Autonomous UAV Base Stations for Next Generation Wireless Networks: A Deep Learning Approach

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Abstract—To address the ever-growing connectivity demands of wireless communications, the adoption of ingenious solutions, such as Unmanned Aerial Vehicles (UAVs) as mobile Base Stations (BSs), is imperative. In general, the location of a UAV Base Station (UAV-BS) is determined by optimization algorithms, which have high computational complexities and place heavy demands on UAV resources. In this paper, we show that a Convolutional Neural Network (CNN) model can be trained to infer the location of a UAV-BS in real time. In so doing, we create a framework to determine the UAV locations that considers the deployment of Mobile Users (MUs) to generate labels by using the data obtained from an optimization algorithm. Performance evaluations reveal that once the CNN model is trained with the given labels and locations of MUs, the proposed approach is capable of approximating the results given by the adopted optimization algorithm with high fidelity, outperforming Reinforcement Learning (RL)-based approaches. We also explore future research challenges and highlight key issues.

Index Terms—6G, next generation wireless communications systems, UAV, deep learning, CNN, reinforcement learning, base station.

I. INTRODUCTION

Ubiquitous and high data rate connectivity has become an indispensable part of modern life, and this has only been exacerbated by the COVID pandemic. Indeed, the Internet-of-Things (IoT), which is a key constituent of many contemporary paradigms, such as Industry 4.0, smart cities, and autonomous connected vehicles, has become increasingly ubiquitous, such that the ever-growing need for higher data rates and better connectivity across highly challenging scenarios and environments necessitates the adoption of extraordinary technological solutions.

Recently, Self-Evolving Networks (SENs) have been proposed to facilitate autonomous network management and reduce human intervention as much as possible. The use of Machine Learning (ML)-based management aspects of Next Generation Wireless Networks (NG-WNs) can support the integration of terrestrial, aerial, and satellite networks to form vertical heterogeneous networks, which is an evolving architecture with the potential to incorporate significant agility into the NGWN infrastructure. However, network management in such highly dynamic conditions presents a challenging research problem.

Within a SENs framework, Unmanned Aerial Vehicle Base Stations (UAV-BSs) constitute highly dynamic infrastructure enablers whose potential advantages are enormous. The availability of Line-of-Sight (LoS) links between UAV-BSs and Mobile Users (MUs) can significantly reduce path loss, which in turn leads to greater coverage and better channel capacity. Furthermore, communications technologies such as millimeter wave and free space optics can benefit from the availability of LoS links. Unprecedented mobility associated with the UAV-BSs enable the network as a whole to behave like a highly dynamic entity (see Fig. 1), which is one of the main pillars of SENs. This makes it possible to restructure the network on an unprecedented scale that can enable an extremely flexible and reliable mobile communication infrastructure. For example, UAV-BSs can be utilized to augment communications infrastructure in locations (especially in metropolitan areas) where there may be significant short-term peaks in demand, such as during large entertainment and sporting events. In fact, the Third Generation Partnership Project (3GPP) has already defined an on-board radio access node
(UxNB) in recognition of the great potential of UAV-BSs (3GPP Release 17). Nevertheless, to leverage the potential advantages of UAV-BSs, many technical challenges still need to be addressed, such as adaptability to dynamic channel characteristics, user mobility, security, robustness, and energy efficiency.

Due to the three-dimensional space, high mobility, and large service area, the channel between a UAV-BS and MU can vary significantly. For this reason, optimizing a single instance of the communication scenario would be a too conservative and an unrealistic approach. Instead, an autonomous UAV-BS should be able to adapt itself according to the dynamic characteristics of the communication medium and user mobility by incorporating the relevant temporal and spatial variables into the decision-making process.

While determining the trajectory of a UAV-BS (and in any real-life problem solving approach) it would be unwise to assume an ideal environment. For it is highly unlikely that the channel estimation would be precise and mobility prediction error-free. Furthermore, the existence of human errors involving inaccurate information flows and threats such as hacking can render the decision-making process more challenging. Therefore, resilience against errors and threats is a necessary requirement in UAV-BS placement optimization.

The limited energy resources of UAVs are among the most challenging problems facing their utilization as UAV-BSs. To get the maximum benefit out of the limited airborne duration of a UAV-BS, it is of utmost importance to optimize its trajectory, while considering the requirements of the MUs it is meant to serve.

Addressing the aforementioned problems is extremely challenging (if not impossible) by employing conventional trajectory optimization approaches (e.g., Mixed Integer Non-Liner Programming – MINLP). But, a Deep Learning (DL)-based trajectory optimization approach has the potential to cope with such challenges [2]. DL is an emerging ML approach that is extremely successful at extrapolating hidden non-linear models between the input and output layers using huge and cumbersome data. Despite the few applications of DL in wireless communications thus far, the performance attained by DL-based solutions are promising [3].

In this study, we propose a DL-based UAV-BS trajectory optimization approach and evaluate its performance against Reinforcement Learning (RL)-based approaches. Once the DL is trained, our proposed approach is shown to be computationally efficient and capable of coping with user mobility, while also being scalable and robust.

The rest of the paper is organized as follows. In Section II, we introduce a generic optimization model for the UAV-BS placement problem. Section III explores the approaches for the solution of the optimization model. Section IV overviews the building blocks of our DL model. In Section V, we present and analyze a use case scenario employing the DL model to solve the optimum coverage problem of a UAV-BS. Section VI discusses potential future research areas and Section VII concludes the paper.

II. REFERENCE MODEL

Optimizing the operations of a UAV-BS is a challenging, multi-faceted problem that involves aspects such as coverage, capacity, quality-of-service (QoS), caching, energy dissipation, dynamic channel and MU characteristics. A generic reference model for the optimization of UAV-BS operations can be expressed as follows:

$$\max \sum_{k \in U, t \in T} w_1 u_{k, t} + w_2 M(z_{k, t}, u_{k, t}) - w_3 E(V_t, a_t).$$

(1)

The model has three objectives, where the parameters $w_1$, $w_2$, and $w_3$ denote the relative importance of each objective. Coverage (i.e., serving as many MUs as possible), arguably, is the foremost objective in our problem, and it can be achieved by positioning the UAV-BS at a given time instant at a position $(d_t)$ that results in the maximum number of users experiencing pathloss values lower than a predetermined threshold ($\gamma$) [4]. In the model, subscript $t$ signifies the temporal characteristics of the problem to account for the dynamics of the channel and the characteristics of MUs as well as the mobility of the UAV-BS. The time horizon and the set of MUs are
denoted by $T$ and $U$, respectively. The variable $u_{k,t}$ is set to one if the MU-$k$ is served at time instant $t$. The bandwidth available to a UAV-BS is limited; therefore, the aggregated capacity allocated to MUs at each time instant $t$ is upper bounded by the total available backhaul capacity [5].

QoS provided to the MUs is an important consideration. The MUs’ QoS requirements can be heterogeneous (e.g., QoS requirements for email traffic, phone calls or video exhibit significant variations) and can change over time (i.e., dynamic). The QoS provided to each MU $k$ depends on $d_t$, and is constrained by the QoS requirement of MU $k$ at time instant $t$. The QoS criteria encompasses many metrics, such as bandwidth and delay.

It is possible for multiple MUs to demand the same content, and for this reason caching popular content is beneficial in reducing the bandwidth usage as well as delay [7]. However, caching a high volume of content is not possible with a resource-constrained UAV-BS. Therefore, the utility function for caching, $M(.)$, which depends on MUs to be served ($u_{k,t}$) and the content demand of the MUs ($z_{k,t}$), should be maximized.

The energy dissipation characteristics of the UAV-BS operation is of utmost importance since the service duration of a UAV-BS is generally determined by its power usage. Indeed, in certain cases the service duration of the UAV-BS is more important than the coverage or QoS. Therefore, energy dissipation, $E(.)$ of the UAV-BS, as a function of its speed, $V_t$, and acceleration, $a_t$ is embedded as a separate term in the objective function.

### III. Solution Approaches

Determining an optimal solution of the reference model is highly challenging. In fact, depending on the functions utilized in the objective and constraints, the problem can turn out to be non-convex. Furthermore, the temporal dimension of the problem can hugely inflate the size of the solution space, which in turn can greatly increase the computational complexity of the solution algorithms. Solving a single time instance of the problem, which is a commonly employed approach, necessitates resolving the problem for each time instant. Solutions that consider only a single time instance can result in suboptimal solutions (for a finite time interval – not an instant) which can lead to unnecessary movements of the UAV-BS. Moreover, due to errors in collecting or obtaining data (e.g., positions of MUs, pathloss values), solutions which cannot tolerate such non-ideal inputs can potentially end up yielding inconsistent or inefficient UAV-BS trajectories.

To overcome such challenges efficiently, an ML-based approach can be created to estimate the optimal location of a UAV-BS. In the literature, RL-based approaches have been proposed to determine UAV-BS locations [8]–[10]. In RL [11], there is an agent which can be found in one of the predefined states. The agent takes actions to move among different states and the actions are rewarded. For each state, the agent decides the action to maximize the total future reward and keep it in the state-action table. RL guarantees the best actions only if the number of iterations is large enough, therefore, convergence can potentially require formidably long time periods depending on the solution space size. Moreover, if RL keeps state-action pairs for all deployment scenarios, then it will be impractical for a resource constrained UAV-BS to adopt an RL-based approach due to limited memory. Deep Reinforcement Learning (DRL) [12] is a form of RL that estimates state-action pairs using a Deep Neural Network (DNN) to mitigate the memory requirements of huge state state-action tables. Several studies have used DNN-based approaches to alleviate the memory requirements of RL [8]–[11], [13]. However, the training time for the establishment and convergence of a fully connected network for each state-action pair of all possible UAV-BS and user deployments can be impractically long. To put it briefly, RL-based approaches work well in unknown environments with stationary users, but in this paper we consider an environment with dynamic MUs for efficient UAV-BS deployment.

A Convolutional Neural Network (CNN) is an Artificial Neural Network (ANN) with multiple hidden layers (more precisely, multiple convolutional layers, where the data from the previous layer is convolved with different filters). CNN-based approaches have been shown to perform well in solving a wide range of complex problems that could not be otherwise solved efficiently. Therefore, in this study, we opt for a CNN-based DL approach to determine the trajectory of an autonomous UAV-BS.

The most computationally demanding part of the proposed approach is the training stage, which is performed offline. Once the model has been trained sufficiently, the solution can be obtained almost instantly. Since the CNN-based approach has a holistic view of the problem, the UAV-BS trajectory is created by considering multiple time instances simultaneously. The proposed model is resilient to varying channel characteristics and movements of MUs (i.e., once the CNN is trained satisfactorily, the trajectory is computed effortlessly for any input vector without the need to rerun an optimization algorithm). Since the CNN filters the input data to eliminate noise and noise-like inputs by considering an extended period of time, it can tolerate a certain number of errors and
IV. CONVOLUTIONAL NEURAL NETWORKS

DL [2] is an ML approach that has begun to receive much attention due to the unprecedented increase of computing capabilities offered by modern GPU’s and advances in algorithms. DNNs built on the extensive experience of ANNs by increasing the overall size of the network using many layers of neurons. Each neuron is formed by linearly weighting multiple inputs supplied to an activation function. Applications of DL-based approaches for communications and optimization problems have resulted in improved performance and functionality compared to existing solutions that do not utilize DL.

One of the most successful DL architectures is CNN [14], which provides superior performance benchmarks never before achieved for a variety of problems. CNNs are comprised of convolutional layers, pooling layers, and fully connected layers and they are generally used with a softmax function to perform classification tasks. CNNs excel at learning spatially localized features by the convolution of the input data with filters in a sliding window arrangement. Initial layers learn generic and simple features, whereas deeper layers learn more abstract and sophisticated features by non-linearly combining the features learned by the preceding layers.

An activation function is generally followed after each convolution operation, which performs a non-linear mapping of the convolution output. Among the plethora of proposed activation functions, we adopt the Rectified Linear Unit (ReLU), which offers both robustness and computational efficiency. After activation, a max pooling operation is generally performed, which is a downsampling operation done to reduce the complexity of activation maps that are further processed in the deeper layers of the network. Finally, a fully connected neural network is used to learn non-linear combinations of all the learned features at the penultimate layer (i.e., the last convolutional block).

We utilize a six-layer CNN architecture, which we found produced the best results through empirical evaluations. The proposed architecture is comprised of four convolutional layers, as illustrated in Fig. 2. The network area is spatially organized into rectangular cells (i.e., a checkerboard structure). Furthermore, each cell encompasses five consecutive time instants. An array consisting of the numbers of MUs in each cell is fed to the model as an input. Utilizing an input, which is embedded with both temporal and spatial characteristics, has several advantages. First, the scalability of the model is not affected by the number of MUs (i.e., the size of the input does not change with the number of MUs). Second, the model is resilient to variability in the number of MUs in the area under consideration. Third, the model facilitates the use of only a subset of the MUs in the input which can be used to decrease the computational complexity. Although spatial and temporal clustering of the MUs can decrease precision, it increases the ability to generalize, which improves the robustness of the model. The output layer of the CNN model utilizes a linear activation function that yields continuous outputs for UAV-BS coordinates. Adam is used for learning rate optimization and the loss function used is the mean absolute error.

V. USE CASE SCENARIO

We generate a UAV-BS deployment scenario to analyze the performance of the CNN-based solution. This scenario only considers coverage aspect of the reference model explained in Section II; however, it is also possible to take the other aspects of the model, such as QoS and caching, into account. To train the CNN, we create a synthetic dataset. First, we obtain the optimal locations of the UAV-BS for a range of MU deployments using reference model parameters [4]. Next, we use the constraints and locations of MUs as inputs and optimal locations of the UAV-BS as the output to train our CNN.
Fig. 3: Locations of the UAV-BS for the optimal and CNN-based solutions.

model. Lastly, we test the CNN model to compute the locations of the UAV-BS for new user deployments (i.e., the test cases). Moreover, we provide comparisons of the solutions obtained with the CNN approach and various RL approaches.

We demonstrate the efficiency of the proposed CNN-based approach by using a typical urban environment communications scenario served by a UAV-BS. 30 MUs are distributed over a 2 km by 2 km area. The locations of MUs are within the radius of a predetermined center, which is found using a uniform random distribution. Each MU moves toward a randomly chosen direction with a constant speed, which is also determined randomly. For this, we employed the well-known random-waypoint mobility pattern [15]. A series of 15 consecutive moves of an MU is called a session. MUs restart their movements at random positions at the beginning of each session. Our scenario consists of 72,000 sessions. The rest of the communication parameters are adopted from [4].

For each instant of the scenario, we compute the best UAV-BS position, which will be used as labels during learning stage, using Eq. 1 by considering only the coverage objective and without considering the temporal dimension. To this end, we utilized the UAV-BS placement approach proposed in [4], where only $w_1$ is 1 (the other weights are zeroed). However, without loss of generality, this scenario can be extended to include the other constituents of the generic reference model.

In Fig. 3, UAV-BS locations given by our model and the optimization algorithm are presented for three test cases. Light blue disks and inverse triangles represent the initial and final locations of MUs, respectively. Dark blue dashes show the trajectory of the users. Red crosses and black diamonds indicate the locations obtained by the optimization algorithm and the proposed CNN approach, respectively. Yellow disks signify the proximity of the estimated locations. Fig. 3 shows that the estimated UAV-BS locations by the CNN-based approach are in close proximity of the optimal locations.

To investigate the performance of the CNN-based solution in comparison to RL-based approaches, we obtained results with DRL, Q-Learning, and Double Q-Learning [8], [9], [11]. Fig. 4 illustrates the block diagram of the RL approaches, where CRL indicates the Conventional RL approaches (i.e., Q-Learning and Double Q-Learning). The parameters utilized to realize the RL approaches are also provided in Fig. 4. Furthermore, the discount factor for DRL is 0.99, and the loss function to update the weights (critical parameters) of the DNN is the mean square error. Fig. 5 presents the instantaneous coverage of different UAV-BS placement
approaches for 500 consecutive steps, where each step is 4 s. The difference between the proposed approach and other learning methods can be as much as 10 covered MUs (e.g., at 50th and 150th steps). The Cumulative Distribution Function (CDF) of the covered MUs is illustrated in Fig. 6 considering 18,000 test scenarios. The difference between the CNN approach and the optimal approach is, on average, 1 MU. By contrast, the difference between the RL-based approaches and the optimal approach is approximately 4.5 MUs.

VI. FUTURE RESEARCH DIRECTIONS

In this study, we consider the positioning of a single UAV-BS. However, especially to cover large areas or to increase aggregate bandwidth offered to MUs, it is imperative to utilize multiple UAV-BSs in a coordinated fashion. Hence, placement of a plurality of UAV-BSs and integration of them to the SEN through learning approaches are promising research avenues.

As mentioned above, any UAV-BS placement approach should not be designed by assuming that the inputs are always consistent or error free. In fact, measurement and communication errors as well as man made intentional disinformation occur in real life deployments. Therefore, the training model should be robust enough to handle such issues. The proposed approach provides an effective solution to the robustness problem by averaging the locations of MUs. Yet, there are many other possible threats and errors. Nevertheless, improving the robustness and stability of a UAV-BS in the face of a wide range of threats and errors is an interesting research challenge.

ML-based UAV-BS positioning algorithms necessitate the use of training data sets. However, there is no publicly available datasets to be used for this purpose. It is possible to generate synthetic datasets (as is done in this study) or create datasets based on extensive measurement campaigns. Both approaches have advantages as well as disadvantages. Synthetic datasets are easy to generate, yet, they fail to represent the real world conditions precisely. Measurement-based datasets reflect the actual scenarios more accurately, however, they are both time consuming and inflexible (i.e., they cannot be modified, easily, to model conditions other than the one they are actually obtained from). Nevertheless, it is extremely important to create a wide range of realistic datasets to be used in the analysis of NGWN scenarios with UAV-BSs, preferably, endorsed by an international communications organization such as IEEE or ITU.

Although DNNs require much less computation during the inference stage when compared to the training stage, it is still challenging to use them on resource constrained embedded systems (such as the ones in UAV-BSs) due to their memory requirements. Therefore, it is of utmost importance to reduce the resource requirements of DL-based approaches to be used by UAV-BSs without sacrificing their performances, significantly.

The point where the learning is carried out is an interesting problem to consider. UAV-BSs have limited memory and processing capabilities, therefore, it
is inefficient to employ them for training. However, using collaborative learning techniques such as federated learning at edges mitigates the challenges of training.

VII. CONCLUSION

Positioning a UAV-BS for the optimal operation of the network is a challenging problem. In this study, we first introduce a comprehensive optimization model for UAV-BS positioning. We present a CNN-based approach for the efficient solution of a special case of the model considering its coverage aspect. Performance evaluations of the proposed CNN-based approach in comparison to RL-based approaches reveal that the CNN-based solutions approach the optimal solutions with negligibly low differences. Yet, the CNN-based approach is four orders of magnitude faster than the optimization approach. The complexity of the proposed approach only depends linearly on grid size. Nevertheless, there are still many challenging issues to be addressed for fulfilling the promise of autonomous UAV-BSs, which we also outlined in this study.

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