Intelligent UAV Base Station Selection in Urban Environments: A Supervised Learning Approach

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Abstract—When Unmanned Aerial Vehicles (UAVs) connect into the cellular network, their wireless channel is negatively impacted by strong Line-of-Sight (LoS) interference from terrestrial Base Stations (BSs), as well as from antenna misalignment due to downtilted BS antennas. Moreover, due to their aerial positions, these UAVs are exposed to a large number of BSs with which they can associate for wireless service. Therefore, to maximise the performance of the UAV-BS wireless link, the UAVs need to be able to choose which BSs to connect to, based on the observed environmental conditions. In this regard, this paper proposes a supervised learning-based association scheme, using which a UAV can intelligently associate to the most appropriate BS. We train a Neural Network (NN) to identify the most suitable BS from several candidate BSs, based on the received signal powers from the BSs, known distances to the BSs, as well as the known locations of potential interferers. We then compare the performance of the NN-based association scheme against strongest-signal and closest-neighbour association schemes.

Index Terms—Cellular-connected UAVs, Machine Learning, Supervised Learning.

I. INTRODUCTION

UAVs (also referred to as drones) are predicted to become a core technology in a wide range of applications, from aerial surveillance and safety to product delivery [1]. Allowing these devices to perform to their full potential in a safe manner will require them to have ubiquitous data communication with their human operators, local authorities, as well as each other. A promising solution to achieve this involves integrating the UAVs into the underlying cellular network as a new type of User Equipment (UE); this approach has drawn significant attention from the wireless community [2], [3], [4].

These UAVs represent a paradigm shift for the cellular network, as they are able to freely move in three-dimensional space, unlike typical terrestrial UEs. As they move in the air, UAVs are exposed to vastly different radio environment conditions as compared to terrestrial UEs, due to the presence of dominant LoS links as well as reduced antenna gains from BS down-tilted antennas [5]. For instance, UAVs can establish unobstructed LoS wireless links to distant transmitters, which allow them to receive a strong, unattenuated wireless signal from their serving BS, but which also make them susceptible to strong LoS interference signals.

Recent 3rd Generation Partnership Program (3GPP) studies on the performance of Long Term Evolution (LTE) connectivity for UAVs suggest that these challenges can be overcome by equipping the devices with steerable, directional antennas [6]. By steering such an antenna towards the desired BS, the UAV can use the strong directional antenna gain to boost the desired signal, while simultaneously attenuating undesirable interfering signals. In our prior work [7], we mathematically modelled the achievable performance of a UAV equipped with a steerable antenna which connects to terrestrial LTE infrastructure. Our results corroborated the conclusions in [6]. In [8], we also investigated the encountered handover of UAVs under practical antenna configurations. Moreover, the authors in [9] examined how factors such as the directional antenna tilt and beamwidth impact the performance of UAVs as well as terrestrial UEs. In [10], the effect of antenna tilting and beamforming is studied for a scenario of UAV and ground UE co-existence. The authors in [11] propose cooperative transmissions to support high-altitude static UAVs.

Given its aerial position, a UAV may have a large number of candidate BSs that it can connect to for cellular service, using its directional antenna. To choose the most suitable BS the UAV needs to be aware of the channel conditions for each candidate BS, which involves steering the directional antenna towards each BS and assessing the resulting channel quality. Depending on the UAV use case and the state of the environment, this process may introduce a large overhead to maintaining cellular connectivity, or (in the case of highly dynamic channels when the UAV is moving) it may not be feasible at all. As an alternative to this iterative channel measurement step, we propose choosing the most suitable candidate BS using available environmental knowledge and a trained NN.

NNs have started to gain popularity in the wireless community as function approximators [12]. In this regard, the authors in [13] have explored the use of supervised learning for training millimeter-wave Multiple Input Multiple Output (MIMO) antennas. The authors demonstrate how the observed channel conditions at one antenna can be used to configure an antenna at another location, using a trained NN. In [14], the authors use BS geolocation information to design a NN-based scheduler that maximises the system throughput in a millimeter-wave multi-BS, multi-UE communication scenario. The work in [15] proposes NN-based coordinated beamforming, where multiple BSs simultaneously serve a single user.

Our contribution in this paper is to propose a NN-based cell selection approach in order to choose the most suitable BS for a UAV to associate with. We consider a UAV equipped with a steerable, directional antenna...
Fig. 1. Side and top view showing a UAV in an urban environment at a height $\gamma$, positioned above $x_0$ with antenna beamwidth $\omega$. The UAV associates with the BS at $x_1$ and centers its antenna main lobe on the BS location; the blue area $W$ illuminated by the main lobe denotes the region where interferers may be found. The BS at $x_2$ falls inside this area and produces interference.

with two sets of antennas: an omni-directional antenna for measuring the received signal power from nearby BSs, as well as a directional antenna which the UAV aligns towards its associated BS and uses for data transmission. Similar to the inference carried out in the works above, we train an NN to infer which BS will give the best performance for the directional antenna connection based on the received signal power, as well as other known environmental information. To benchmark the performance of our NN we compare the results against simpler BS selection strategies, based on both simulations as well as mathematical derivations from our prior works \cite{7} and \cite{8}.

II. SYSTEM MODEL

We consider an urban environment where a flying UAV uses an underlying cellular network for its wireless connectivity, as depicted in Fig. 1. The underlying cellular network consists of BSs which are horizontally distributed as a homogeneous Poisson point process (PPP) $\Phi$ = \{ $x_1$, $x_2$, ...\} $\subset \mathbb{R}^2$ of intensity $\lambda$, at a height $\gamma$ above ground. Elements $x_i \in \mathbb{R}^2$ represent the projections of the BS locations onto the $\mathbb{R}^2$ plane. The coordinates of the UAV are denoted as $x_0 \in \mathbb{R}^2$, with the UAV height above ground denoted as $\gamma$. Let $r_i = ||x_0 - x_i||$ denote the horizontal distance between the coordinates $x_0$ and $x_i$, and let $\phi_i = \arctan(\Delta \gamma / r_i)$ denote the vertical angle, where $\Delta \gamma = \gamma - \gamma$. Without loss of generality we set the horizontal coordinates of the UAV $x_0$ as the origin $(0,0)$.

The UAV is equipped with two sets of antennas: an omni-directional antenna for BS pilot signal detection and signal strength measurement, as well as a directional antenna for communicating with the UAV’s associated BS. The omni-directional antenna has an omni-directional radiation pattern with an antenna gain of 1, while the directional antenna has a horizontal and vertical beamwidth $\omega$ and a rectangular radiation pattern; following \cite{7}, the antenna gain is given as $\eta(\omega) = 16\pi/(\omega^2)$ inside of the main lobe and $\eta(\omega) = 0$ outside. We denote the coordinates of the BS which the UAV is associated with as $x_s \in \Phi$ and its horizontal distance to the UAV as $r_s$. The UAV aligns its directional antenna towards $x_s$; this results in the formation of an antenna radiation pattern around $x_s$ which we denote as $W \subset \mathbb{R}^2$, as depicted in Fig. 1. This area takes the shape of a ring sector of arc angle equal to $\omega$ and major and minor radii $v(\gamma, r_s)$ and $u(\gamma, r_s)$, respectively, where

$$
v(\gamma, r_s) = \begin{cases} 
\frac{\Delta \gamma}{\tan(\phi_s - \omega/2)} & \text{if } \omega/2 < |\phi_s| < \pi/2 - \omega/2 \\
\frac{\Delta \gamma}{\tan(\pi/2 - \omega)} & \text{if } |\phi_s| > \pi/2 - \omega/2 \\
\infty & \text{otherwise}
\end{cases}
$$

$$
u(\gamma, r_s) = \begin{cases} 
\frac{\Delta \gamma}{\tan(\omega/2 - |\phi_s|)} & \text{if } |\phi_s| < \pi/2 - \omega/2 \\
0 & \text{otherwise}
\end{cases}
$$

with $|.|$ denoting absolute value. The BSs which fall inside the area $W$ are denoted by the set $\Phi_W = \{ x \in \Phi : x \in W \}$. The BSs in the $\Phi_W$ are capable of causing interference to the UAV-BS communication link, as their signals may be received by the UAV’s directional antenna with non-zero gain.

As we are considering an urban environment, buildings will affect the wireless signals by blocking LoS links. For each UAV-BS link there exists a probability that the channel will be LoS; this probability is a function of the horizontal distance, the heights of the devices, and the building parameters in the environment. We apply the LoS probability model from our prior work \cite{7}, which is omitted here for brevity.

We assume that the BSs are equipped with Uniform Linear Array (ULA) antennas, with $N_t$ antenna elements. The vertical gain of these antennas is a function of the angle between the UAV and the BS and is defined similar to \cite{10} as

$$
\mu(\phi) = \frac{1}{N_t} \sin^2 \frac{\pi N_t}{2} \sin(\phi) \sin(\phi).
$$

For simplicity we consider the BS horizontal gain to be omnidirectional with a value of 1.

When the UAV is connected to the BS at $x_s$, the Signal-to-Interference-and-Noise Ratio (SINR) of the signal received by the directional antenna is given as

$$
\text{SINR} = \frac{pH_s \eta(\omega) \mu(\phi_s^2 + \Delta \gamma^2 - \alpha_s/2)}{I_L + I_N + \sigma^2}
$$

where $p$ is the BS transmit power, $H_s$ is the random multipath fading component, $\alpha_s$ is the pathloss exponent, $t_s \in \{L, N\}$ is an indicator variable which denotes whether the UAV has LoS or non-Line-of-Sight (NLoS) to its serving BS $x_s$, $c$ is
the near-field pathloss, $\sigma^2$ is the noise power, and $I_L$ and $I_N$ are the aggregate LoS and NLoS interference, respectively.

We define an SINR threshold $\theta$ for the wireless UAV link: if SINR $< \theta$ this represents the UAV failing to establish a wireless link of the required channel quality and therefore being in an outage state.

We assume that the UAV has the 3D coordinates of the BS network $\Phi$, either from a map supplied by the network operator, or through sensing by the UAV itself. Using this information, in addition to measurements received by the UAV omni-directional antenna, the UAV makes a decision about which BS in $\Phi$ it should associate with, for the purpose of maximising the SINR of its communication link. In the next section we describe our proposed supervised learning-based NN architecture to carry out this process.

III. MACHINE LEARNING APPROACH
A. Neural Network Architecture and Configuration

The architecture of a NN model includes the number of layers, number of neurons per layer, and how these neurons are connected. This architecture determines how complex it will be to calculate the optimal values for a specific task. A NN with more layers and neurons typically requires a larger dataset for training. Our NN is composed of the input layer, two hidden layers, and one output layer.

For NN approaches, it is essential to define which features of the environment will be relevant to an effective solution. We use these features as the inputs of our model so that it may accurately react to the conditions of the environment. Our objective for the NN model is to have it identify which of the BSs in $\Phi$ will give the highest SINR when connected via a directional antenna. This corresponds to a classification problem, wherein the NN is trained to choose from one of several discrete options, given a provided input. Let $\Phi_\zeta \subset \Phi$ denote the $\zeta$ closest BSs to the UAV; the NN will choose the serving BS from among this set.

The NN takes several measurements relating to the BSs in $\Phi_\zeta$ as inputs. First, it takes the time-averaged BS received signal power as measured by the omni-directional antenna $P_\zeta = \{p_1, p_2, \ldots, p_\zeta\}$, where $p_i = pu(\phi_i)\left(r_i^2 + \Delta \gamma^2\right)^{-\alpha_i/2}$. The signal is time-averaged to remove the multipath fading effects. As the UAV has access to the position information of the BSs, the NN takes the horizontal distances $R_\zeta = \{r_1, r_2, \ldots, r_\zeta\}$ to the BSs in $\Phi_\zeta$ as inputs.

Using this same position information along with knowledge of its directional antenna, the NN only accounts for interfering BSs within its directional antenna beamwidth by taking in the horizontal distances only to these BSs. We denote a $\zeta \times \xi$ matrix as $F_\zeta$, where each row corresponds to one of the candidate BSs, and each column corresponds to one of the $\xi$ closest BSs that would cause interference for the UAV if it attempted to communicate with one of the candidate BSs. In other words, $F_\zeta(i, j)$ represents the distance from the UAV to the $j$-th closest BS belonging to $\Phi_{W_i}$, which is the set of BSs within the area $W_i$ illuminated by the UAV directional antenna when aligning towards BS $i$. In the event that $\Phi_{W_i}$ contains less than $\xi$ BSs, the remaining entries in the $i$-th row of $F_\zeta$ are set to null values.

Finally, the UAV takes its own height above ground $\gamma$ as an input into the NN.

The NN training itself requires the fine-tuning of parameters related to the learning rate and convergence of the classification, known as the hyperparameters. Hyperparameters are parameters chosen before the training process that can improve the learning process.

We detail our choices for the hyperparameters below:

- Learning Rate: is the amount by which the weights in an NN model are updated. We set it to $10^{-5}$; with this value, the model does not overfit to our training data.
- Epoch: is an iteration of the training process where the model is filled with all the elements of the training dataset. If a model is trained with too many epochs, it can overfit to the training data, while if a model uses too few epochs, it might not learn the necessary features to perform the classification. After testing several values, we set the number of epochs to 200.
- Optimiser: is the function that modifies the weights of each neuron with the purpose of minimising the loss function. The loss function indicates how close the output of the model is to the expected result. The main objective of the learning process is to optimise the loss function, making the predicted output closer to the expected one without over-fitting to the training data. We choose the optimiser AdaMax because it has the feature of accelerating the search for the minimum value of the loss function and reducing oscillations. In addition, it is less sensitive to the choice of the hyper-parameters when compared to the Adaptive Moment Optimisation (Adam) optimizer.

B. Dataset

In supervised learning, for a model to learn it must first be trained with a set of labelled data, and then tested with a second set to evaluate its accuracy. To avoid overfitting the model this second dataset cannot be used in the training process itself. To generate our datasets, we simulate the environment described in the System Model section, with a random PPP distribution of BSs $\Phi$, random building deployment, and the UAV at $x_0$ at a random height $\gamma$. We record the values of $P_\zeta$, $R_\zeta$, and $F_\zeta$, as observed by the UAV. We then have the UAV iteratively align its directional antenna with each of the candidate BSs in $\Phi_\zeta$ and we measure the time-averaged SINR. The index number of the BS with the highest SINR is stored as the label. This process is repeated a number of times, with random BS positions, UAV heights and building deployments, to populate our datasets. Having generated the two datasets we train our NN model to infer through the chosen features which BS the UAV should associate with, for a given set of environmental parameters.

IV. NUMERICAL RESULTS

In this section we evaluate the performance of our NN-based BS association. For comparison, we additionally evaluate
TABLE I
NUMERICAL RESULT PARAMETERS

| Parameter                  | Value                  |
|----------------------------|------------------------|
| Carrier Freq               | 2 GHz                  |
| Building density           | 300 / km²              |
| Building land coverage     | 0.5                    |
| Building height scale parameter | 20 m                |
| $\alpha_L$                 | 2.1                    |
| $\alpha_N$                 | 4                      |
| $m_L$                      | 1                      |
| $m_N$                      | 1                      |
| $p$                        | 40 W                   |
| $c$                        | -38.4 dB [17]          |
| $\theta$                   | 0 dB                   |
| $\sigma^2$                 | 8 · 10^{-13} W [17]    |
| $\gamma_G$                 | 30 m                   |
| $\zeta$                    | 10                     |
| $\xi$                      | 20                     |

Fig. 2. Coverage probability of the UAV as a function of the height $\gamma$, given beamwidth $\omega$ of 45 degrees and a BS density $\lambda$ of 5 / km². The blue line denotes the performance under our NN association approach, the black line denotes the mathematically-derived performance for closest-BS association derived in [7] and [8], and the red line denotes strongest SINR association as measured from the omni-directional antenna.

Fig. 3. Coverage probability of the UAV as a function of the BS density $\lambda$, given beamwidth $\omega$ of 45 degrees and a UAV height $\gamma$ of 100 m. The blue line denotes the performance under our NN association approach, the black line denotes the mathematically-derived performance for closest-BS association derived in [7] and [8], and the red line denotes strongest SINR association as measured from the omni-directional antenna.

Fig. 4. Coverage probability of the UAV as a function of the UAV antenna beamwidth $\omega$, given BS density $\lambda$ of 5 / km² and a UAV height of 100 m. The blue line denotes the performance under our NN association approach, the black line denotes the mathematically-derived performance for closest-BS association derived in [7] and [8], and the red line denotes strongest SINR association as measured from the omni-directional antenna.

The results in fig. 2 show that the NN association strategy gives a 5-20% improvement to the coverage probability when compared to the non-NN closest-BS or strongest SINR association, depending on the height of the UAV. At low heights the NN strategy gives very similar performance to the strongest SINR association, as interference effects are less of an issue, and therefore choosing the BS with the strongest SINR observed by the omni-directional antenna appears to be the optimum strategy. At large UAV heights, due to BS antenna downtilt the stronger SINR measured by the omni-directional antenna will come from more distant BSs, which will result in more interference for the directional antenna if the UAV associates with one of them (due to a shallower tilt angle and greater area $\mathcal{W}$). As a result, at large heights the UAV must prioritise connecting to a closer BS, even if this will result in a lower BS antenna gain, due to a bigger misalignment between the BS antenna tilt, and the UAV-BS vertical angle. The NN recognises this, and so allows the UAV to massively improve its coverage probability over the strongest SINR association case. The biggest NN gains are achieved in the middle range of heights, where both the closest and strongest SINR association strategies give poor performance. This is due to the fact that at these heights, on one hand the UAV has unobstructed LoS channels to distant interfering BSs, while on the other hand the UAV is not so high up that it can mitigate interference through tilting its antenna down. The NN is able to reduce the performance loss at these heights by choosing a BS which
offers a good tradeoff between a high sidelobe antenna gain, low signal pathloss, as well as low interference.

The results in fig. 5 show that the overall network performance deteriorates as the BS density increases, due to increasing interference. At lower densities better performance is achieved by associating to the BS with the strongest measured SINR, while at larger densities connecting to the closest BS gives better results. The NN is able to outperform both association strategies, with a bigger performance improvement observed for the higher BS densities where the UAV experiences more interference.

In fig. 4 we show the impact of the UAV directional antenna beamwidth $\omega$ on the coverage probability. Increasing the beamwidth causes performance to deteriorate for all association policies, due to the resulting increase in interference observed by the UAV. Note that as the beamwidth increases the performance gain offered by our NN solution decreases compared to the strongest association, as at larger beamwidths the intelligence of the NN is not sufficient to mitigate the impact of interference.

The plot in fig. 5 shows the probability of the NN choosing a certain BS to associate with, for different UAV heights. We can see that the UAV will be served by the closest BS approximately half of the time for the tested heights, due to the impact of antenna misalignment when the UAV and the BS are a short horizontal distance apart. The NN will instead sometimes prefer to connect to BSs further away, with the shape of the BS sidelobes having a noticeable impact on the probability distribution of the chosen BS. Consider, for example, how the NN will very rarely choose the third-closest BS when the UAV is at 100 meters; the NN has learned during training that the fourth, fifth and sixth BSs are more likely to give a better SINR, even if the distance-dependent pathloss and the interference is greater.

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