A Heuristic K-Means-based Unsupervised Machine Learning Model for Unmanned Aerial Vehicle Mounted Reconfigurable Intelligent Surface for Enhanced 5G and Beyond Networks Performance

Raymond Sabogu-Sumah
Department of Telecommun. Engineering,
Kwame Nkrumah Univ. of Sci. and Tech.
Kumasi, Ghana

Opare Kwasi Adu-Boahen
Department of Telecommun. Engineering,
Kwame Nkrumah Univ. of Sci. and Tech.
Kumasi, Ghana

James D. Gadze
Department of Telecommun. Engineering,
Kwame Nkrumah Univ. of Sci. and Tech.
Kumasi, Ghana

Kwame Opuni-Boachie Obour Agyekum
Department of Telecommun. Engineering,
Kwame Nkrumah Univ. of Sci. and Tech.
Kumasi, Ghana

Edmund Y. Fianko
National Communications Authority
NCA Tower
Accra, Ghana

Dennis N.A. Gookyi
Institute for Scientific and Technological Information
Council for Scientific and Industrial Research
Accra, Ghana

ABSTRACT

This paper investigates the use of Reconfigurable Intelligent Surfaces (RIS) installed on Unmanned Aerial Vehicles (UAVs) for a Non-Orthogonal Multiple Access (NOMA) mobile cellular system coverage extension and sum rate maximization. The UAV only acts as a medium to mount the RIS and therefore does not expend any other energy aside from that used to keep it flying.

The study formulates a non-convex optimization problem to maximize the sum rate of the NOMA Cellular system by optimizing the transmit power and the location of the UAV. Due to the complexity of the formulated optimization problem, the study devised a heuristic clustering model using the Angle of Arrival (AoA) of User Equipment (UEs) signals at the Base Station (BS). The simulation results show that the use of the UAV-RIS system improves the coverage probability of the 5G and B5G network. Further, the proposed heuristic clustering technique improves the system sum rate between 8.3 to 87% depending on the transmit power of the BS.

General Terms

UAV, RIS, Heuristic K-means, clustering

Keywords

Machine Learning, NOMA, 5G, B5G, Power Domain NOMA, Sum Rate, AoA, Coverage, Probability

1. INTRODUCTION

One of the revolutionary techniques which is anticipated to improve 5G and B5G wireless systems is Reconfigurable Intelligent Surfaces. RIS technology anticipates to create a very smart radio propagation environment in which its conditions can be re-engineered with the physical-layer signaling [1]. The RISs allow wireless channel modelers to compensate the negative effect of multipath fading by constructively combining the radio waves i.e. reflected, refracted, scattered and diffracted from large surfaces [2]. The core technology behind RIS concept is the metamaterials which makes up the surfaces.

It is important to note the following distinguishable features between RIS and other related technologies such as MIMO beamforming, backscatter communication and relaying (DF and AF) [3]:

—RIS are considered as a contiguous surface, thus, can shape the wave impinging on it at any point through soft programming.

—They are practically passive in nature.

—Also, RIS are not affected by receiver noise, and do not require analog-to-digital/digital-to-analog converters (ADC/DAC) and power amplifiers.
—They can work on any operating frequency and thus, have full-band response characteristics.
—RIS can quickly and easily be deployed, for example on buildings, human clothing, ceilings of factories and indoor spaces.

Due to these distinctive features, future wireless systems are evolving towards network functional virtualization and reconfigurable platforms and every single aspect of the network will have the ability to adapt itself to the changes in its propagation environment [4]. The authors in [5], demonstrated that microwave modulators installed separated apart have the ability to passively, complicate microwave electromagnetic fields located in rich cluttered and complex wireless environments. The shaping can be done using only binary phase state tunable meta-surfaces. In their [6] attempt to alter and or control indoor coverage, 3-D reflectors were mounted on wireless Access Points (APs). These non-optimized static-shaped reflector designs have been introduced decades ago to extend the wireless coverage in indoor as well as outdoor environments. A software controlled hyper-surfaces concept was proposed by [7] to enable complete manipulation of the EM waves. A lightweight IoT gateway; the intelligent surfaces comprising super thin meta atoms receive commands from a controller to adjust their behavior by steering, absorbing and focusing impinging EM waves in any direction.

Emil Bjornson et'al in [8] provided a comprehensive tutorial on the basic properties of RIS technology based on signal processing perspective. The work was to serve as a complement to existing scenarios/studies on electromagnetic and hardware aspects [9], acoustics [10], communication theory, and localization [8]. Tractable mathematical derivations were provided to fully understand and analyze RIS-aided systems using signal processing. The derived formulas were used to illustrate how RIS can improve wireless communication, localization, as well as sensing through simulation.

Despite the significance of RIS in future wireless system, there are challenges associated with the optimal positioning of the RIS to improve performance. The authors of [11] performed downlink coverage analysis on an RIS assisted network comprising one base station and one user equipment. The orientation and the distance between the BS and RIS significantly influences the cell coverage which motivated the authors to formulate an RIS placement optimization problem. To solve the optimization problem, a coverage maximization algorithm (CMA) was proposed, and a closed-form optimal RIS orientation was obtained to produce very good results. [12, 13] used a conjugate gradient and particle swarm optimization scheme to jointly optimize the RIS phase shifts and Aerial Base Station (ABS) altitudes. The formulated problem was divided into sub-problems and was solved by applying an alternative optimization method. A detailed system level modelling of RIS-assisted cellular network was conducted in [12] in which a 3-dimensional channel model between the BS, RIS and UE was considered. It was proved that, to achieve optimal coverage, the best RIS placement is exactly opposite the BS with a constraint of using one RIS for each sector of the BS.

Further, the transition to mmWave implies that 5G and beyond systems will primarily depend on LOS in contrast to heavy cluttered lower Gigahertz (below 6GHz) communication. If an LOS is absent, the performance of the system degrades and therefore necessities the development of techniques to improve the propagation environment [14]. RIS technology is a suitable technique designed to alter the propagation channel to improve performance especially for cluttered users. In previous studies, UAVs serve as flying base stations which transmits signals to users underlay thereby exerting power constraints on the UAV [15].

This study identified two main challenges in UAV and RIS technologies for 5G and B5G NOMA Cellular Networks; powering a flying UAV has been identified as one of the main challenges of future 6G aerial networks and also optimal positioning of the RIS to maximize system performance is another challenge of RIS.

To address the aforementioned challenges, this study proposed a UAV mounted RIS scenario where the UAV only needs power to keep it afloat (not acting as a BS). Further, the mobility nature of the UAV is leveraged to optimally position the RIS in order to maximize the cellular sum rate as well extending coverage. A heuristic k-means based unsupervised learning scheme is therefore developed to group the UEs into two clusters (blocked and unblocked) and the 5G/B5G cellular system allocate appropriate transmit powers using PD-NOMA technique.

The rest of the paper organized as follows; Section II presents our proposed RIS UAV mounted scenario, Section III gives the received signal strength analysis. In Section IV, the results are presented while conclusions are drawn in Section V.

2. UAV MOUNTED RIS 5G/B5G CELLULAR NETWORK SCENARIO

2.1 Re-configurability and Intelligence of the Elements

In this section, the study develops a UAV-RIS mounted system to provide coverage to users which are blocked by impairments such as trees, high rise buildings, etc. This scenario is most applicable in urban areas characterized by heavy clutter. An RIS is a planar array comprising many elements which are passive in nature. The passiveness lowers the cost of these devices since there is no need to integrate it with radio frequency circuits in the surface. A controller coherently adjust the phases of each element to alter the phases of signals sent to users. This configuration has been reported to provide optimal wireless systems performance for 5G and beyond systems [20].

Re-configurability is a very vital property of RIS technology which may be provided autonomously by the RIS controller or externally by the BS. RIS configurations can be static or dynamic. Static configuration is for example, used to extend coverage to specific black spots; however, to achieve better performance, the configuration must be dynamic or semi-static because the served user terminal(s) may change its (their) location(s) [16]. This study adopted the dynamic configuration to accommodate the mobility of the user terminals. There is little SNR improvement by the addition of the RIS to the cellular system if the elements are not intelligent to control the phase of the signals to the users [21]. Without the intelligence and phase tuning, the elements just act as reflectors and this could result in the cancellation of the direct and reflected signals. Thus, it is essential that the phase of the RIS elements are controlled in order to coherently combine the individual element reflections. This will enable the arrival of the direct and reflected signals with the same phase [21].

For the above to be realized, the channel state information is required. Several works on wireless radio resource allocation presumed a perfectly known CSI between the transmitter and UEs [22- 23]. The RIS setup in the system model shown below fully implements the phase tuning, i.e. the intelligence using the CSI from the users. This study assumes that the phase shifting capability of the RIS is ω, and the RIS can generate phase shift in a range of 0 to ω. The parameter ω is k-bit uniformly quantized. That is the programmable components such as varactor diodes or PIN diodes are controlled, to generate 2^k patterns of the reflection coefficients. For details on in-depth analysis of the phase shifting capability, an interested reader is referred to [22].

2.2 System Model and Received Signal Strength Analysis for Blocked and unblocked Users

The figure below shows the system model considered in this paper. The UAV is only acting as a medium to mount the RIS and therefore does not expend any other energy aside from that used to keep it flying.

The BS is deployed on ground with transmit power (p_t). The BS serves several users within its coverage area; however, due to the heavy clutter (high rise buildings, tress and other impairments), many of the users are unserved. As shown in the system model in Figure 1, some of the signals are sent to the RIS mounted on the UAV; which are in turn reflected intelligently by its elements to serve the blocked users.
This study assumes the unblocked users are only served by the BS and their received signal is given as

$$\gamma = p_t g_t \alpha^{-n} + \sigma, \tag{1}$$

where g_t is the antenna gain of the BS, α^{-n} is the pathloss from the BS to the unblocked users and σ is the noise in the channel.

For the blocked users, the received signal is given as

$$\gamma_1 = \Gamma p_t g_t \alpha^{-n} \alpha_1^{-n} + \sigma, \tag{2}$$

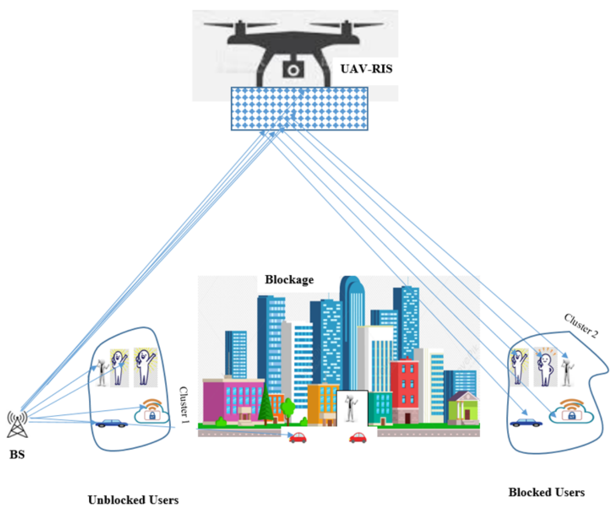

Fig. 1. System Model for RIS UAV mounted RIS

where α_1^{-n} is the pathloss from the RIS to the blocked users, Γ is the reflection coefficient of the RIS given as

$$\Gamma = (\psi_{air} - \psi_{RIS})(\psi_{air} + \psi_{RIS})^{-1}, \tag{3}$$

The value of Γ depends on the metamaterials which make up the RIS. For free space (air) the impedance (ψ_{air}) is 377Ω. Note that the above expression implements the RIS like a normal reflector without any phase tuning. This study implements the tuning and reconfiguration at the RIS controller. Using MatLab, this study estimate the channel state information and repeat the simulation to obtain the channel phase as similarly done in [22].

2.3 Power Domain NOMA Resource Allocation

The above received signal strength analysis considers uniform power transmission to both the RIS and the unblocked users. However, this will put the blocked users a huge disadvantage given that their signals passes through two routes coupled with high attenuation, i.e. additional propagation losses (PL) from the RIS to the users. The power domain NOMA (PD-NOMA) scheme [24] is adopted here to allocate optimal power to both the unblocked and blocked users.

The received signal at a given unblocked user is therefore given as

$$\gamma' = h_1 \epsilon p_t + \sigma, \tag{4}$$

In PD-NOMA systems, different powers are allocated to different users based on their PL and channel conditions. For ease of analysis and without loss of generality, the study assumes that all unblocked users have similar if not the same propagation conditions and are allocated equal power i.e. ϵp_t with ϵ defined as the fraction of the transmit power allocated to the respective users.

For the users served by the RIS, the received signal strength is

$$\gamma_1' = (\psi_{air} - \psi_{RIS})(\psi_{air} + \psi_{RIS})^{-1} h_2 h_3 (1-\epsilon) p_t + \sigma, \tag{5}$$

where h_2, h_2 and h_3 are the channel responses BS to an unblocked user, BS to the RIS and RIS to a blocked user respectively. From the principle of power domain NOMA, users with better channel conditions are allocated less power than those with worse channel conditions [22, 23]. From the foregoing, $\epsilon p_t < (1-\epsilon)p_t$. The authors in [22] enumerated the fundamental power allocation strategies for downlink multi-users NOMA considering different users target rates which serves as a baseline for this study.

2.4 Sum Rate Analysis

Sum rate in wireless communication is the total achievable transmission from all users connected to the network. For easy understanding, this study derives the throughput for both blocked and unblocked UEs as well as the system sum rate. The throughput for a single unblocked user is given as

$$R_{ub_i} = W \log_2 \left(1 + \frac{\gamma_i'}{\sigma + \sum_{=1}^{K-1} \gamma_i}\right), \tag{6}$$

where σ is the noise in the channel and W is the bandwidth.

The sum rate for a total (T) unblocked users is

$$R_{ub}^{T} = \sum_{i=1}^{T} R_{ub_i} \tag{7}$$

The throughput for a blocked user served by the RIS is

$$R_{b_i} = W \log_2 \left(1 + \frac{\gamma_1^{'}}{\sigma + \sum_{i=1}^{K-1} \gamma_i} \right), \tag{8}$$

Likewise, the sum rate for a total (L) blocked users is

$$R_{b}^{T} = \sum_{j=1}^{L} R_{b_j} \tag{9}$$

The overall system sum rate for both blocked and unblocked is given as

$$R_T = W \log_2 \sum_{i,j=1}^{T,L} R_{ub_i} + R_{b_j} \tag{10}$$

2.5 Sum Rate Maximization

Our aim is to maximize the system sum rate through the use of the UAV installed RIS and the optimum NOMA power allocation. Several studies have analyzed and devised objective functions with associated constraints to maximize the sum rate for both terrestrial and UAV based non terrestrial networks [23]. This paper therefore formulated the optimization problem below:

$$\max_{p} R_T \text{s.t.} \mathbf{V}_{uav} \in \mathbf{U} \sum_{j=1}^{T} p_j \sum_{i=1}^{L} p_i \leq P_{max} p_{i,j} > 0 \forall i,j \tag{11}$$

where $p = p\{i, j\}, j \in \{j.....l\}, i \in \{i.....L\}$

Constraint (1) ensures that the UAVs position is guarded within a certain volume of space **U** whereas (2 and 3) ensures that the sum of the allocated powers do not exceed the overall available power and each must also be positive respectively.

Optimizing the transmit power and location of a UAV system is difficult due to the UAVs continuous mobility [24]. To mitigate the above difficulty, the authors in [25] proposed a low-complexity scheme to maximize the sum rate of NOMA-UAV networks through updating the decoding features. This method though effective is not applicable to the current study since the UAV is not a BS but acting as a medium to mount the RIS. Thus, the formulated optimization problem is a non-linear, i.e. non-convex and computationally expensive to solve particularly when the number of blocked and unblocked users grow larger.

Solving non-convex optimization problems is very difficult and time consuming. Some of the methods of solving these type of optimization problems are the semi-definite relaxation (SDR) method [26], Gauss randomization method, Stochastic Variance Reduced Gradient (SVRG) method, Stochastic Gradient Descent method, Mini-batching method and Momentum method.

Motivated by the similar propagation characteristics that exist between users within a given location, the study develops a simplified k-means-based machine learning scheme which groups the users and allocate same powers to those within a given cluster.

2.6 Fundamentals of K-Means Unsupervised Leaning

It is a methodology in the field of unsupervised machine learning. K-means algorithm attempts to find each data point (hereafter, a user) a cluster represented by a centroid. The algorithm first chooses the K centroids and determine the number of clusters [28]. Each user is then assigned to the closest centroid based on its Euclidian distance. Thus, each collection of users assigned to the same centroid forms a cluster. The assignment of users to clusters is repeated until the centroids remain unchanged. The figure below illustrates a group of users put into different clusters for an unsupervised machine learning model.

As indicated in Figure 2, all the red and blue datasets/users belong to clusters one and two respectively with their centroids marked by the black cross. $X = \{x_i\}$, $i \in U$ is the set of M-dimensional points to be clustered in K-clusters.
The application of k-means clustering for NOMA cellular networks has been studied in research community to allocate resources to users in different clusters [29]. The clustering of users is done based on their distances from the available centroids. The distances are usually computed heuristically using the Euclidean distance formula. The number of clusters and centroid selection is done, either randomly or based on a predefined rule such as the leader election [30].

Due to the integration of the terrestrial network with the RIS installed on the UAV, there is the introduction of extra layers of complexity. For example, the BS needs to learn the AoA of the blocked users signals at the RIs; when the signal is refelected from the RIS to the BS in the uplink, there will be the need to re-estimate the signal again to get the AoA of the refelected signal at the BS. Also, the BS needs to designate the centroids for the k-means clustering model either randomly or through the leader selection. This makes the application of the conventional K-means clustering technique to the model considered in this study very difficult and hard to implement. A simplified, but accurate learning model is thus, needed to group the users for effective NOMA power allocation.

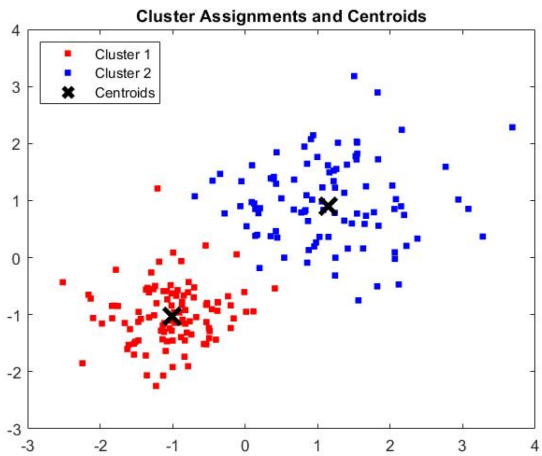

Fig. 2. Illustration of K-means Clustering

2.7 Proposed Heuristic K-means based Clustering Model

A simplified clustering model is therefore developed and implemented in this study as shown in Figure 3, below. This model follows the conclusions drawn by authors in [31] that for optimum performance the number of clusters in any unsupervised K-means clustering machine leaning model must be two.

The model is principally built on the AoA of the UEs signals at the BS of the cellular network. The BS determines the AoA based on the direction of the signal as illustrated on the Cartesian plane in Figure 4.
The implementation of the model through an algorithm is as follows
[H] algorithm**Heuristic Unsupervised Learning Algorithm** [1] **Start** BS Estimate CSI to obtain AoA of Users Collate AoA of new users at the BS Create an unstructured database of the Users AoA Apply Heuristic K-means clustering scheme to group users $0^o \leq AoA \leq 270^o$, classify UE as a unblocked user **if** $270^o \leq AoA \leq 360^o$, classify as blocked user Re estimate the CSI to obtain AoA value. Repeat step 2 to 7

3. RESULTS AND DISCUSSIONS

3.1 Impact of Increasing the Surface Area of an RIS, DF and AF Relays

It has been well established by research that increasing the number of the RIS elements improves the wireless system's performance [32]. The figure below shows that, the larger the surface area of the RIS, the better the system performance. To increase the surface area, more elements are added to the RIS. The figure further compares the use of an RIS with that of a Decode Forward (DF) relay using a multi-antenna system deployed at the same place [32] and an Amply Forward (AF) relay. For smaller surface area, the DF and AF systems perform better than the RIS until it reaches a surface area of one square meter $(1m^2)$ when the RIS performance outperforms the AF and DF by following a square law fashion as compared to the direct proportionality of the DF and AF systems.

In cooperative communications systems, AF amplifies the system noise as well interference despite its simplicity in implementation. On the other hand, DF decodes the signal, correct errors, remove and or suppress noise before relaying it which makes it give superior performance despite the complexity involved in its design [32]. Thus, a better performance of DF over AF relay is clearly shown in the results as well.

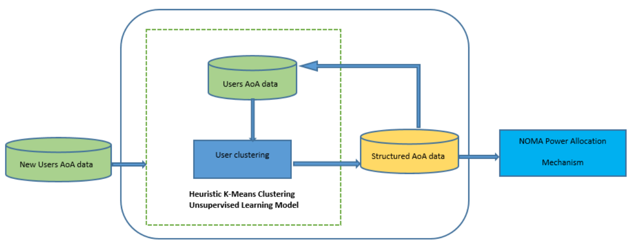

Fig. 3. Illustration of K-means Clustering

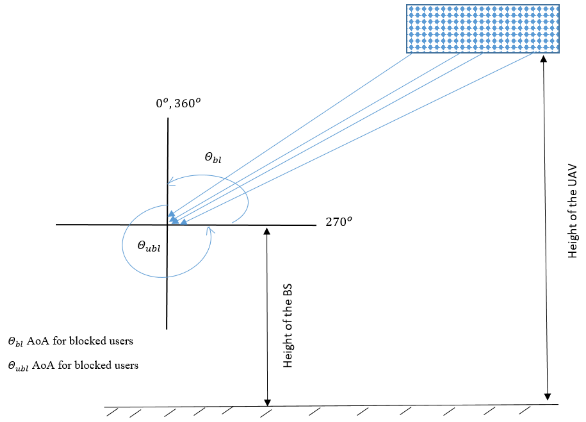

Fig. 4. Illustration of BS Determination of UEs AoA

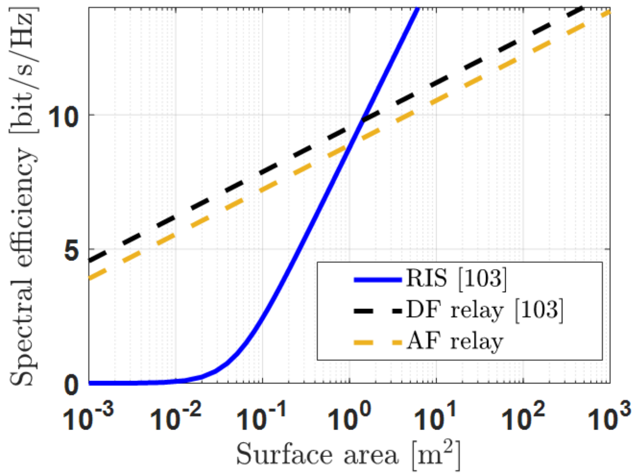

Fig. 5. Effect of Increasing Surface Area of RIS/DF/AF Relay on Spectral Efficiency

Parameter	Description	Value
F_c	Carrier Frequency	28GHz
h	Height of RIS (UAV)	500m
NxM	Number of RIS Elements	10x20
d_n, d_m	Inter Element Spacing	$5.4x10^{-4}$

3.2 Effect of RIS Phase Control on SNR

The following simulation parameters in Table I are used for subsequent results unless otherwise stated.

From the results demonstrated below, the use of the RIS without phase control gives suboptimal performance. This results is expected because, as explained in section 2.1, the elements operate as reflectors which results in the cancellation of the reflected and direct signals. The figure further shows improved SNR performance with perfect RIS phase control. Interestingly, the SNR performance in the LOS and NLOS are at par confirming the established conclusion in literature that RIS helps to alter the propagation environ-

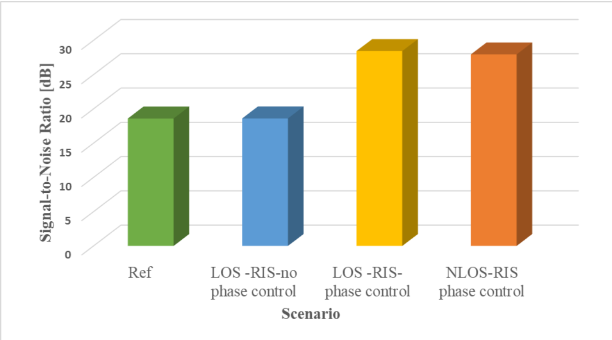

Fig. 6. Effect of RIS Phase Control on SNR

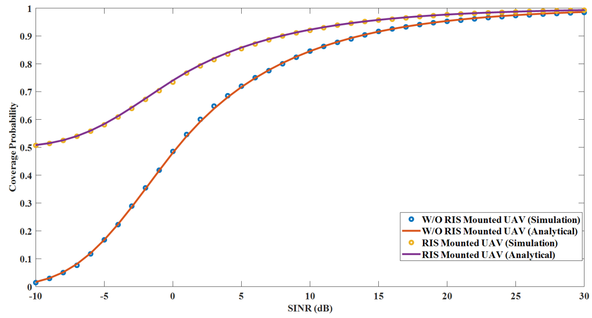

Fig. 7. Comparison of Coverage Probabilities for RIS Mounted UAV and no RIS Scenarios

ment to improve performance. In nominal terms, the RIS gives extra 9.8958dB gain in SNR which represents 53.21% (on dB scale). On the linear scale this corresponds to 300% performance gain. Details of the RIS configuration and simulation can be found at mathworks.com.

3.3 Coverage Probability Performance of RIS Mounted UAV

Figure 7 demonstrates the coverage probability performance of a cellular system deployed with and without an RIS installed UAV. At lower SINR thresholds, the RIS mounted UAV with the proposed clustering model gives excellent performance than a scenario without the deployment of the RIS. This because, most users are cut out of connectivity by blockade when the RIS is absent. For an SINR threshold of say -5dB, the coverage probabilities are 13% and 52% for a system without and with UAV RIS deployed respectively. Another insight reveled is the perfect match of the simulation and analytical results.

3.4 Sum Rate performance with a reflector and RIS

The sum rate performance of the UAV mounted RIS and a conventional signal reflector is evaluated here. As can be observed from Figure 8, the system sum rate is best when there no clutter and no RIS and or reflector. Thus, the cellular system operates just as the legacy network without any propagation impairments. However, when clutter is introduced to mimic a realistic scenario, it is observed that the clutter and RIS scenario outperforms the clutter and reflector scenario. This result is expected since the RIS improves the channel gain.

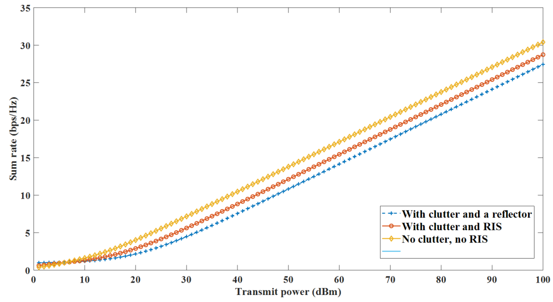

Fig. 8. Comparison of Coverage Probabilities for RIS Mounted UAV and no RIS Scenarios

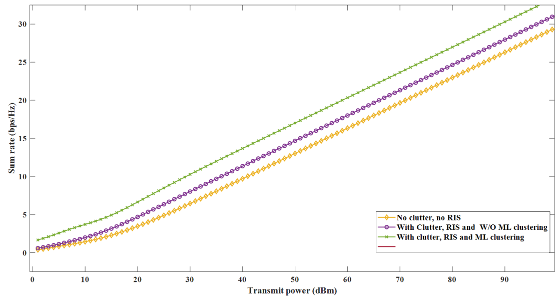

Fig. 9. Sum Rate Performance with and without Proposed ML Clustering

3.5 Sum Rate performance with and without ML clustering

The figure above demonstrate the superiority of the proposed clustering learning technique over a conventional cellular system operating in a clutter or clutter free environment. It also shows that the use of the RIS even without the proposed technique bring some performance improvement. The explanation from above applies to this scenario as well.

3.6 Impact of Clutter, Reflector and RIS on Sum Rate

The results in Figure 10 and the summary in Table 2, demonstrate the significant role the RIS plays in increasing the sum rate. The absence of clutter also means the UEs are able to receive signals in LOS from the BS which results in high performance. Further, the results demonstrate that increasing the maximum BS transmit power corresponding increases the system sum rate. This is because an increase in the BS transmit power enables it to allocate high powers to the UEs especially the blocked users to improve their individuals rates which translates to the overall system performance. However, increasing the maximum BS transmit power means that, the cellular system will be operating on macro cells which comes with other challenges such as inefficient spectrum utilization and harmful interference issues. A right balance must therefore be ensured to reap the benefits of the proposed technique.
The result from the above figure is summarized table 2 below:

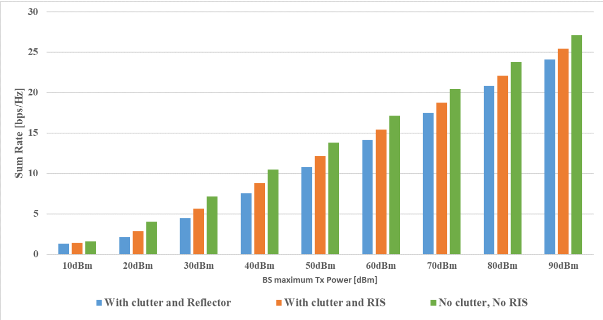

Fig. 10. Impact of RIS, Reflector and Clutter on Sum Rate

Scenario	Sum		Rate		bps/H				
	10dBm	20dBm	30dBm	40dBm	50dBm	60dBm	70dBm	80dBm	90dBm
With clutter and Reflector	1.3238	2.1709	4.47996	7.5555	10.8354	14.1513	17.4725	20.7943	24.1163
With clutter and RIS	1.4195	2.892	5.6242	8.8236	12.126	15.4453	18.7669	22.0888	25.4107
No clutter, No RIS	1.6195	4.0153	7.1742	10.4739	13.7923	17.1739	20.4358	23.7577	27.0796

3.7 Impact of ML Clustering on Sum rate

From the results depicted in Figure 11 and summarized in Table 3, it is evident that the heuristic unsupervised machine learning clustering technique improves the system sum rate between 8.3% to 87%. Increasing the BS transmit power also improves the sum rate as explained previously.
The result from the above figure is summarized Table 3 below:

Scenario	Sum		Rate		bps/H				
	10dBm	20dBm	30dBm	40dBm	50dBm	60dBm	70dBm	80dBm	90dBm
No clutter, No RIS	1.6195	4.0153	7.1742	10.4739	13.7923	17.1739	20.4358	23.7577	27.0796
With clutter, RIS and No ML clustering	1.9797	4.6848	8.0166	11.3509	14.6748	17.9971	21.319	24.641	27.9629
With clutter, RIS and ML clustering	3.7037	6.6393	10.2671	13.6706	17.0059	20.3294	23.6516	26.9735	30.2955

4. CONCLUSION

To extend coverage to blocked 5G/B5G users in densed urban settings, this paper proposed the use of a Reconfigurable Intelligent Surface installed on a flying UAV. Signals from the 5G/B5G BS are reflected to blocked users by the RS and vice versa.

An optimization problem is formulated to maximize the system sum rate through appropriate power allocation and UAV positioning. Due to the non-convexity of the formulated problem, a heuristic k-Means based unsupervised machine learning model which classifies the users into clusters based on the Angle-of-Arrival of their signals at the BS is proposed. Optimal transmit power is thereby allocated using power-domain NOMA technique to maximize the system sum rate.

The use of a Reconfigurable Intelligent Surface on a flying UAV is very effective in extending mobile connectivity to users (blocked) especially in densed urban environment. The study reveals that when an RIS is deployed, on a flying UAV, the coverage probability for a given SINR (eg. -5dB) is improved by 39% i.e. (13% for no RIS, 52% for RIS). NOMA resource allocation is one of the key enablers of 5G and beyond networks. Power Domain NOMA is most widely studied, it allocates optimal power to users primarily based on their propagation losses. Thus, low power is allocated to users with adverse PL whereas high power is allocated to UEs with poor channel conditions. The heuristic K-means based unsupervised Machine Learning developed in the study aids the BS to allocate appropriate transmit power to UEs. The sum rate performance is improved between 8.3% to 87% depending on the 5G/B5G cellular systems BS transmit power.

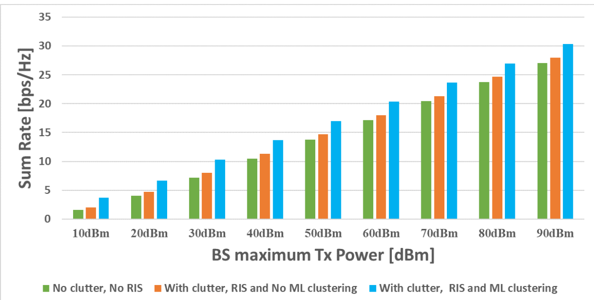

Fig. 11. Impact of proposed ML Clustering on Sum Rate

Acknowledgements

This work was supported by the KNUST Engineering Education Project (KEEP).

5. REFERENCES

[1] M. D. Renzo et al.,,, Smart radio environments empowered by reconfigurable AI meta-surfaces: an idea whose time has come, *EURASIP J. Wirel. Commun. Netw.*, vol. 2019:129, 2019.

[2] E. Basar,,, Transmission through large intelligent surfaces: A new frontier in wireless communications, in *Proc. Eur. Conf. Netw. Commun. (EuCNC), Valencia, Spain*, Jun. 2019, pp. 1–6. [Online]. Available: https://arxiv.org/pdf/1902.08463.pdf.

[3] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. -S. Alouini and R. Zhang,,, Wireless Communications Through Reconfigurable Intelligent Surfaces, in *IEEE Access*, vol. 7, pp. 116753-116773, 2019, doi: 10.1109/ACCESS.2019.2935192.

[4] M. Di Renzo, H. Haas and P. M. Grant, Spatial modulation for multiple-antenna wireless systems: A survey,,, *IEEE Commun. Mag.*, vol. 49, no. 12, pp. 182-191, Dec. 2011.

[5] N. Kaina, M. Dupré, G. Lerosey and M. Fink,,, Shaping complex microwave fields in reverberating media with binary tunable metasurfaces, *Sci. Rep.*, vol. 4, no. 1, Oct. 2014.

[6] X. Xiong, J. Chan, E. Yu, N. Kumari, A. A. Sani, C. Zheng, et al.,,, Customizing indoor wireless coverage via 3D-fabricated reflectors,,, *Proc. 4th ACM Int. Conf. Syst. for Energy-Efficient Built Environ.*, 2017.

[7] C. Liaskos, A. Tsioliaridou, S. Nie, A. Pitsillides, S. Ioannidis and I. Akyildiz,,, Modeling simulating and configuring programmable wireless environments for multi-user multi-objective networking, *arXiv:1812.11429*, Dec. 2018, [online] Available: https://arxiv.org/abs/1812.11429.

[8] Emil Björnson, Henk Wymeersch, Bho Matthiesen, Petar Popovski, Luca Sanguinetti, and Elisabeth de Carvalho,,, Reconfigurable Intelligent Surfaces: A Signal Processing Perspective With Wireless Applications, *arXiv:2102.00742v2* [eess.SP] 31 Dec 2021.

[9] O. Tsilipakos et al.,,, Toward intelligent metasurfaces: The progress from globally tunable metasurfaces to software-defined metasurfaces with an embedded network of controllers, *Advanced Optical Materials*, no. 2000783, 2020.

[10] B. Assouar et al.,,, Acoustic metasurfaces, *Nature Reviews Materials*, vol. 3, pp. 460–472, 2018.

[11] S. Zeng, H. Zhang, B. Di, Z. Han and L. Song,,, Reconfigurable Intelligent Surface (RIS) Assisted Wireless Coverage Extension: RIS Orientation and Location Optimization, in *IEEE Communications Letters*, vol. 25, no. 1, pp. 269-273, Jan. 2021, doi: 10.1109/LCOMM.2020.3025345.

[12] M. Misbah, Z. Kaleem, W. Khalid, C. Yuen and A. Jamalipour,,, Phase and 3-D Placement Optimization for Rate Enhancement in RIS-Assisted UAV Networks, in *IEEE Wireless Communications Letters*, vol. 12, no. 7, pp. 1135-1138, July 2023, doi: 10.1109/LWC.2023.3263224.

[13] C. Liu et al.,,, Reconfigurable Intelligent Surface Assisted High-Speed Train Communications: Coverage Performance Analysis and Placement Optimization, in *IEEE Transactions on Vehicular Technology* vol. 73, no. 3, pp. 3750-3766, March 2024, doi: 10.1109/TVT.2023.3325627.

[14] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang,,, Wireless Communications Through Reconfigurable Intelligent Surfaces,*IEEE Access*, vol. 7, pp. 116 753–116 773, 2019.

[15] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah,,, Mobile unmanned aerial vehicles (UAVs) for energy-efficient internet of things communications, *IEEE Transactions on Wireless Communications*, vol. 16, no. 11, pp. 7574–7589, Nov 2017.

[16] Yang, L., Yang, Y., Hasna, M. O., and Alouini, M.-S.,,, Coverage, Probability of SNR Gain, and DOR Analysis of RIS-Aided Communication Systems, *IEEE Wireless Communications Letters,* 1–1. doi:10.1109/lwc.2020.2987798.

[17] Mohamed A. Elmossallamy, Hongliang Zhang, Lingyang Song, Karim Seddik, Zhu Han, and Geoffrey Li,,, Reconfigurable Intelligent Surfaces for Wireless Communications: Principles, Challenges and Opportunities, *IEEE Trans. on Cognitive Communications and Networking,* V9l. 6, No. 3, September 2020.

[18] D. T. Ngo, S. Khakurel, and T. Le-Ngoc,,, Joint sub-channel assignment and power allocation for OFDMA femtocell networks,,, *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 342–355, Jan. 2014.

[19] L. Cao, H. Yin, X. Pei and L. Tan,,, RIS with Practical Reflection Coefficients: Modeling and Experimental Measurements, *2024 18th European Conference on Antennas and Propagation (EuCAP), Glasgow, United Kingdom,* 2024, pp. 1-5, doi: 10.23919/EuCAP60739.2024.10501671.

[20] C. Zhang, W. Yao, Y. Zuo, J. Gui and C. Zhang,,, Multi-Objective Optimization of Dynamic Communication Network for Multi-UAVs System, in *IEEE Transactions on Vehicular Technology,* vol. 73, no. 3, pp. 4081-4094, March 2024, doi: 10.1109/TVT.2023.3323382.

[21] J. Liu, M. Sheng, R. Lyu and J. Li,,, Performance Analysis and Optimization of UAV Integrated Terrestrial Cellular Network, in {IEEE Internet of Things Journal, vol. 6, no. 2, pp. 1841-1855, April 2019, doi: 10.1109/JIOT.2018.2878802.

[22] Wang, Y. Liu, S. Niu and H. Song,,, Extensive Throughput Enhancement For 5G-Enabled UAV Swarm Networking, in *IEEE Journal on Miniaturization for Air and Space Systems,* vol. 2, no. 4, pp. 199-208, Dec. 2021, doi: 10.1109/JMASS.2021.3067861.

[23] D. Kim, S. Kwon, H. Jung and I. -H. Lee,,, Deep Learning-Based Resource Allocation Scheme for Heterogeneous NOMA Networks, in *IEEE Access,* vol. 11, pp. 89423-89432, 2023, doi: 10.1109/ACCESS.2023.3307407.

[24] R. Tang, J. Cheng and Z. Cao,,, Joint placement design admission control and power allocation for NOMA-based UAV systems, *IEEE Wireless Commun. Lett.*, vol. 9, no. 3, pp. 385-388, Mar. 2020.

[25] Xinfu Liu and Ping Lu,,, Solving Non-Convex Optimal Control Problems by Convex Optimization, in *Journal of Guidance, Control, and Dynamics,* Vol. 37, No. 3, 2014, pp. 750-765, doi: 10.2514/1.62110.

[26] Cui, Z. Ding, P. Fan and N. Al-Dhahir,,, Unsupervised Machine Learning-Based User Clustering in Millimeter-Wave-NOMA Systems, in *IEEE Transactions on Wireless Communications,* vol. 17, no. 11, pp. 7425-7440, Nov. 2018, doi: 10.1109/TWC.2018.2867180.

[27] Y. Lin, K. Wang and Z. Ding,,, Unsupervised Machine Learning-Based User Clustering in THz-NOMA Systems, in *IEEE Wireless Communications Letters,* vol. 12, no. 7, pp. 1130-1134, July 2023.

[28] Sediyono, Eko et al.,,, Leader election of dynamic wireless intelligent control machine in sensor network distributed processing. *J. King Saud Univ. Comput. Inf. Sci.* 34 (2022): 9146-9162.

[29] J. Cui, Z. Ding, P. Fan and N. Al-Dhahir,,, Unsupervised Machine Learning-Based User Clustering in Millimeter-Wave-NOMA Systems, in *IEEE Transactions on Wireless Communications* vol. 17, no. 11, pp. 7425-7440, Nov. 2018, doi: 10.1109/TWC.2018.2867180.

[30] A. Goldsmith,,, Wireless communications, *Cambridge university press,* 2005.

[31] S. Rohde and C. Wietfeld,,, Interference aware positioning of aerial relays for cell overload and outage compensation, in *2012 IEEE Vehicular Technology Conference (VTC Fall)*, Sept 2012, pp. 1–5.

[32] Bjornson, O. Ozdogan and E. G. Larsson,,, Reconfigurable Intelligent Surfaces: Three Myths and Two Critical Questions, in *IEEE Communications Magazine,* vol. 58, no 12, pp. 90-96, December 2020.