Community Healthcare Mesh Network Engineering in White Space Frequencies

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COMMUNITY HEALTHCARE MESH NETWORK ENGINEERING IN WHITE SPACE FREQUENCIES

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ABSTRACT

The transition from analog to digital television has availed new spectrum called white space, which can be used to boost the capacity of wireless networks on an opportunistic basis. One sector in which there is a need to use white space frequencies is the healthcare sector because of existent protocols which are using it and the white space frequency is not as crowded as Wi-Fi. However, design simulations of wireless communication networks in white space frequencies have revealed dense network topology because of better signal propagation and penetration properties of white space frequencies. Consequently, communication networks designed in white space frequencies will require topology reduction for better communication and routing. Therefore, this paper proposes a link-based topology reduction algorithm to reduce a dense mesh network topology designed in white space frequencies into a sparse mesh network topology. The paper also proposes a network optimization function to introduce a hierarchical backbone-based network topology from the sparse network topology for better scalability. Performance evaluation on the proposed designs show that the designs can guide network engineers to select the most relevant performance metrics during a network feasibility study in white space frequencies, aimed at guiding the implementation process.

Keywords - Hierarchical backbone network, mesh network, network topology reduction, sparse network, white space

1. INTRODUCTION

The multi-hop wireless mesh networks in Wi-Fi frequencies induce prohibitive costs for network carriers to deploy ubiquitous Wi-Fi, as revealed by many in-field trials [1]. White space frequencies provide a better and affordable option for deployment of multi-hop wireless mesh networks, which have a far greater transmission range and better penetration properties than the Wi-Fi frequencies. It is predicted that white space frequencies will address geographic disparities that exist between cities and remote and under-served areas in terms of broadband internet access. Once that is addressed, the realization of telehealth, which has the potential to improve healthcare in these areas [2, 3, 4], is easy.

However, designing communication networks such as mesh networks in white space frequencies that accesses the spectrum on an opportunistic basis comes with its own challenges that may have never been met before by network planners and designers. The temporal and spatial variations of the white space is one of the challenges that makes the planning and designing of communication networks in white space frequencies a difficult task. Due to the temporal and spatial variations of the white space, it is difficult to find a common control channel that nodes can use to exchange necessary control information. Zhao *et al.*, [5] found that it is easier to find a common control channel for neighboring nodes than finding a network-wide availability of a common vacant channel. Cognitive radio technology is expected to eliminate this challenge as it has the ability to sense the spectrum widely and reconfigure itself to transmit in some targeted spectrum [6]. Another challenge that makes the planning and designing of communication networks in white space frequencies difficult is the dense network topology revealed by design simulations of wireless communication networks in white space frequencies because of better signal propagation and penetration properties of white space frequencies. The dense network topology entails many nodes being in communication range of each other, which may result in too many network packet collisions in the network. This is a complex operation for the MAC protocol and too many paths to choose from for a routing protocol [7, 8]. Therefore, network design in white space frequencies will require network topology control to 1) to improve the energy efficiency and battery lifetime of the network and 2) to reduce packet collisions, protocol overhead, and interference by means of a better control over the network connections and redundancy without affecting important network performance such as connectivity and throughput.

This paper proposes a link-based topology reduction algorithm to reduce a dense mesh network topology network designed in white space frequencies into a sparse mesh network topology. The paper also proposes a network optimization function to introduce hierarchical backbone-based network topology from the sparse network topology for better scalability of the network. The designs have been proposed to guide network engineers when selecting the most relevant performance metrics to favour during a network feasibility study aimed at guiding the actual implementation process. To evaluate engineering efficiency achieved by the proposed designs, a performance evaluation was conducted on a simulated public safety mesh network design connecting police stations in Cape Town, South Africa and the results show the designs can guide network engineers to select the most relevant performance metrics during a network feasibility study aimed at guiding the implementation process.

The rest of the paper is structured as follows: section 2 introduces topology reduction and discusses the approaches used to achieve it; section 3 discusses the proposed network optimization function that is used to introduce hierarchical backbone network topology from sparse network topology; section 4 discusses the proposed link-based topology reduction algorithm for reducing dense mesh network topology to sparse mesh network topology; section 5 discusses the backbone network topology algorithm used to introduce hierarchical backbone network topology from sparse network topology; section 6 is a performance evaluation of the proposed designs; and section 7 concludes the paper.

2. TOPOLOGY REDUCTION AND APPROACHES

While algorithms discussed in this section are designed for application in physical networks, the designs proposed in this paper are for predesigning a network topology offline before it is replicated in reality. In general, topology control can be achieved through three main mechanisms: power control technique, power mode mechanism and hierarchical formation technique.

In power control technique the communication range of the wireless nodes is controlled by modifying the transmission power parameter of the nodes in the network. This way the network nodes are able to better manage their neighborhood size, interference level, power consumption and connectivity [9]. In power mode mechanism, the node activity is controlled by switching between active and sleep operation modes to dispense with redundant nodes and still achieve the desired connectivity [10]. The main idea of the algorithms using these first two mechanisms is to produce a connected topology by connecting each node with the smallest necessary set of neighbors and with the minimum transmission power possible [11]. These first two techniques are the main options for flat networks, where all nodes have essentially the same role [7, 13], i.e., in an homogeneous infrastructure.

Controlling the transmission power of the nodes or their activities only reduces the network topology to help save energy but the approach does not prevent the transmission of redundant information when several nodes are close to each other and may not simplify the network topology enough for scalability [11]. The hierarchical formation technique addresses the scalability problem. In hierarchical formation technique, a reduced subset of the nodes in the network is selected and given more responsibilities on behalf of a simplified and reduced functionality for the majority of the nodes [11]. This approach greatly simplifies the network topology and saves additional energy by assigning useful functions, such as information aggregation and filtering and routing and message forwarding to the reduced subset of nodes [11]. A hierarchical topology can be constructed by using either a backbone network or a cluster-based network.

The main goal of the backbone-based techniques is to find a connected subset of nodes in a network that guarantee connectivity by allowing every other node in the network to reach at least one node on the backbone in a direct way [11]. A communication backbone can be created by selecting nodes that form a connected dominating set (CDS). From graph theory, a CDS of a graph is a connected subset in which all other nodes that do not belong to that subset have at least one adjacent neighbor inside the subset. Advantages of this CDS-based topology control are collisions control, protocol overhead control and energy consumption reduction, efficient network organization and scalability improvement [10].

3. NETWORK OPTIMIZATION FUNCTION

The network design consists of finding a network configuration expressed by the graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ is the set of nodes while $\mathcal{L}$ is the set of links connecting the nodes with the objective of optimizing an objective function representing a penalty to be minimized or a profit/reward to be gained. In this paper, the network engineering profit function $P(\mathcal{G})$ is considered. It combines reliability and quality of service (QoS) features, which are based on three metric measures; node degree, link margin and Euclidean distance.

3.1 Network engineering design

The profit function $P(\mathcal{G})$ is expressed as follows:

$$P(\mathcal{G}) = \sum_{i \in N} P(i) \tag{1}$$

$$P(i) = \alpha * nd_i + \beta * lm_i + \gamma * sp_i \tag{2}$$

where, α, β and γ are coefficients of proportionality used to express the preference for a given metric measure. A high value of one of the coefficients reveals a preference for the corresponding metric measure. The profit $P(i)$ expresses the resultant preference of node $i \epsilon \mathcal{N}$ to be part of the backbone. The metric measures are explained below.

1. **Node degree:** Nodes with a higher node degree lead to reduced network topology for the backbone network, which is preferred to nodes with a lower node degree. Therefore, preference is given to nodes with a higher node degree than nodes with a lower node degree. The node degree $nd(i)$ of node i in a network graph with N number of nodes is calculated as:

$$nd(i) = \sum_{j=1}^{N} x_{ij} \tag{3}$$

where $x_{ij} = 1$ if there is a link between node i and node j and $x_{ij} = 0$ otherwise.

2. **Link margin:** Links with higher link margins are better for communication than links with lower link margins. Furthermore, nodes whose corresponding links have smaller differences in link margins are better for communication than nodes whose corresponding

links have bigger differences in link margins. Therefore, to know which nodes are well connected, the link margin of each node is considered as the coefficient of variation corresponding to the link margins of all the links connected to that node. For a node i, the coefficient $lm(i)$ of variation is calculated as follows:

$$lm(i) = \frac{Avg_{lm}(i,x)}{Std_{lm}(i,x)} \; \forall\, x : (i,x) \in \mathcal{L} \qquad (4)$$

where $Avg_{lm}(i)$ and $Std_{lm}(i)$ is the mean and the standard deviation of the link margins of the links connected to the underlying node respectively. The numerator makes a node better if it is high and the denominator supports the idea that large differences in link margins of the links connected to node i make the node less efficient in communication.

3. **Average shortest path:** It is the average distance from a node i to all other nodes using the Dijkstra's shortest path algorithm [12] given by equation *5* and denoted by $sp(i)$.

$$sp(i) = Avg_{sp}(i,x) \; \forall\, x : (i,x) \in \mathcal{L} \qquad (5)$$

The link lengths are considered to be the Euclidean distances separating the connected nodes. Nodes with lower average shortest paths are the more likely ones to be part of the backbone than nodes with higher average shortest paths.

4. SPARSE NETWORK TOPOLOGY DESIGN

The sparse network topology design consists of finding a network configuration that maximizes/minimizes a network optimization function (a reward to be maximized or a penalty to be minimized) subject to QoS constraints expressed in terms of expected throughput by setting a link margin threshold and reliability by setting a minimum requirement on the path multiplicity to enable alternative path routing when an active path fails. Mathematically formulated, it consists of finding a network configuration C_{opt} derived from the graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ such that

$$\hat{\tau}_{opt}(C_{opt}) = \max_{C_n \in \mathcal{G}} \sum_{k \in \mathbb{N}[C_n]} P(k) \qquad (6)$$

subject to

((*6*).1) $\tau_{lm}(x,y) > \tau_{lm} \;\; \forall \;\; x,y \in C_{opt}$

((*6*).2) $k_{sp}(x,y) > \tau_{sp} \;\; \forall \;\; x,y \in C_{opt}$

where $\mathbb{N}(X)$ is the set of nodes in the configuration X. Note that constraints *(6)*.1 and *(6)*.2 express the QoS in terms of link margin and reliability respectively.

4.1 The K-shortest path algorithm

Finding disjoint paths may be difficult when a network contains a trap topology between a source and a destination node as revealed by Figure 1. The trap topology presented

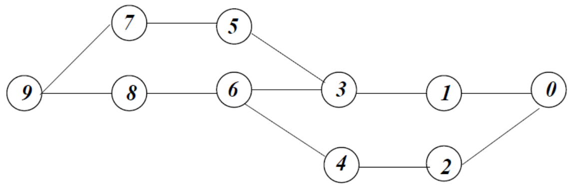

Figure 1 – Trap network topology

in the figure has three different paths between node 9 and 0, which can be found by the K-shortest path algorithm [14] by repeating k sequences of shortest path finding followed by pruning the links of the found shortest path to find k disjoint paths between any source destination pair of the network. However, the myopic deployment of the K-shortest path algorithm may fail to find more than one disjoint paths between node 9 and 0 if path 9−8−6−3−1−0 is found first. We propose in this paper a topology-aware K-shortest path finding algorithm using a link weight/metric over-subscription model to mitigate the impact of the presence of a trap topology in a mesh network. The link weight over-subscription will lead to paths 9 − 7 − 6 − 3 − 1 − 0 and 9 − 8 − 6 − 4 − 2 − 0 being selected first before path 9 − 8 − 6 − 3 − 1 − 0. A high-level description of the proposed algorithm is as described by the two-steps KSP_{coarse} algorithm described below

KSP_{coarse} **Algorithm:**

Step 1. Link weight over-subscription. Adjust the link weights

For each link $\ell \in \mathcal{L}$, set $w(\ell) = w(\ell) + d_s(\ell) + d_d(\ell)$ where

- $w(\ell)$ is the weight on link ℓ
- $d_s(\ell)$ is the node density of the source node on link ℓ
- $d_d(\ell)$ is the node density of destination node on link ℓ.

Step 2. Disjoint paths computation. For each source-destination pair (S, D)

- *path finding:* Find a shortest path p between S and D
- *network pruning:* Prune the links of p from the network topology $\mathcal{T}^*$
- *stopping condition:* If $\mathcal{T}^*$ is disconnected then $Exit$ else set $\mathcal{K}(S,D)$=$\mathcal{K}(S,D) + p$

KSP_{loose} **Algorithm:** Note that pruning the network to discard selected links imposes a coarse constraint on the network topology. The KSP_{coarse} algorithm can be relaxed by pruning from the network topology $\mathcal{T}^*$ only the links that do not meet a given criteria, such as links with lower margins or links with poor white space quality, such as links where there is no common white space channels between the source and destination of the links.

4.2 Sparse network topology design algorithm

A link-based topology reduction (LTR) algorithm (Algorithm 1) is designed to reduce a dense mesh network topology into a sparse mesh network topology. The objective of the

Algorithm 1: LTR algorithm

```
mark all links in dense mesh network as non-visited;
for each non-visited link of the network do
    select worst non-visited link of the network; // i.e.,
        link with lowest link margin.
    artificially delete the link;
    run the K-shortest path to detect if the network is still
        k-connected; // it is k-connected if you
        can find k-disjoint shortest paths for
        each source-destination pair of the
        reduced network.
    if it is k-connected then
        remove the link permanently;
    else
        leave the link and mark it as visited;
end
```

algorithm is to improve i) quality of the links by retaining the links of high margin and pruning those of low margin and ii) maintain the reliability of the network at a predefined level. In order to design fault-tolerant networks, the algorithm uses the K-Shortest Path (K-SP) algorithm in [14] to compute K-shortest paths between source-destination pairs where $K > 1$. Links that provide K-disjoint shortest paths from each node to the network sink are considered and included in the sparse network.

5. HIERARCHICAL BACKBONE NETWORK TOPOLOGY DESIGN

The backbone design consists of finding a network configuration that maximizes the reward function subject to similar QoS constraints as in the sparse network design but with the objective of partitioning the network into two sets: a dominating set, which form the backbone and a dominated set forming the edge of the network. Mathematically formulated, the design process consists of finding a network configuration C_{opt} derived from the graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ such that $\mathcal{N}$ is divided into a dominating set $\hat{\mathcal{N}}$ and a dominated set $\check{\mathcal{N}}$, and the design objective is achieved and its constraints are met.

$$\hat{\tau}_{opt}(C_{opt}) = \max_{C_n \in \mathcal{G}} \sum_{k \in \mathbb{N}[C_n]} P(k) \qquad (7)$$

subject to

((7).1) $l_m(x, y) > \tau_{lm} \; \forall \; x, y \in C_{opt}$

((7).2) $k_{sp}(x, y) > \tau_{sp} \; \forall \; x, y \in C_{opt}$

((7).3) $\forall n \in C_{opt} : n \in \hat{\mathcal{N}} \vee \exists m \in \hat{\mathcal{N}} : (n, m) \in \mathcal{L}$

((7).4) $\hat{\mathcal{N}} \cup \check{\mathcal{N}} = \emptyset \wedge \hat{\mathcal{N}} \cap \check{\mathcal{N}} = \mathcal{N}$

where $\mathbb{N}(X)$ is the set of nodes in the configuration X. Note that constraints *(7)*.1 and *(7)*.2 express the QoS in terms of link margin and reliability respectively, while constraints *(7)*.3 and *(7)*.4 represent the topology control model in terms of backbone connectivity based on the K-dominated set model [17, 18, 19].

5.1 Backbone network design algorithm

The algorithm for creating a hierarchical backbone network topology is provided by Algorithm 2. It uses a graph coloring approach, where the nodes of the network are initially assigned a white color and thereafter, they are colored black or gray, depending on whether they have qualified for backbone or edge status. This algorithm returns a network configuration

Algorithm 2: Backbone formation

1. Initialisation.
   Assign a white colour and zero height to all nodes of the network,
   Select a node n from $White$ whose profit/reward is highest,
   $Backbone \leftarrow \{n\}$,
   $Grey \leftarrow$ all neighbours of n,
   $White \leftarrow N \setminus (\{n\} \cup Grey)$.
2. Select a node k from $Grey$ whose profit/reward is highest and height is lower.
   Include k into the $Backbone$,
   Assign a black colour to k and update its height,
   Remove k and its neighbours from $White$,
   Include the neighbours of k in $Grey$.
3. Repeat Step 2 whenever $White \neq \emptyset$.

where the backbone nodes are colored into black and the edge nodes are colored into gray.

6. PERFORMANCE EVALUATION

We conducted different experiments to evaluate the performance of our designs. The network engineering process in Figure 2 is proposed and was followed to evaluate our designs. Building upon the elevation maps of an area where the network is to be designed, network planning software tool such as Radio Mobile [15] or SPLAT [16] is used to produce feasible links of the targeted mesh network. Using the network report generated from the network planning tool, the proposed topology reduction process is

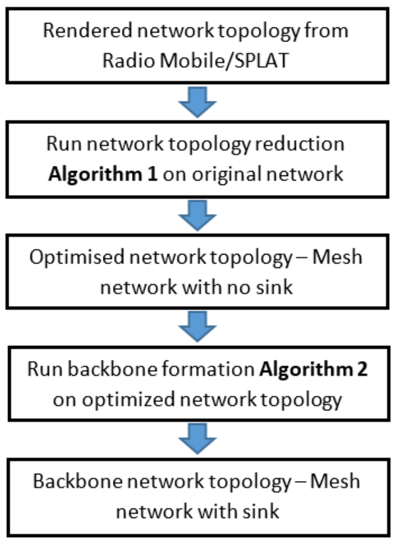

Figure 2 – Network engineering process

applied to map the targeted dense mesh network into a sparse network. The final step of the network engineering process consists of deriving a hierarchical backbone-based topology as a topology that may be more scalable than the flat sparse network topology.

The public safety mesh network design connecting police stations in the city of Cape Town in South Africa depicted in Figure 3 was used. The network design was simulated in TV white space frequency using the Radio Mobile network planning tool [15]. 42 network nodes were considered in the simulation.

A Python code implementation of the LTR Algorithm 1 was run on the network reports generated by the Radio Mobile network planning tool [15] to map the dense mesh network into sparse network topology. First, the GPS coordinates of the nodes were transformed into 2-dimensional Cartesian coordinates, which were used to compute Euclidean distances separating the nodes before running the LTR algorithm. During the reduction process, links that provided two disjoint shortest paths from each node to the network sink were considered and included in the sparse network topology. The reduced network topology is shown in Figure 4.

6.1 Sparse network topology reliability using the link length

We evaluated the reliability of the computation by looking at the number of disjoint shortest paths computed by considering the sparse network topology with the link length as the routing metric. The algorithm described in section 4.1 was used to compute the disjoint paths for each node of the sparse topology. In the rest of this paper, we refer to the number of disjoint paths from a node to all the other nodes of the sparse network as the disjoint path multiplicity (DPM) for that node. We considered the following performance metrics:

1. **The average number of disjoint shortest paths per node.** We let each node be a sink and evaluated the standard deviation in the number of shortest to the sink from each node of the network.

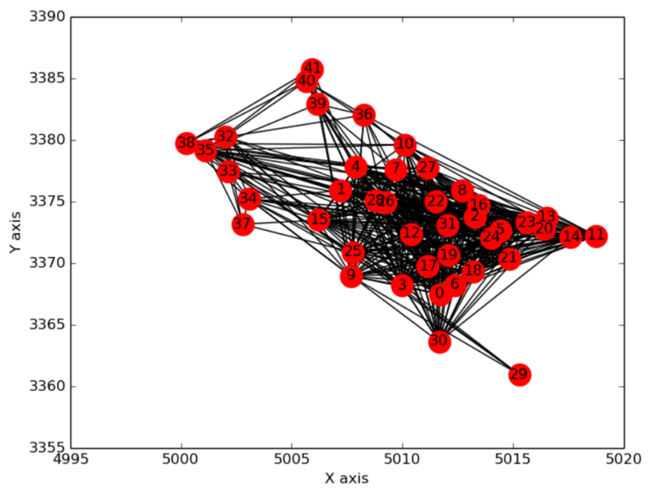

Figure 3 – Public safety mesh network of police stations in Cape Town, South Africa

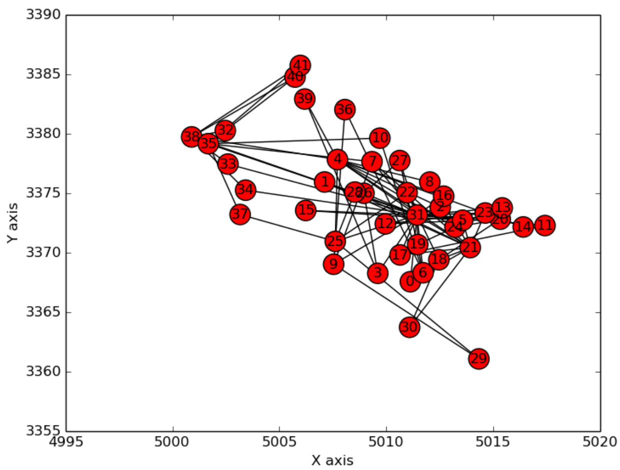

Figure 4 – Sparse network topology

2. **The variation of number of shortest paths per node.** We let each node to be a sink and evaluated the standard deviation in the number of shortest to the sink from each node of the network.

3. **The maximum number of shortest paths.** To determine the liability of nodes (to be sinks), we computed this metric, which shows the node to which other nodes can reach using more alternatives paths.

Figure 5 shows that node 0 is the most reliable since it has the highest average number of disjoint shortest paths and in this case, node 29 is less reliable. Figure 6 shows when node 29 is chosen to be the sink, the number of shortest paths from each node to it varies less. However, choosing node 0, the number of shortest paths from each node varies most. Figure 7 confirms that node 1 is the most reliable but reveals that when node 29 is the sink, the number of shortest paths from each node is minimum.

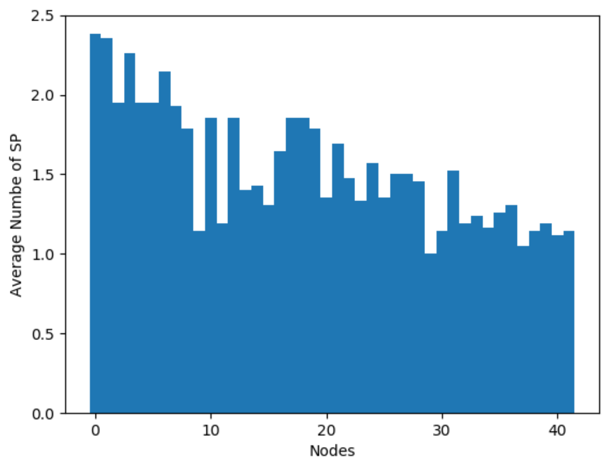

Figure 5 – Average DPM

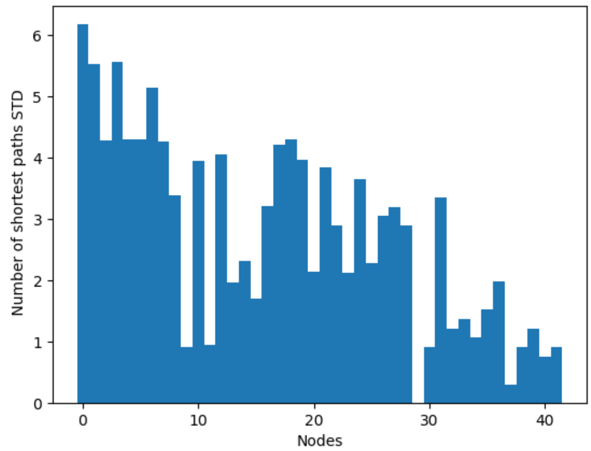

Figure 6 – DPM Variance

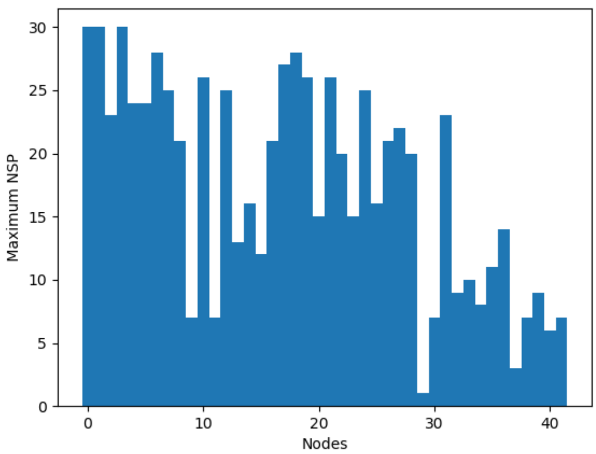

Figure 7 – Maximum DPM

6.2 Hierarchical backbone topology design

A Python code implementation of Algorithm 2 was run on the network reports for the sparse network topologies to introduce hierarchical backbone network topologies. Using the coefficient parameters in Equation *(1)* set as $\alpha = \beta = \gamma = 10$, the hierarchical backbone network topology produced is shown in Figure 8.

6.3 Impact of backbone design on network performance

Experiment 1: Using the link length. Table 1 shows the main characterization of the formed backbone network and the sparse network for the Cape Town Public Safety network. The average node degree and the coefficient of the link margin variation for the backbone are greater than that of the sparse network. This is because a node with the highest degree or coefficient of variation is likely to be chosen as a backbone node according to Algorithm 2. On the other hand, the table shows that the average shortest path for the backbone is smaller. This is because the nodes closest to many nodes in

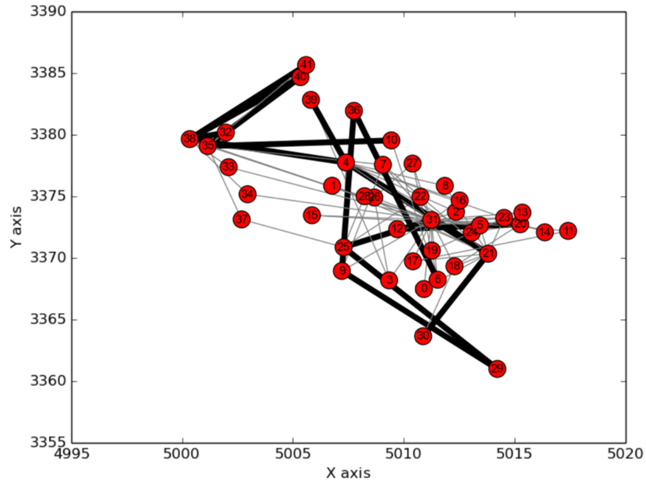

Figure 8 – Hierarchical backbone network topology

the network are also likely to be chosen as backbone nodes according to Algorithm 2.
The table reveal the advantage of using a backbone model by showing links with better quality in terms of link margin and a higher node degree, representing the potential of finding alternative paths for the traffic when a link/node fails. However, this is balanced by the path multiplicity, which is 1 because all the edge nodes are directly connected to the cluster heads thus offering a single path for the edge nodes while a flat network has the potential of building 2 paths for the edge network.

6.4 Impact of the design parameters on the backbone size

In this subsection, we study the effect of parameters on the size of the backbone. In each case, two parameters were fixed as the third parameter was being varied from 0 to 100. Figure 9 shows how the size of the backbone changed by varying the node degree. The figure shows that the size of the backbone varied but generally decreased down to the convergent point (10 nodes) as the node degree increased.
Figure 10 shows how the link margin parameter affects the size of the backbone. Like the trend shown by Figure

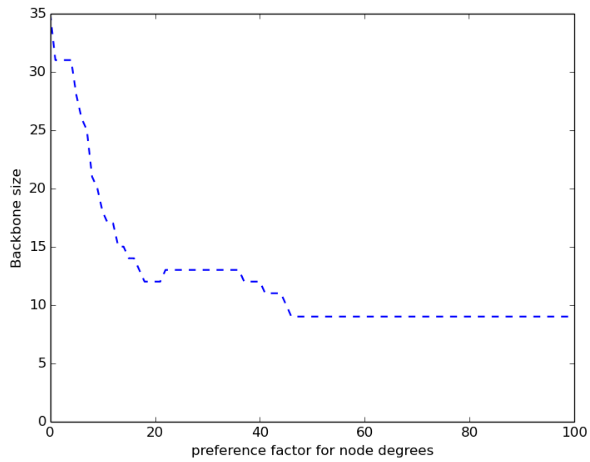

Figure 9 – Impact of α on backbone size

Table 1 – Backbone network topology vs sparse network topology

Network performance	Reduced network	Backbone
Node degree	3.81	4.03
Coefficient of variation (link margin-(dBm))	2.83	3.86
Shortest distance (km)	12.88	12.31
Path multiplicity	2	1

9, the network backbone decreased towards a convergence. However, the decrease is slower and hence the backbone size converges to a higher number of nodes.

Considering the effect of shortest distance between nodes, Figure 11 shows a different trend. The size of backbone increased in general until it converges to a maximum.

The conclusions drawn from the three graphs depicting impact of the design parameters on the backbone size are as follows: the backbone size is affected by change of each of the three parameters. These results also reveal that the node degree has a much higher positive influence on the backbone size, leading to smaller backbones, which can allow networks to scale while keeping the size of the backbone constant and smaller.

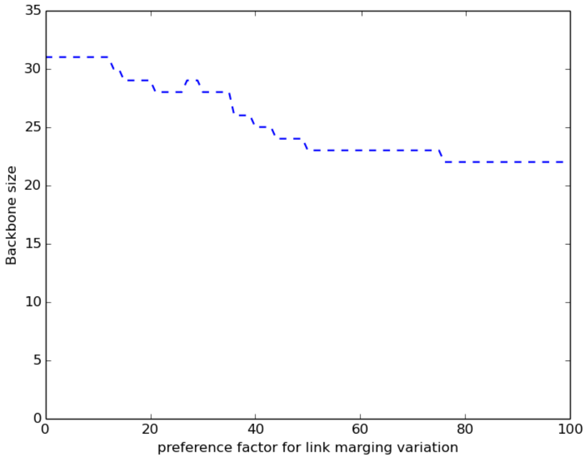

Figure 10 – Impact of β on backbone size

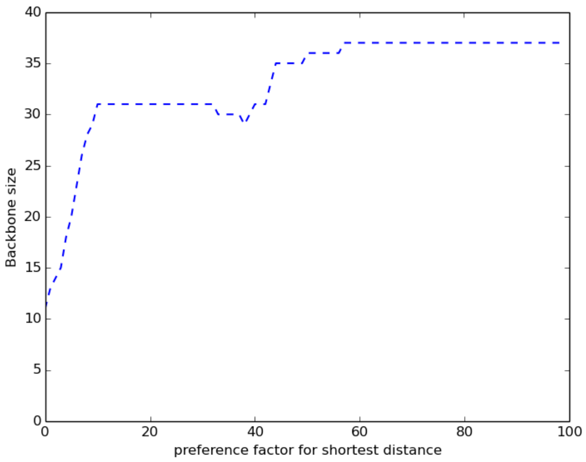

Figure 11 – Impact of λ on backbone size

7. CONCLUSION

In this paper, design challenges expected to be met when designing mesh networks using opportunistic access to the white space frequencies were explored and discussed. Dense network topology was highlighted as one of the design challenges that network planners and designers in white space frequencies will face and the paper focused on addressing this challenge. A link-based topology reduction algorithm has been developed to reduce a dense mesh network topology designed in white space frequencies into sparse mesh network topology and a network optimization function based on three metrics has been developed to introduce hierarchical backbone-based network topology from the sparse network topology. Performance evaluation on the designs were carried out and the results show that the designs can guide network engineers to select the most relevant performance metrics during a network feasibility study in white space frequencies, aimed at guiding the implementation process.

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