new connection is added between two nodes, it is allocated a random weight. When a new node is inserted between two existing connected nodes. While the link between the previous start and new nodes keeps the old connection parameters, the other link is assigned a weight of 1.

**Solution preservation.** This component enables, through speciation, novel topologies, which may initially perform poorly, to be constructed and optimized without the worry of being destroyed before they can be fully investigated. Speciation, basically, divides a generation into several species based on topological and connectivity similarities. If a compatibility distance, which is proportional to the weighted sum of the number of excesses, disjoïnts, and the variations in weights of matching connection, is less than a compatibility threshold $\delta_k$, a two NNs are said to belong to the same species [10]. A number of species are created in the first episode and sequentially ordered. At subsequent episodes, a random NN is selected to represent each species. Any other generated NN is assigned to the first species that is compatible with its representative NN. A new species is created in case there is no compatibility.

**Solutions reduction.** To avoid having a species takes over the entire generation by getting too big, an adjusted reward function is introduced [10]. The idea is that the reward of every solution in a species gets normalized by the number of NNs belongs to the species. Each species gets assigned only number of NNs proportional to the sum of the adjusted reward of corresponding species members. That as a consequence may result in eliminating the solutions with the lowest performance and reduce number of solutions within a species.

The last four components of ProSky, which are mainly based on NEAT [10], determine how NNs in ProSky are evolved. However, the initialization and evaluation components are designed by us to get the most out of NEAT and make it learn the 3D network environment effectively and manage resources efficiently as we will show in the next section.

V. ProSky PERFORMANCE EVALUATION

A. Implementation Settings

ProSky is trained for 1000 episodes, or generations, with 300 time steps each and $G_s$ of 50 NNs which are assumed to be feed-forward, fully-connected at the initialization, and activated using ReLU. Weight and biases are generated from standard normal in a range of $[-30, 30]$ with a mutation rate 0.8 and 0.7 respectively. A node, and connection, add or delete probabilities are all set to 0.2, $\delta_{ib}$ is chosen to be 3.

The proposed framework is simulated for a $100 \times 100$ m$^2$ urban area with $N_{\text{UG}} = 4$. Users are located, relative to the center of $A$, at $(4, 15), (-44, -49), (-5, 21)$ and $(47, 49)$. The UAV is assumed to keep a minimum height of 10 m, and, at the beginning of each episode, to be deployed at $(0, 0, 50)$ and
assign 0.5\(P_f\) for each user. The change in the PA coefficient is set to ±0.01 for all users. \(\delta_c\), \(\delta_p\), and \(\delta_b\) are all set to be 1 m. Channel is modeled according to [14], where the path loss intercept and exponent are set to \(10^{-6.4}\) and 2 respectively. Thermal noise power \(\sigma^2\) is assumed to be \(-84\) dBm. The transmit power \(P_f\) is set to 20 dBm. Antenna configurations \(N_{UAV} \times N_{UE}\) are chosen to be 8\(\times\)8. System bandwidth \(W\) and carrier frequency \(f_c\) are taken as 2 GHz and 28 GHz respectively.

### B. Performance Analysis

In this subsection, we provide the performance of ProSky in managing 3D NOMA-UAV network both in training and testing scenarios. We compare our finding with the state-of-art (SoA) framework. In [3], the authors solved the non-convex NOMA PA and UAV placement problem, disjointly while restricting the UAV placement to a 2D plane, set at a height of 50 m in our analysis, using the conventional optimization framework.

In addition, we compare the ProSky performance with the DRL-based algorithm AdaptSky, not just because we are examining the performance of the two different AI tools these algorithms are built on, but also because AdaptSky, for the best of our knowledge, is the only AI-based framework proposed to solve the 3D UAV placement and NOMA PA jointly.

For evaluation, we introduce the performance metrics \(R_{\text{tot}}\) defined as achieved average sum-rate per generation in case of ProSky and by averaging the average rate per episode and over the most recent 100 episodes for AdaptSky. \(R_{\text{tot}}\) of AdaptSky equals zero for all episodes \(e_p < 100\). The average total rate varies drastically from episode to another in case of AdaptSky, hence averaging over 100 episodes was needed to smooth out the data. Using some performance metrics, including \(R_{\text{tot}}\), we evaluate ProSky training and testing performance in the following aspects:

#### Learning rate

In order to show how efficient and fast ProSky can handle the problem in hand, we, in Fig. 2, show the average reward for ProSky and AdaptSky, as they both learn the UAV environment. The average rewards is defined similar to \(R_{\text{tot}}\), i.e., it is the episode and 100 episodes reward average for ProSky and AdaptSky respectively. The training parameters are set as \(R_{\text{min}}/W = 0.5\), \(w_s = 100\), \(w_r = 1\), and \(w_u = 1\). To demonstrate the consistency of our proposed method, the figure includes the confidence interval (CI) of one standard deviation of 10 different simulation runs. Interestingly, ProSky achieves 96.17% of the average reward convergence value more than 3.3 times faster than that for AdaptSky, even though AdaptSky is built based on dueling architecture, which advances DRL learning rate [16]. This speedup rate is 96% higher than the average, and only 2% off of the highest, achieved end-to-end speedup rate of Actor\(Q\) network [17] which leverages low-precision quantized actors to speed up the learning process.

Furthermore, based on Fig. 2, ProSky converges to a slightly better reward, or total sum data rate, than AdaptSky with less uncertainty.

#### Rate and fairness (training)

In this scenario, we vary the minimum SE required \(R_{\text{min}}/W\), as a way to impose fairness among users, and observe \(R_{\text{tot}}\). We depict the convergence value of \(R_{\text{tot}}\) over a thousand training episodes in Fig. 3 and show the CI of 5 runs. The reward function in this scenario is structured to give a higher reward whenever a user exceeds \(R_{\text{min}}\), which can be achieved through setting the rewards parameters as \(w_r = 10\), \(w_s = 100\), and \(w_u = 1\). We can observe from Fig. 3 that ProSky outperforms SoA, very consistently i.e. with tight CI, and improvement of up to 59.23%. In addition, when the minimum SE is less than or equal 2 bit/s/Hz, ProSky outperforms AdaptSky with average of 5.85% which corresponds to 1.99 Gbit/s improvement. The uncertainty at a higher SE minimum requirement is expected.
as ProSky finds the best model by parallelly trying number of random solutions which may lead to a lower average performance than AdaptSky, as feasible solutions are getting very limited.

**Energy efficiency (testing).** In this scenario, we train ProSky to optimize the sum rate objective with a setup similar to that in the learning rate scenario, but with $R_{min}=0$. The best NN model from training is imported and tested for every power in the range $-20 \, \text{dBm}$ to $80 \, \text{dBm}$ with a step size of 0.1 dBm, over 300 time steps through which the UAV interacts with the observed states. We determine the average SE over all time steps and calculate the corresponding EE, defined as SE divided by power required for signal transmission plus some other consumed power assumed to take the value of 40 dBm. In Fig. 4, we plot the EE for ProSky and the two baselines, which ProSky obviously outperforms. At the green point, the highest EE point in the curves, ProSky shows an improvement of 21.93% and 35.71% over AdaptSky and SoA respectively. ProSky exhibits a fast adapting learning model and offers, while meeting fairness requirements, huge gain in terms of SE and EE over the model-based solution proposed in [3], which seem to fall short in handling complicated networks. Similarly, ProSky demonstrates some improvement over the DRL-based algorithm proposed in [8] in terms of SE and EE, and significant enhancement in learning rate.

### VI. CONCLUSION AND DISCUSSION

In this paper, we proposed ProSky, a novel AI-based framework built on NEAT algorithm which merges GA and deep learning. ProSky optimizes the UAV 3D location while allocating NOMA resources in the mmWave spectrum such that fairness is guaranteed and the users’ sum rate is maximized. ProSky significantly outperforms a model-based scheme, in terms of SE and EE. Moreover, ProSky has shown a huge gain in learning speed and some gains in SE and EE over a DRL-based baseline. To get the most out of integrating GA and deep learning, nonetheless, and to draw a more comprehensive performance analysis, more studies about the applicability of NEAT and its advances in more generic channel models in multi-UAV networks are encouraged considering the improvement our findings exhibited in resources management. We believe NEAT will require more investigations in terms of the NN evolution and selection process in such cases.

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