# Efficient Airborne Network Clustering for 5G Backhauling and Fronthauling


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***Abstract*—Interests in the exploration and use of Unmanned Aerial Vehicles (UAVs) for service provision have risen in recent years. However, the use of UAVs to extend or solely provide Fifth Generation (5G) wireless network coverage in rural and low income areas is one application area that is yet to be extensively researched. To this end, this paper proposes a topological design model for building an airborne network to provide coverage in rural areas. The model uses a combination of Low Altitude Platform (LAP) as a base station and a cluster of UAVs as cellular access points to provide wireless access to ground users. A combination of performance metrics including Signal-to-Noise Ratio, communication range and residual energy of UAVs are used as guide for designing a robust airborne network with multiple sink nodes. Topology relaxation techniques are applied to design these meshed airborne networks respectively called Multi-Sink Airborne Network with Inter-Cluster Communication through the LAP (MSLBACK) and Multi-Sink Airborne Network with an Inter-Cluster Connection through UAV Gateways (MS-GBACK). Compared to myopic approaches (that may lead to isolated UAVs), these airborne networks have more economic relevance as they ensure effective utilization of all UAVs in providing 5G connectivity to ground users. Simulation results reveal that MSLBACK and MSGBACK outperform the state-ofthe-art algorithms.**



***Index Terms*—Clustering, Energy Efficiency, Low Altitude Platform, Unmanned Aerial Vehicles, Wireless Sensor Network**


## I. Introduction

The Arpanet experiment [1] laid the foundation upon which the most powerful engine that drives social and economic growth in the world was built. Access to this global engine called the Internet can be achieved using either wired or wireless networks. The introduction of mobile phones, laptops and tablets have in recent times tipped the scale in favour of wireless networks. It is however paramount that these wireless network connections be secure, trustworthy and accessible to anyone from anywhere [2]. Despite the widespread adaptation, there are areas where people are disconnected from the Internet due to the lack of or limited wireless network coverage. This is possibly because these areas are perceived as low-income and unprofitable to network service providers; hence little investments are made in terms of deploying communication equipment. The promise of fifth-generation (5G) networks with reduced installation and maintenance costs [3] could change this. 5G provisioning through Unmanned Aerial Vehicles (UAVs) is a promising solution to limited wireless networks coverage in rural areas. This can be achieved by capitalising on the interaction between aerial and terrestrial network links [4], [5]. Though UAVs have attracted substantial interest for various applications in the context of smart solutions and internet-of-things (IoT) [6]; 5G mobile wireless is however still in its infancy. The advent of ubiquitous mobile devices and IoT has resulted in an unprecedented growth in the demand for wireless access. Similarly, recent improvement in micro-embedded computing technologies and reduction in costs have resulted in the proliferation of UAVs. This has encouraged their use in extending mobile wireless network coverage to make-shift emergency situations or peculiar areas such as rural and low-income communities [3], [5]–[7]. Recent literature has shown that clustering nodes in dense aerial-terrestrial wireless network can minimise energy consumption [4], [7]–[10]. The ability of UAVs to self-organise on-demand makes them ideal for providing resilient aerial-to-terrestrial 5G cellular network coverage. A clustered 5G network topology provides benefits such as: eradication of single points of failure, resource re-usability and inter-clusters traffic routing across virtual backbones [3], [12]. The usage of UAVs to provide wireless network coverage is not without challenges, some of which are: optimal 3D placement, energy limitation, node mobility, transmission interference management and backhaul connectivity [12], [13]. With respect to energy, attaching a base station to a UAV and powering it with the UAV's battery has been shown to reduce flight time by about 16% [6], [13]. These challenges notwithstanding, UAVs wireless access network has seen numerous applications in various scenarios including but not limited to public safety and remote healthcare supports [4], [6].

## II. Related Work

### A. UAV in Wireless Networks.

There are numerous exciting use-cases and research work in the applications of UAVs in wireless networking, some of which are presented in [13]. Despite the growing interest in UAVs, deploying UAVs for the purpose of providing network cellular coverage in rural and low-income areas has not been extensively researched. The possibility of mounting cellular nodes on UAVs and have them periodically or permanently provide network coverage is now being explored. Example of which are Nokia's Saving Lives initiative [14], Google's Project Loon [15] and Ericsson and China Mobile's 5G enabled drones [16]. The authors in [3] demonstrated the feasibility of providing cellular connectivity in rural and low-income areas by mounting Remote Radio Heads (RRHs) on UAVs. The nodes were powered by battery and solar energy enabling them operate all day long. In [12] multi-hop communication was used to extend the reach of UAV ad-hoc mesh network. Authors in [17] proposed an intelligent deployment of UAVs in a 5G heterogeneous communication environment to improve coverage using macro base station. In [18] and [19] it was concluded that 3D deployment of multiple UAVs can minimise transmission power, UAV altitude and elevation angle can improve Line-of-Sight (LoS) links and Signal-to-Noise Ratio (SNR) can be a measure of Quality of Service (QoS).

### B. Research on Clustering Techniques.

In [11], the authors discuss common clustering schemes for mobile ad-hoc networks. Their work provided a descriptive mechanism for evaluating the performance and costs of clustering schemes. Ref. [6] and [20] proposed a clustering mechanism aimed at improving energy efficiency in aerial-based access systems during disasters. The authors in [5] investigated user and network-centric approaches to optimal 3D placement of UAVs in 5G wireless networks. In [4] a clustering algorithm was designed using density-aware, distance-aware and hybrid selection policies; while in [4] and [21], the authors improved energy efficiency by grouping nodes into clusters for data gathering.

From a meta-heuristic perspective, researchers have used Particle Swarm Optimization (PSO) to cluster nodes [22]–[25]. In [23], the focus was on maximising the lifetime of sensor nodes by enhancing a basic PSO with energy optimisation technique. Authors in [22] and [24] improved energy efficiency through PSO load balancing during routing, while in [25] a two-tier PSO was developed which used a novel particle encoding scheme and fitness function to determine optimal routes between cluster heads (CH) and base stations.

A number of works [23], [25]–[29] have focused on hierarchical clustering, specifically improving the popular Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. A dual-phase approach was proposed in [26], [27], wherein CH selection was done in the first phase and data transmission mechanisms addressed at the second phase. Ref. [28] proposed an extension to the LEACH by focusing on isolated nodes; while in [29] the aim was extending the lifetime of node via Super-Cluster Head (SCH). This SCH was selected from the CHs using fuzzy logic and was designated to communicate with the BS. The authors in [30] proposed a decentralised hierarchical clustering scheme for hopping traffic across inter-clusters.

### C. Our Contribution.

The main contribution of this paper is to propose an efficient clustering approach for 5G backhaul and fronthaul access for the purpose of utilizing UAVs to provide wireless connections in rural low-income and remote areas. Two types of airborne were proposed to achieve this, namely: i) a Multi-Sink Airborne Network with Inter-Cluster Communication through the LAP and ii) a Multi-Sink Airborne Network with Inter-Cluster Communication through UAV gateways. Compared to [20], the proposed airborne networks are fully meshed and leave few or no UAV isolated, hence more economically relevant.

The outline of the rest of the paper is as follows: section III describes the system and formalises the solution, section IV discusses the proposed clustering mechanism. Section V presents simulation results; while in section VI, concluding remarks are given.

## III. System and Solution Formalisation

UAV wireless networks would allow the adaption of a function virtualization, enabling network functionalities run in software rather than on hardware [31], [32]. They would also enhance mobile networks, providing support for Multiple-User, Multiple-Input, Multiple Output technologies (MU-MIMO) as well as increasing data rate achievable by end users.

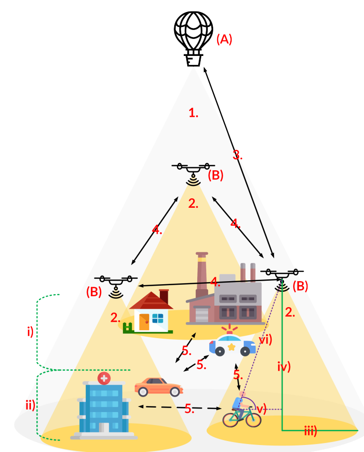



Fig. 1. Coverage Model with logical connection lines. (A) RRH–Balloon, (B) RRH-UAV, 1. Balloon Coverage Area, 2. UAV Coverage Area, 3. Backhaul Radio Link, 4. Fronthaul Radio Link, 5. DTN, i) Free Space Path loss, ii) Excessive Path loss, iii. UAV Coverage Radius, iv) UAV Height, v) UE Radius, vi) UE distance to Access Point

Inline with these forthcoming trends, Figure 1 depicts our envisioned rural and low-income area coverage model. The system consists of $N_c \in N$ unmanned aerial vehicles indexed by $i$ or $j$, where $i \neq j$ and $i, j \in 1, 2, 3, \ldots, N_c$. Index $i, j = 0$ represent the LAP. To calculate the number of 5G RRH-UAVs $N_c$ we use the expression given in (1).

$$N_c = max(\frac{2 * A}{\sqrt[3]{3 * {R_c}^2}}), \frac{N_u * \alpha * T}{\gamma}) \quad (1)$$

where $R_c$ is the radius of the hexagonal cell coverage area, A is the size of the prescribe area, $N_U$ is the total number of users, $\alpha$ is the ratio of active users in the network, $T$ is the average throughput per subscribed user, and $\gamma$ is the peak capacity of the RRH-UAV network cell. The components of the model are described as follows:

**Remote Radio Head (RRH)–Balloon:** This is labelled A in Figure 1 and is a Low Altitude Platform (LAP) that act as a Base Station (BS) to the UAVs. The LAP floats at about ten kilometres above sea-level and can communicate with all the UAV nodes. It has a processing unit and runs Software Defined Networking (SDN) alongside Network Function Virtualization (NFV) with support for multiple network slicing. The LAP processes low-level network slices and allocates same to network service providers, fog-computing and industries. The RRH performs basic radio operations including digital to analogue conversion, analogue to digital conversion, power amplification and signal filtering.

**Remote Radio Head – Unmanned Aerial Vehicle:** labelled B in Figure 1 and consist of a cluster of nodes. Only the CHs communicates directly with the LAP. Other nodes communicate with the LAP through the CHs. The UAVs are mounted with low capacity processors with support for SDN and NFV. The virtual network can be customised to meet high-level slicing specifications with a focus on individual end-users. Data is transmitted using millimetre waves with frequencies between 30 and 300 GHz range; thus, able to avoid interference from surrounding signals and pass through physical barriers.

**Balloon Coverage Area:** labelled 1 in Figure 1. The radio heads in the RRH-Balloon and UAVs operate with communication frequencies of 100 GHz or higher, which helps reduce latency and improve bandwidth utilization. UAVs have 3D positioning systems and must be high enough in altitude to reduce the effect of free space path loss (labelled i in 1).

**Unmanned Aerial Vehicle Coverage Area:** depicted as 2 in Figure 1 is the coverage area within which end-users have access to the network. UAVs use a combination of network data, neural network and spatial clustering algorithms to predict the best position to hover.

**Backhaul Radio Link:** This is labelled 3 in Figure 1 and is the up/down communication link between UAVs and the LAP. It is defined with properties represented in (2).

$$l_b = \varphi_{i0}, \Phi_{i0}, \delta_{i0}, \delta_{\xi i0} \tag{2}$$

where $\varphi_{i0}$ is the distance in meters between $i^{th}$ RRH-UAV and the LAP and is defined in (3), $\Phi_{i0}$ is the slow fading random wireless channel envelope between $i^{th}$ RRH-UAV and the LAP, $\delta_{i0}$ is the path loss between $i^{th}$ RRH-UAV and the LAP, $\delta_{\xi i0}$ is the mean path loss between $i^{th}$ RRH-UAV and the LAP.

$$\varphi_{i0} = \sqrt{({r_{i0}}^2 + {h_{i0}}^2)} \tag{3}$$

where $r_{i0}$ is the radius from the cell to the coverage centre of the LAP and $h_{i0}$ is the difference in altitude of RRH-UAV and LAP.

**Fronthaul Radio Link:** Labelled 4 in Figure 1, is the up/down communication link between $i^{th}$ and $j^{th}$ RRH-UAVs, and has properties represented as shown in (4).

$$l_c = \varphi_{ij}, \Phi_{ij}, \delta_{ij}, \delta_{\xi ij}, \tag{4}$$

where parameters are similar to those described for Backhaul Radio link in (2).

## IV. CLUSTERING TECHNIQUE

Let us assume that all communication links are Air-to-Ground and UAV nodes have autopilot feature. If we also assume that all cellular nodes have similar characteristics and each UAV can communicate telemetric information (such as their Residual Energy (RE) and location) across the network. The clustering algorithm for the air-to-ground network proposed in [20] can therefore be borrowed and adapted to fit the proposed 5G network.

In this work, we propose two models for communication between the UAVs and the BS. In the first model called Multi-Sink Airborne Network with Inter-Cluster Communication through the LAP (MSLBACK), all backhaul communication are directed to the LAP. In this model, the LAP acts as the sole BS for all UAVs.

In certain situations where the LAP is overwhelmed, UAV(s) can be selected to act as pseudo-BS, offloading some of the traffic from the LAP. This is our second model, which we refer to it as Multi-Sink Airborne Network with Inter-Cluster Communication through UAV Gateways (MSGBACK). The process of selecting CHs and cluster members for both models are as follows:

1) **Cluster Head Selection - MSLBACK:** Though the LAP is the sole base station, UAVs do not communicate directly with the LAP but instead go through CHs. CH selection is based on P(i) and expressed by: (5)

$$P(i) = \alpha * \Gamma_{SNR}(i) + \beta * E(i) \tag{5}$$

where $\Gamma_{SNR}(i)$ is the signal-to-noise-ratio of the LAP link to node $i$, $E(i)$ is the residual energy of node $i$ expressed by (6). $\alpha$ and $\beta$ should be $\mathbb{R}$ such that $\alpha$+$\beta$ must be 1.

$$E(i) = \overline{\mathrm{E}} - E_{RSD}(i) \tag{6}$$

where $\overline{\mathrm{E}}$ and $E_{RSD}(i)$ are respectively the average energy in the network and the residual energy of node $i$ and

2) **Cluster Head Selection - MSGBACK:** In this model, CHs are selected in a similar manner as with MSLBACK. However, with MSGBACK, a CH can be ”upgraded” to become pseudo-BS for other UAVs. The selection of this pseudo-BS is based on (7)

$$P(i) = \alpha * C_{UAV}(i) + \beta * C_{nodes} + \gamma * E(i) \tag{7}$$

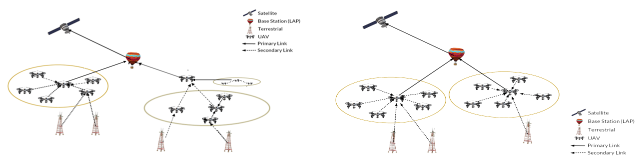
where $C_{UAV}(i)$ is the centrality measure for UAVs relative to the LAP, $C_{nodes}(i)$ is the centrality measure relative to normal nodes and $E(i)$ is the residual energy of node $i$ defined in (6). $\alpha$, $\beta$, and $\gamma$ should be $\mathbb{R}$ such that $\alpha$ + $\beta$ + $\gamma = 1$ .

3) **Cluster Member Selection:** For both models, once the CHs have been determined, selection of cluster members

can be based on various metrics including: distance to a CH or density (number of nodes in each cluster) or a hybrid combination of both. Also, the models can have as many clusters as possible, so long as each CH has members.

For MSGBACK, once the backhaul clustering set (group of CHs) has been obtained, optimal inter-cluster communication links are obtained by: i.) calculating the average SNR value of all links between the CHs; ii.) creating links between CHs with highest SNR values (fronthauling links); iii.) obtaining the pseudo-BS (the CH(s) with the best RE and SNR to the LAP). Figures 2(a) and 2(b) show network topologies for both MSGBACK and MSLBACK respectively.

In both figures, the thick black lines depict primary links of CHs, which serve as backhauling communication links; while the thin dash lines are secondary links or fronthauling communication links. Figure 2(a) depicts MSGBACK, with the pseudo-BS shown to be at a level higher than other UAVs. For MSLBACK depicted in Figure 2(b) within each cluster, all nodes connect to the LAP via the CHs.



(a) MSGBACK (b) MSLBACK

Fig. 2. MSGLACK vs MSLBACK Network Layout.

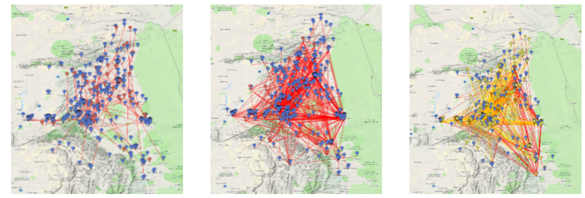
In the proposed mechanism, the backhauling connection are formed by the LAP using telemetric information received from the UAVs. Conversely, the inter-cluster and fronthaul links are formed by the UAVs. By splitting the mechanism this way, the complexity of managing clusters and routing traffic is reduced. In addition, the clusters are reassigned periodically using updated beacon packets received from UAVs reporting their corresponding parameters in the network.

## V. SIMULATION

In our models the backhauling links are used to access the LAP while the fronthauling links are used for local communication between UAVs. These are then combined with clustering mechanisms (described in section IV). Monte-Carlo simulations are carried out using random data and the proposed multi-sink airborne network clustering algorithms are compared with other myopic clustering algorithms in literature. The simulation processes are described in the next sub-section.

### *A. Case Study.*

Places with high human density were selected as UAV positions from Mopani district municipality, Limpopo, South Africa. These included Schools, Health Centres, Farms, Police Stations, Shopping Centres, and Religious places. A total of 591 locations were selected using Google Maps.



(a) K-Means Clustering (b) MSLBACK (c) MSGBACK

Fig. 3. Clustering Comparison.

### *B. Comparison of Clustering Techniques.*

We compared the clustering mechanism of MSGBACK and MSLBACK with the classic K-Means clustering algorithm. We used the number of isolated nodes as a measure of performance. Figures 3(a), 3(b), and 3(c), show the results plotted on Google Map for the 591 locations. In the figures, the red lines represent inter-cluster communication links between CHs and CMs, while the yellow lines represent intra-cluster links. Figure 3(a) shows that K-Means did not perform well as many nodes were left isolated. This is in contrast to our models where few or none was left isolated. Comparing MSLBACK and MSGBACK, Figure 3(c) shows the effect of the Pseudo-BS in MSGBACK with less red lines and more yellow lines compared to MSLBACK (Figure 3(b)).

### *C. Comparison of Backhauling Techniques.*

Compared to the backhauling algorithm in [20], hereafter referred to as "Myopic"; both MSGBACK and MSLBACK incorporate a mechanism that ensures no node is isolated. Furthermore, multi-sink nodes [33], [34] are used to improve the transmission of local packets. In contrast to having only a direct backhauling link to the LAP, these models create secondary links to through CHs to the LAP.

In the Myopic model, all communication go through the LAP. Though this might be beneficial as it allows for monitoring and control, the design can shorten the battery life of the LAP due to the large volume of traffic going through it. To cater for this, MSGBACK and MSLBACK create clusters and use fronthaul links to communicate between CHs and CMs.

To validate the effectiveness of our models with regards CH and CM selection, we compared them with the following backhauling techniques: i) **Random Selection Backhauling**, where CHs are randomly selected; ii.) **Energy-Aware Selection Backhauling**, wherein nodes with Residual Energy (RE) higher than the median are selected CHs; iii.) **Ranked Energy-Aware Selection Backhauling**, where UAVs are sorted in descending of RE and sequentially selected as CHs.

Figure 4 shows a comparison of our proposed models with other backhauling models. In the figure, Model-Name CH means the number of Cluster Heads utilized by the model while Model-Name Unassigned represents the number of nodes left isolated by the model. The figure shows that Myopic and k-means left more nodes isolated and had considerably higher number of CHs, while MSLBACK and MSGBACK mostly left no node isolated.

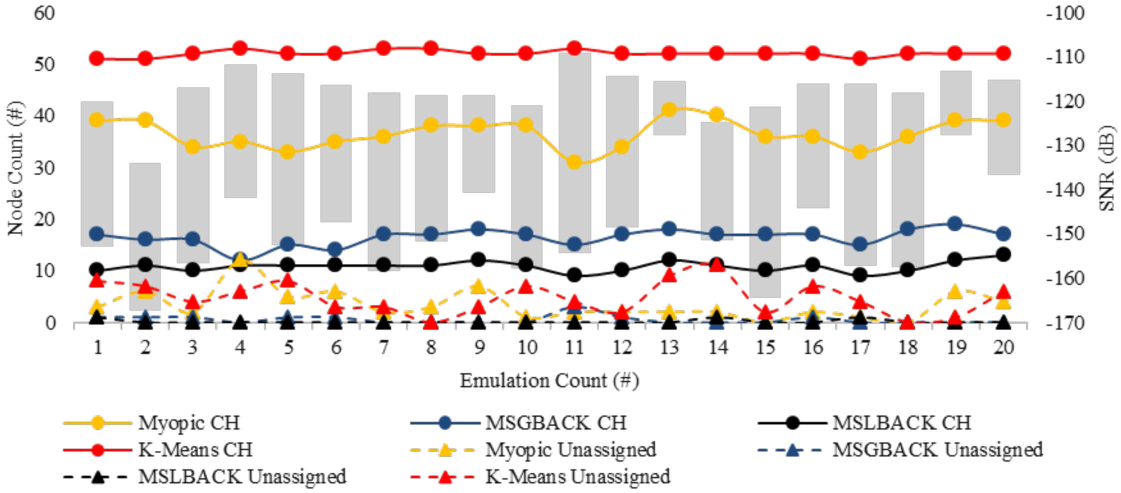



Fig. 4. Comparison of Backhauling Models in Soweto Township

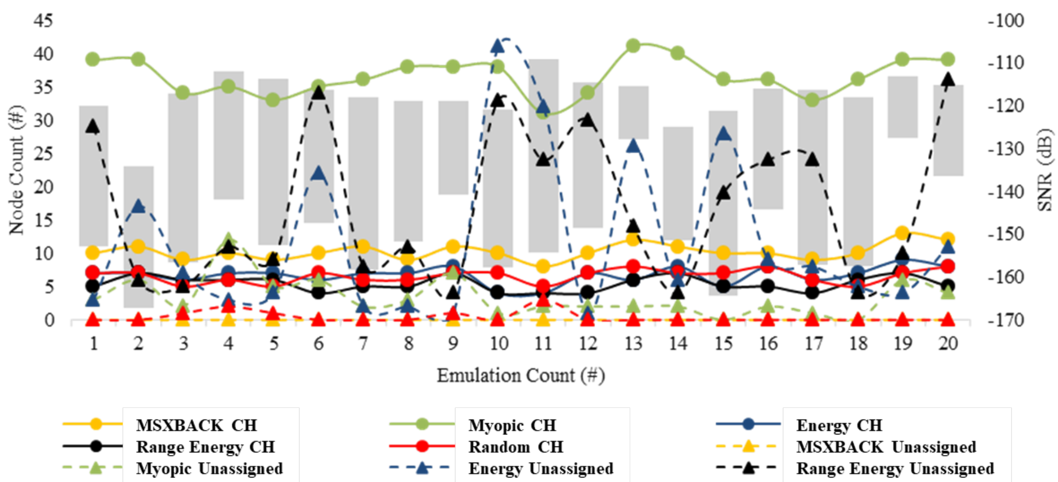



Fig. 5. Improved Backhauling Models in Soweto Township

### *D. Effect of Signal-to-Noise Ratio Distribution.*

This sub-section discusses how distribution of signal-to-noise ratio affects clustered network. We sample SNR and RE with Gaussian, regular and uniform distribution to show that our proposed models leave few or no node isolated.

Since MSLBACK and MSGBACK use similar criteria for selecting CHs and CMs, we simply refer to them as MSXBACK in this section. The results of simulations carried out are depicted in Figures 4 and 5. Residual energy (RE) distributions were selected from a million random variables. The normal probability density for the Gaussian distribution was applied on both simulations, with the mean set to $\mu = -78dB$ and variance set to $\sigma^2 = 16.59$.

The grey coloured bars represent the bounds of SNR distribution in each simulation, with values on the right scale. Lines with circle interludes represent the total number of nodes assigned as CHs, while broken line with triangle interludes represent total number of isolated nodes. Our backhauling method used for MSLBACK and MSGBACK, depicted as MSXBACK in Figure 5, outperformed the other techniques. The figure also shows that both Energy aware selection algorithms left the most number of nodes isolated, while the Myopic had the highest number of CHs. The Random Selection algorithm on the other hand, left no node isolated except for two instances when SNR had the highest dB bound. From the result shown in Figures 4 and 5, it can be concluded that compared to the other algorithms, the backhauling model proposed in this paper is most suited for UAV-based 5G wireless networks; especially if the UAVs are in constant motion. However, with perfect LoS and at similar height, the UAVs would have a very similar SNR to the LAP; thus, equally effective.

## VI. Conclusion

Wireless connections are now the de facto method through which mobile devices connect to the Internet. The Internet is now a necessity as it indirectly powers industries, economies and inter-societal lives. Great strides have been made in Internet technologies and 5G network is one of such recent developments. Unfortunately, Internet facilities are not available globally, particularly in remote and low-income areas. UAVs have emerged as a potentially cheap way of providing wireless coverage to these areas. In this paper, models for deploying 5G networks in remote areas were presented. The models incorporates features that improve the backhaul connection to the base station and fronthaul links interconnecting UAVs. It also conserves energy and efficiently utilized UAVs in a cluster leaving none isolated. The developed models called MSG-BACK and MSLBACK use multi-sink clustering algorithm and are backhaul aware. They were benchmarked against the K-Means clustering algorithm as well as several backhauling algorithms and simulation results showed that both performed better than the other algorithms in terms of utilising the highest Signal-to-Noise ratio as well as engaging all the UAVs. Though positive results have been shown in this work, deployment considerations such as ideal hovering altitudes, effect of obstacles were not considered. These could make for interesting future works. Furthermore, performance parameters regarding network lifetime and bandwidth utilisation could also be considered.

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