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Energy Management Framework for 5G Ultra-Dense Networks Using Graph Theory

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ABSTRACT The next-generation 5G networks are being developed with high promised capabilities. Beyond just multitudes faster data speed, 5G is expected to serve billions of connected devices and the Internet of Things (IoT), with the right trade-offs between speed, latency, and energy at an affordable cost. 5G radio networks will strongly depend on using ultra-dense integrated Small Cells (SCs) beside the Macro Cells (MCs). This kind of Ultra-Dense Networks (UDN) consisting of a large number of MCs and SCs will significantly increase network energy demands. A practical method to control energy consumption is by dynamically controlling power-saving modes in radio networks. In this paper, we propose a novel cooperative energy management framework for 5G UDN using graph theory. The 5G network is first modeled as a graph, then graph theory methods are exploited to determine the order of nodes at which power-off/on procedure is applied. We also show that significant power savings are achievable by considering only a subset of network nodes and thus reduce traffic migration and control plane signaling. We evaluated the proposed algorithm at different network densification levels and several load factors including two real-life networks. We also present the convergence of the proposed algorithm and the robustness of networks optimized using it. We also show that power savings up to 25% at full load and 65% during off-peak can be achieved using the proposed algorithm. These power savings increase further if no constraints are imposed on traffic migration and control signaling.

INDEX TERMS 5G, energy efficiency, graph theory, power saving, sleep mode.

I. INTRODUCTION

Several operators around the world started commercial 5G network deployments beginning of 2019 based on 3GPP Rel-15. In 2023, it is expected that 20% of mobile data traffic will be carried by 5G networks [1]. The requirements from the next generation networks are to support hundreds of millions of connected devices, 10 to 100 times higher user data rate, and 10 times longer battery life at similar cost and energy dissipation as of today [2]. The integration of the new radio concepts such as Massive Multi-Input Multi-Output (MIMO), UDN, Direct device to Device (D2D) Communication, Ultra-Reliable Communication, Massive Machine Type Communication (MTC) and the exploitation of new spectrum bands will allow supporting these huge demands [2]. Considering energy and spectrum are the most important resources in mobile communication, energy consumption however is growing significantly. The Information and Communication Technology (ICT) field is responsible for about 3% of energy consumption and 2% - 4% of CO_2 emissions in the world [3], [4]. Energy consumption is increasing at a rate of 15% - 20% annually which means double consumption after about 5 years [5]. Base Stations (BSs) consume 60% - 80% of the total energy [6], [7]. These expectations and figures motivate more research on energy management especially in 5G UDN towards green cellular networks [8].

In 5G, operators will deploy hundreds of Macro Cells (MCs) to cover a city of few million inhabitants. Each of these MCs will coordinate tens of underlying Small Cells (SCs) in high traffic areas [9], [10]. SCs consist of femto and pico cells with coverage radius up to 200 meters, in comparison with MCs of coverage radius up to 1km. The population of SCs is expected to be 100 million subscribers with 500 million UEs in 2020 [11], [12]. These SCs will be deployed to offload the traffic from over-crowded MCs. This radio densification will significantly improve network

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capacity [8]. However, it also raises the issue of resource management concerning spectrum and energy efficiency. Even though SCs are of low power compared to MCs, the sum of energy consumed on ultra-dense SCs together with the MCs is non-negligible and energy management is not trivial. This brings focus on how to efficiently manage energy consumption in UDN. Especially that due to the variations of users' and traffic distributions, it is expected that different mobile cells will have different load demands at each time. Thus, some of these cells can be put into sleep mode depending on the level of utilization and power consumption [13]. A solution can be achieved using an exhaustive search, however, this will be very complex and time consuming for UDN. Also, achieving the optimal solution is not guaranteed due to the trade-off between network capacity and energy efficiency. In this work, we investigate this problem and propose an energy management framework for UDN using graph theory and its properties.

Graphs have been used widely to model many types of relations and connections [14], [15]. Recently due to the advancements in graph theory simulation tools, it is getting more momentum in social networks, computer networking, and security. However, it is still of limited use in mobile networks [15]. After modeling the 5G UDN as a graph where nodes and connections are represented by vertices and edges, respectively. Weights on these edges and vertices are then being associated with traffic and power consumption. We used graph theory methods and properties such as Algebraic Connectivity [16] and Weighted Degree Centrality to switch-off/on nodes and offload traffic while maintaining full network coverage. The main contributions of this work are summarized as follows:

1) We propose to model UDN 5G networks using graphs. Then we design an energy management framework to optimize power consumption of the graph model by putting low-loaded nodes into power-saving (sleep) mode.
2) We propose to use graph-theory based methods such as the Weighted Degree Centrality to determine the order at which nodes are inspected for power-off/on procedure in STAR5. We show also that such methods would achieve significant power savings with minimum control plane signaling by applying the STAR5 procedure to only a subset of the network nodes.
3) We evaluate the proposed algorithm at different network densification levels and many load factors. We also show the convergence of STAR5 and the robustness of networks optimized using it.

The rest of this paper is organized as follows: We review some related work in Section II. Graph theory and its properties are introduced in Section III. In Section **??** we describe problem formulation and energy management system. Experiment results are presented in Section V and concluding remarks are drawn in Section VI.

II. RELATED WORK

A plethora of works have studied optimizing power consumption during peak and off-peak periods by applying power-off/on procedure for light loaded Base Stations (BSs) [8], [14], [17]–[24]. These works vary in terms of the energy management framework and applied constraints. For example, in [18], Chiaraviglio et al. proposed to switch-off some BSs in UMTS networks during off-peak traffic periods while guaranteeing certain call blocking probability and electromagnetic exposure limits. This work was extended in [14] to an energy-aware dynamic network planning framework that reduces the number of underutilized BSs constrained to complete radio coverage. Marsan *et al.* [19] built on previous work to propose an energy-aware management framework for realistic regular cell architectures. Centralized and decentralized management frameworks were proposed in [20]. In the centralized greedy algorithm, BSs are switched off based on the traffic distribution. However in the decentralized algorithm, users associate themselves with BSs based on a utility function, then all remaining unoccupied cells are switched off. To avoid frequent mode (active or sleeping) switching, Gong *et al.* [21] proposed an energy management framework in which BSs hold their working modes for at least a given interval. In [22], Xiang et. al., considered the ratio between dynamic and fixed power of BSs in the proposed load balancing energy management framework. While in [23], Lorincz et al. proposed an energy management framework for UMTS cellular access network based on the average distance between BSs and UEs. Bousia et al. in [24] also propose a distance-aware energy management algorithm but for LTE systems.

Recently, more advanced energy management techniques have been proposed [25]–[29]. For example, in [25], Pen et. al. proposed a location-dependent energy management framework through which the geographical coverage area is divided into multiple grids. In each grid area, the maximum number of Small BSs (SBSs) is determined based on users' traffic during peak periods. In off-peak periods, only a subset of these SBSs are kept active and remaining SBSs are turned off. This strategy yields up to 53% and 23% energy savings in dense and sparse areas, respectively. To enhance the reliability of energy management frameworks, Soliman and Song [26] proposed a dynamic/opportunistic technique to determine the set of active nodes in a network. In this technique, overloaded nodes offload traffic to one or more sleeping nodes after being activated. These nodes are identified based on location and coverage information. In another work [27], an analytical model is proposed and used to determine the optimum number of active nodes in the network to meet the quality of service demands from all users. In [28], Alsharif. et. al. proposes a cooperative energy management approach between LTE and 5G technologies. The proposed algorithm tries to achieve an equilibrium between network performance and energy savings via switching off/on nodes in the 5G small cell networks (SCNs) based on instantaneous load traffic and ensuring service coverage through the remaining active LTE macro nodes. Also, Çelebi et. al. in [29] proposed a load-based smart-on/off scheduling strategies for SCNs, where a certain fraction of small cell nodes are put into less sleeping states to save energy. The authors first represent the overall SCN traffic as a load variable and analyze its statistics using Gamma approximation. They then propose two power-on/off scheduling algorithms by exploiting this load variable in centralized and distributed fashions. They showed that 50% energy savings can be achieved without sacrificing the average throughput.

In spite of all these advances in energy management frameworks, energy savings can be further improved by utilizing modern approaches, especially with the increase in network heterogeneity and densification such as in 5G UDN and beyond. In [14], Chiaraviglio et. al. investigated energy saving in Internet networks by switching off nodes and links while guaranteeing network connectivity and maximum utilization limit. By using graph theory, the authors managed to switch-off around 50% of nodes depending on network size. However, this work is limited to the nature of internet networks and can't be applied to UDN 5G networks.

In this work, we propose an energy management framework for the heterogeneous UDN 5G network with the assistance of graph theory. We start by modeling the network as a graph, then we apply graph theory methods to reduce power consumption by switching-off/on 5G nodes and traffic migration based on node type (Macro and SC) and traffic distribution constrained to full radio coverage. Besides, we design prioritization methods for the proposed framework based on graph theory methods to reduce network signaling due to traffic migration and to reduce the complexity of the energy management algorithm. The evaluation of the management algorithm shows that power consumption can be reduced during peak and off-peak periods, with different network densification scenarios, and for various dynamic to fixed node power ratios. We have also shown that power savings can be increased significantly if no constraints are imposed on control plane signaling and traffic migration.

III. PRIMER ON GRAPH THEORY

Graph theory is a natural framework for the mathematical representation of complex networks. For example, a mobile network can be depicted as a graph $G = (V, E)$ composed of vertices V representing nodes and edges E representing connecting links. In a weighted graph, the nodes may have various attributes attached to them such as fixed power consumption of BSs, and weights on edges may represent link capacity and traffic load. A weighted graph with n nodes can be represented using an adjacency matrix $A(G)$ and degree matrix $D(G)$. In $A(G)$, the entry $a_{i,j}$ is equal to the weight (capacity or traffic load) of edge $\{i, j\}$, otherwise 0 if not connected. However, $D(G)$ is an $n \times n$ diagonal matrix where the entry d_{ii} is equal to the degree (fixed power consumption) of vertex i. The algebraic connectivity of graph G expressed as the second smallest eigenvalue of the Laplacian matrix $L(G) = D(G) - A(G)$ shows how well a network is connected [16], [30]. The number of zero-valued eigenvalues of the Laplacian matrix is equal to the number of connected components in the graph G. Consequently, the second smallest eigenvalue being 0 is equivalent to the graph having at least two connected components and thus being disconnected.

IV. SYSTEM MODEL AND THE POWER SAVING ALGORITHM

In this section we present our **NE**twork m**O**dele **(NEO)** of the 5G UDN with graphs. Then we explain how graph theory properties are utilized to optimize power consumption constrained to the required bandwidth. Power optimization is achieved by putting some nodes into power-saving (sleep) mode based on specific criteria without jeopardizing radio coverage.

A. SYSTEM MODEL WITH GRAPHS

In NEO, the network is represented by un-directed graph $G = (V, E)$, where vertices V represent core and radio nodes, and edges E represent links between nodes. The wights of graph edges reflect the importance of these links for connecting two nodes expressed by link load. The vertices and edges have a pre-set maximum capacity values that are used as limiting boundaries for the random traffic distribution over the network. The power consumption by any of these nodes consists of static power P_{stat} and dynamic power P_{dyn} expressed as:

$$P = P_{stat} + P_{dyn} \tag{1}$$

The static part is the baseline node power consumption (e.g., signal processing, site cooling, power supply and battery backup), which depends on both the hardware and software configurations of nodes and is independent of the traffic load, while the dynamic part accounts for the power consumed in RF transmission and depends on the traffic load [22]. And thus the power consumption per unit load at any node can be expressed as:

$$P_u = \frac{P_{dyn-full}}{C} \tag{2}$$

where $P_{dyn-full}$ and C are the full-load dynamic power and the full capacity of the node, respectively.

Our system assumes a network with N nodes of which N_S are SC nodes, N_M are MC nodes, and N_A are aggregation MC nodes. Each MC node MC_i, $i = 1, 2, \ldots, N_M$ serves a cluster of $N_{S,i}$ SCs and each aggregation MC node MCA_j, $j = 1, 2, \ldots, N_A$ provides nodal connection for a cluster of $N_{M,j}$ MCs. An illustration of the system model is shown in figure 1. Clusters of several MCs and SCs are also shown in figure 2. In NEO, the total power consumption can now be expressed as:

$$P_t = \sum_{i=1}^{N} P_{i,stat} + P_{i,dyn} \tag{3}$$

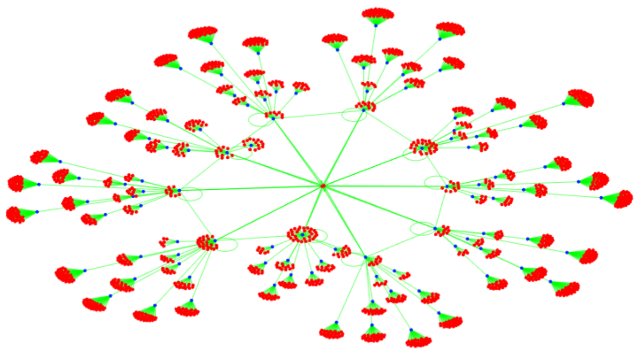


FIGURE 1. Illustration of NEO for a network with $N_S = 2000$ radio nodes, $N_M = 200$ MC nodes, and $N_A = 20$ aggregate MC nodes.

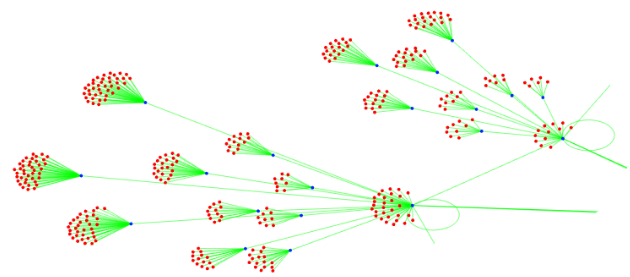


FIGURE 2. SC and MC nodes clustering based on a discrete uniform distribution.

where $P_{i,stat}$ and $P_{i,dyn}$ are the static and dynamic power consumed by node i, respectively.

In order to optimize power consumption in NEO, the system may power-off selected SC nodes, or transceivers (TRXs) in MCs depending on their load. In this work, MCs guarantee full radio coverage by providing umbrella coverage to all SC clusters, and thus only some transceivers of each MC can be put in power saving mode. In this case, the static power reduces in proportional to the number of TRXs in sleep mode. Also, traffic carried on SCs that are put in power saving mode will be migrated to the covering MC or to neighboring capable SCs in the same cluster provided that their capacity limits are satisfied. Traffic migration to MCs is associated with an increase in dynamic power consumption at MCs due to the increase in signal transmission distance [12]. However, the power consumption of these SCs put in sleep mode and the dynamic power of connecting edges will be saved. None of the edges connecting between MCs to core network or aggregation ring is allowed to be in power saving mode, this is vital to keep the network connected.

B. ENERGY MANAGEMENT ALGORITHM

In order to optimize power consumption in NEO, we present our energy **S**aving algori**T**hm for **5**G utr**A**-dense netwo**R**k (**STAR5**). The proposed algorithm aims to maximize power savings and thus optimize power consumption by intelligently putting selected set of nodes into sleep mode. In this work, $\mathcal{N}$ and $\mathcal{I}$ represent the set of all nodes and their indices, respectively. STAR5 scans ψN of the nodes in $\mathcal{N}$ sequentially based on a predefined order $\mathcal{I}_o$ determined by $\phi()$. This is to decide whether node $\mathcal{N}_i$ should be put in sleep mode through the power-off procedure, or turned-on based on the power-on procedure. $\mathcal{N}_{off}$ is a subset of $\mathcal{N}$ and includes all nodes in sleep mode. The selection of these nodes to be in sleep mode depends on node type $\mathcal{N}_{i,type}$ and node traffic $\mathcal{N}_{i,trf}$. MC nodes in NEO guarantee full radio coverage by providing umbrella coverage to all SC clusters, and thus only some transceivers of each MC can be put in power saving mode. I.e., in sleep mode the capacity $\mathcal{N}_{i,cap}$ of MC node $\mathcal{N}_i$ will be reduced. However, for SC nodes, their full traffic is migrated to MCs if put in sleep mode. The full process of STAR5 is presented in Algorithm 1 where power saving is activated if node traffic $\mathcal{N}_{i,trf}$ is less than $\beta\mathcal{N}_{i,cap}$. However, if $\mathcal{N}_{i,trf}$ is greater than $\alpha\mathcal{N}_{i,cap}$, power-on procedure is triggered. The idea is to keep traffic of node $\mathcal{N}_i$ within $[\beta, \alpha]$ of its capacity $\mathcal{N}_{i,cap}$. In STAR5, only ψN nodes are inspected to reduce the amount of network signaling associated with traffic migration due to power-off and power-on procedures. Also, scanning all nodes requires a lot of overhead, especially that network densification is considered as key driver for enabling 5G.

Algorithm 1 STAR5

Input: Graph G generated by NEO
Output: G', $\mathcal{N}_{off}$

$\mathcal{I}_o \leftarrow \phi(G)$
for $i = 1$ to $i = \psi N$ **do**
    $l \leftarrow \mathcal{I}_o(i)$
    if $\mathcal{N}_{l,type} = SC$ **then**
        if $\mathcal{N}_{l,trf} < \beta\mathcal{N}_{l,cap}$ **then**
            Algo. 2: SC Power-off Procedure
        else if $\mathcal{N}_{l,trf} > \alpha\mathcal{N}_{l,cap}$ **then**
            Algo. 4: SC Power-on Procedure
    else if $\mathcal{N}_{l,type} = MC$ **then**
        if $\mathcal{N}_{l,trf} < \beta\mathcal{N}_{l,cap}$ **then**
            Algo. 3: MC Power-off Procedure
        else if $\mathcal{N}_{l,trf} > \alpha\mathcal{N}_{l,cap}$ **then**
            Algo. 5: MC Power-on Procedure
    $G \leftarrow G'$

The power-off procedure for SC nodes is described in Algorithm 2. It starts by determining the MC which provides an umbrella radio coverage for node $\mathcal{N}_l$. The index k of this MC is determined by $U_{MC}(\mathcal{N}_l)$. The SC is put in sleep mode and traffic $\mathcal{N}_{l,trf}$ is migrated to MC provided that total MC traffic won't exceed $\beta\mathcal{N}_{l,cap}$. In this procedure, the small load at the SC is migrated to unloaded MC. As a result of this procedure, MC dynamic power increases and the static and dynamic power of SC are reduced.

The power-off procedure for MCs is achieved by reducing the number of active transceivers and making the capacity of each MC close to its actual traffic. So for an MC node

Algorithm 2 SC Power-Off Procedure

Input: G
Output: G'
$k \leftarrow U_{MC}(\mathcal{N}_l)$
if $\mathcal{N}_{l,trf} + \mathcal{N}_{k,trf} \leq \beta \mathcal{N}_{k,cap}$ **then**
  $\mathcal{N}_{k,trf} \leftarrow \mathcal{N}_{k,trf} + \mathcal{N}_{l,trf}$
  $\mathcal{N}_{l,trf} \leftarrow 0$
  $\mathcal{N}_{off} \leftarrow \{\mathcal{N}_{off}, \mathcal{N}_l\}$

loaded with traffic $\mathcal{N}_{l,trf}$ less than $\gamma \mathcal{N}_{l,cap}$, the node capacity $\mathcal{N}_{l,cap}$ is set to equal the actual traffic plus $\zeta \mathcal{N}_{l,cap}$. I.e., some transceivers are put in sleep mode so that $\mathcal{N}_{l,trf} + \zeta \mathcal{N}_{l,cap}$ MC capacity is maintained. The number of transceivers put in sleep mode and the number of remaining active transceivers depend on the capacity of each of the transceivers in the MC node. I.e, transceivers will be switched off successively until the capacity of the MC node $\mathcal{N}_l$ is set to $\mathcal{N}_{l,trf} + \zeta \mathcal{N}_{l,cap}$. The $\zeta \mathcal{N}_{l,cap}$ capacity margin is necessary to allow for a sudden increase in traffic. A minimum capacity of $(\gamma + \zeta)\mathcal{N}_{l,cap}$ is assumed at all MC nodes to maintain an overall minimum capacity for the whole system as illustrated in Algorithm 3. Power savings in MCs are attained by reducing the static power of non-utilized transceivers while there will be no change in dynamic power consumption.

Algorithm 3 MC Power-Off Procedure

Input: G
Output: G'
if $\mathcal{N}_{l,trf} > \gamma \mathcal{N}_{l,cap}$ **then**
  $\mathcal{N}_{l,cap} \leftarrow \mathcal{N}_{l,trf} + \zeta \mathcal{N}_{l,cap}$
else
  $\mathcal{N}_{l,cap} \leftarrow (\gamma + \zeta)\mathcal{N}_{l,cap}$

The power-on procedures for SC nodes and MC nodes are described in Algorithm 4 and Algorithm 5, respectively. For SC node $\mathcal{N}_l$ with traffic $\mathcal{N}_{l,trf}$ greater than $\alpha \mathcal{N}_{l,cap}$, STAR5 activates all transceivers in the MC which provides umbrella coverage to the node. This is only if the MC is in power saving mode and thus can carry the migrated traffic. In this case, $(\alpha - \lambda)\mathcal{N}_{l,trf}$ traffic is migrated to the MC. I.e., node $\mathcal{N}_l$ will have traffic $\mathcal{N}_{l,trf}$ close to λ of its capacity. However, if the MC is working in full capacity ($> \alpha \mathcal{N}_{l,cap}$), the $(\alpha - \lambda)\mathcal{N}_{l,trf}$ traffic will be offloaded to all SCs in the same cluster with $\mathcal{N}_l$ and are in power-saving mode. In here, we assumed that there is an overall increase in traffic in this cluster and thus all SC nodes are wakened up. The indices of these SCs are determined by $U_{SC}(\mathcal{N}_l)$ in Algorithm 4. Another option would be to make $U_{SC}(\mathcal{N}_l)$ returns the indices of a subset of the SC nodes in the same cluster with $\mathcal{N}_l$. This could be based on the position, capacity, or load of these nodes. Similarly for MC power-on procedure in Algorithm 5, STAR5 tries first to activates the full capacity of the MC.

Algorithm 4 SC Power-On Procedure

Input: G
Output: G'
$k \leftarrow U_{MC}(\mathcal{N}_l)$
if $\mathcal{N}_k \in \mathcal{N}_{off}$ **then**
  $\mathcal{N}_{off} \leftarrow \mathcal{N}_{off} \setminus \mathcal{N}_k$
  $\mathcal{N}_{k,trf} \leftarrow (\alpha - \lambda)\mathcal{N}_{l,trf}$
else
  $\mathcal{K} \leftarrow U_{SC}(\mathcal{N}_l)$
  for k in $\mathcal{K}$ **do**
    $\mathcal{N}_{off} \leftarrow \mathcal{N}_{off} \setminus \mathcal{N}_k$
    $\mathcal{N}_{k,trf} \leftarrow \frac{(\alpha - \lambda)}{|\mathcal{K}|}\mathcal{N}_{l,trf}$

Algorithm 5 MC Power-On Procedure

Input: G
Output: G'
if $\mathcal{N}_l \in \mathcal{N}_{off}$ **then**
  $\mathcal{N}_{off} \leftarrow \mathcal{N}_{off} \setminus \mathcal{N}_l$
else
  $\mathcal{K} \leftarrow U_{SC}(\mathcal{N}_l)$
  for k in $\mathcal{K}$ **do**
    $\mathcal{N}_{off} \leftarrow \mathcal{N}_{off} \setminus \mathcal{N}_k$
    $\mathcal{N}_{k,trf} \leftarrow \frac{(\alpha - \lambda)}{|\mathcal{K}|}\mathcal{N}_{l,trf}$

Otherwise, $(\alpha - \lambda)$ of MC traffic is offloaded to all underlying SCs which are in power-saving mode. In the power-on algorithms, nodes are activated and removed from $\mathcal{N}_{off}$ using the $\setminus$ set operator before carrying any traffic. Also, an MC that doesn't belong to $\mathcal{N}_{off}$ is working in its full capacity.

At the end of each procedure an updated graph G' is produced with new traffic weights on edges. This G' is used to update the NEO graph G after every iteration in STAR5. The total power saving P_{save} is then computed as

$$P_{save} = P_{t,after} - P_{t,before} \tag{4}$$

where $P_{t,before}$ and $P_{t,after}$ are the total power consumption in NEO before and after applying STAR5, respectively. In order to determine P_t, the dynamic power consumption of node $\mathcal{N}_i$ can now be expressed as

$$P_{i,dyn} = P_{i,u} \times \mathcal{N}_{i,trf} \tag{5}$$

where $P_{i,u}$ is the power per until load at node $\mathcal{N}_i$.

C. GRAPH THEORY METHODS IN STAR5

The overall power savings of STAR5 will depend on nodes' ordering method $\phi(G)$ and the number of nodes inspected ψN. In this work, we propose to use graph theory to determine the order of nodes before applying power-off and power-on procedures. The Node Degree Centrality method will order the graph vertices (nodes) according to degree centrality without considering the weights (traffic) on edges (links). The maximum node degree $\phi_{MaxD}(G)$ and minimum node degree $\phi_{MinD}(G)$ will order nodes based on their degree centrality in descending and ascending orders, respectively. These methods depend on the number of links and ignore traffic distribution. However, the Weighted Node Degree Centrality method will order the graph vertices according to degree centrality considering the weights (traffic) on edges (links). The maximum weighted node degree $\phi_{MaxWD}(G)$ and minimum weighted node degree $\phi_{MinWD}(G)$ will order nodes based on their weighted degree centrality in descending and ascending orders, respectively.

The proposed STAR5 should work on operation and support subsystems connected to mobile networks and fed by statistical reports in periodic intervals. The algorithm will run at specific intervals or each time it receives updates from the network. As this is a centralized method, the computational time plays an important role so that the output of STAR5 is in response to the current network status. The complexity of STAR5 $O(f(N))$ is $O(n)$ where $f(N)$ is a linear function [31]. The size of the input is the number of nonzero elements in the incidence matrix reflecting the number of vertices and edges.

V. SYSTEM PERFORMANCE EVALUATION

In this work, we model a 5G UDN network using NEO as described in subsection IV-A. In the 5G network modeled here, SC and MC nodes are clustered and attached to the network randomly. I.e., for every MC node in the network, the number of SC nodes $N_{S,i}$ associated with MC node MC_i and the number of MC nodes $N_{M,j}$ attached to the aggregation MC node MCA_j are determined randomly based on a discrete uniform distribution. More specifically, each MC is set to serve a cluster of $N_{s,i} \in [6, 100]$ SC nodes and each aggregate MC is set to serve a cluster of $\mathcal{MC}_j \in [9, 15]$ MCs. An alternative option is to assume a random geographical distribution of users and nodes and apply cell associating algorithms [10], [32] to construct the network. However, the random geographical distribution of devices in the latter method will lead to a random clustering of SC and MC nodes. Also in our network, the traffic at every node $N_{i,trf}$ is the summation of the loads at its links which are set randomly. This traffic is the peak traffic profile of the network, and thus it is the 100% load factor. The capacity of the MC nodes is also set to equal 10 times the capacity of SC nodes $\mathcal{N}_{i,cap}$ which is set to unity (100%). The other node configurations and power parameters used in our model are listed in table 1.

To evaluate the proposed algorithm, we set $\alpha = 90\%$ to avoid operating any node above 90% of its capacity, $\beta = 70\%$ so that resources at nodes with traffic greater than 70% of their capacity are considered efficiently utilized and thus no need to inspect for sleep mode, $\gamma = 30\%$ to guarantee 35% $(\gamma + \zeta)$ of MC capacity is functional in order to provide umbrella coverage to all nodes, and $\zeta = 5\%$ to provide 5% additional capacity margin for MCs over current traffic and capacity utilization. These STAR5 parameters can be

TABLE 1. Node configurations and power parameters.

Parameter	MC	SC
Full Load Power	1200W	20W
Full Load P_{stat}	80% × 1200 = 960W	40% × 20 = 8W
Full Load P_{dyn}	20% × 1200 = 240W	60% × 20 = 12W
Number of TRXs	8	1
P_{stat} per TRX	120W	8W

modified to comply with the requirements of network operators without affecting the procedures in STAR5.

In the following subsections we evaluate the performance of the proposed algorithm by measuring the power saving gain P_G as the percentage of power saved in NEO after applying STAR5 expressed as:

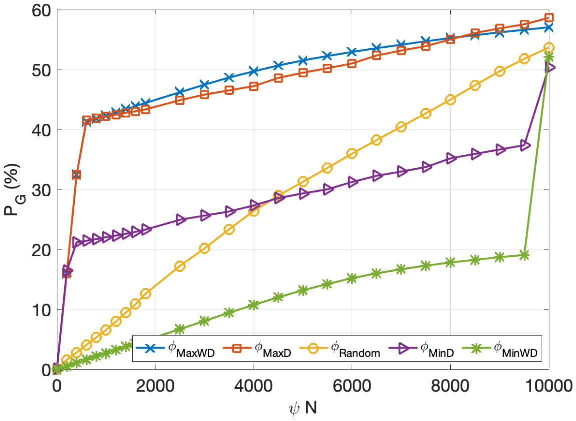
$$P_G = \frac{P_{save}}{P_{t,before}} \tag{6}$$

A. NODE SELECTION METHODS IN STAR5

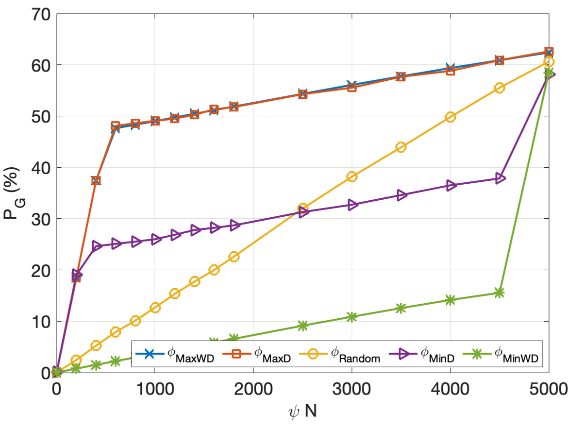
In this subsection, we evaluate the performance of STAR5 with the graph-theory based ordering methods presented in subsection IV-C. We compare these methods with each other and benchmark them against the random selection of nodes $\phi_{Random}(G)$. It can be observed from figure 3 that 60% power savings can be achieved using STAR5 during off-peak when the load factor is 30%. These power-saving values depend also on the order at which nodes are inspected for sleep mode and thus the ordering method $\phi(G)$ in STAR5. I.e., the order at which traffic at the nodes is compared to the threshold parameters for power-off/on procedure. It is clear that the $\phi_{MaxWD}(G)$ and $\phi_{MaxD}(G)$ methods outperform the other three methods. This becomes more significant when only some of the nodes are inspected by STAR5. In both methods, more than 50% power savings are achieved when the procedure of the proposed algorithm is applied to only 40% of the nodes ($\psi = 40\%$). This is because $\phi_{MaxWD}(G)$ and $\phi_{MaxD}(G)$ tend to save power by putting nodes with many low-loaded links in sleep mode. It can also be observed that $\phi_{MaxWD}(G)$ offers more power savings when $\psi \in [10\%, 80\%]$ as compared to $\phi_{MaxD}(G)$. This means that putting nodes with many low-loaded links to sleep mode offers more power savings as compared to unloaded nodes if STAR5 is applied to ψN nodes only.

B. POWER SAVINGS AND NETWORK DENSIFICATION

In this subsection, we evaluate STAR5 for different levels of network densification. In figure 4a, densification is introduced by increasing the number of SC nodes N_S while number of MC nodes N_M is fixed. The increase in N_S could be due to the increase in the number of user equipment (UE) and Internet of Things (IoT) devices in an area covered by the same N_M MC nodes. Power savings are achieved at all network densification scenarios in figure 4a. It can also be observed that increasing the number of SC nodes will increase

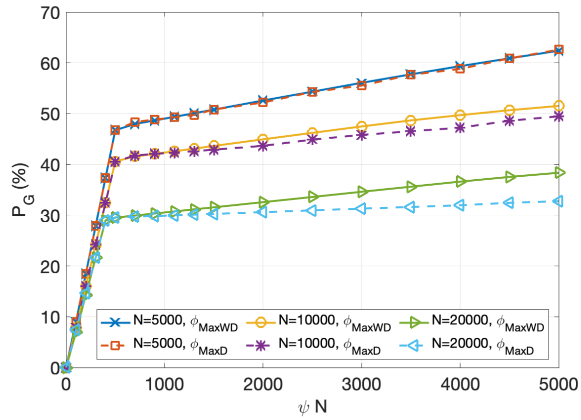


(a) N = 10000, N_S = 9500, and N_M = 500

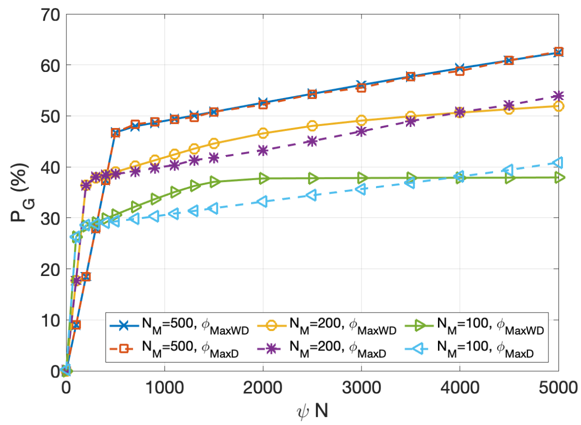


(b) N = 5000, N_S = 4500, and N_M = 500

FIGURE 3. Power saving gains after applying STAR5 with various graph theory based ordering methods during off-peak when load factor is 30%.



(a) N_M = 500



(b) N = 5000

FIGURE 4. Power saving gains of different densification scenarios during off-peak when load factor is 30%. (a) Densification of SC nodes in the network while number of MC nodes N_M is 500. (b) Densification of MC nodes while number of nodes is fixed.

the total consumed power and reduce P_G. I.e., power savings p_{save} is not directly proportional to total power P_t, *before*. This is because the number of MC nodes N_M is kept fixed ($N_M = 500$) while significant power savings are attained from putting MC nodes in sleep mode. Similarly in figure 4b, the number of MC nodes increases while the number of SC nodes is fixed. In this case, power savings gain p_G increases with the increase of N_M. The increase in the number of MC nodes could be to overlay more user plane and control plane traffic in the system. In both figures, $\phi_{MaxWD}(G)$ graph ordering method provided better power savings compared to $\phi_{MaxD}(G)$ at different ψ values as discussed earlier. More power savings gains for other densification scenarios are also presented in table 2. Some of these scenarios represent ultra-dense networks covering a large geographical area ($N_M > 1500$) such as Scenarios 1 and 2 with $N = 10000$ and $N = 20000$ nodes. While other scenarios represent a UDN covering a small geographical area (few MCs) such as Scenarios 4 and 5 with $N = 10000$ and $N = 20000$ nodes. The performance of STAR5 over less dense network is expressed in other scenarios such as Scenarios 1 and 2 with $N = 2000$.

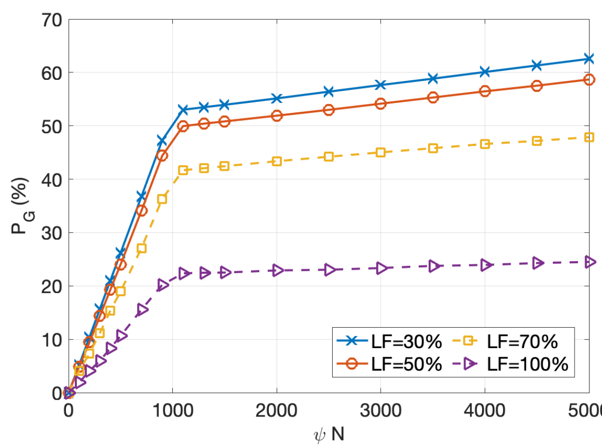


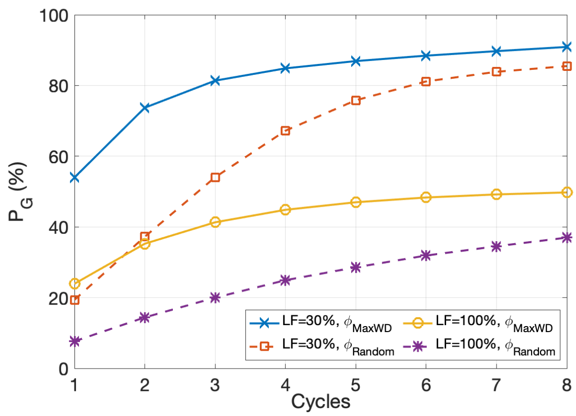
FIGURE 5. Power savings of STAR5 with $\phi_{MaxWD}(G)$ at different load factors for UDN with $N = 5000$ and $N_M = 1000$.

C. STAR5 AND NETWORK TRAFFIC PROFILES

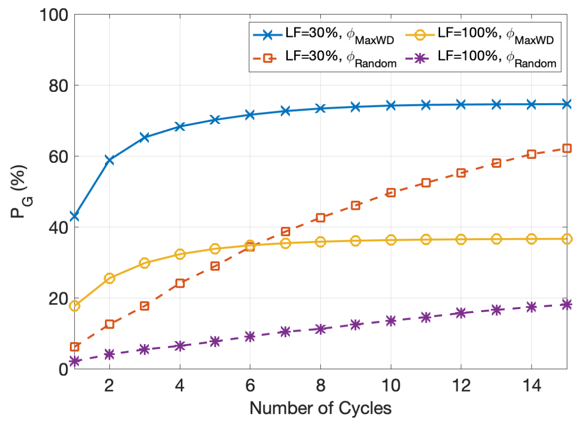
In this subsection we evaluate the proposed algorithm at different load factors. More than 60% power savings are attainable during off-peak when load factor is 30% as shown in figure 5. This reduces to 58% and 47% when the load factor

TABLE 2. Power savings and network densification levels.

Scenario Description		$\phi_{MaxWD}(G)$					$\phi_{MaxD}(G)$					$\phi_{Random}(G)$				
Scenario	N	10%	20%	30%	40%	100%	10%	20%	30%	40%	100%	10%	20%	30%	40%	100%
Scenario 1 $\frac{N_M}{N}=20\%$	20000	26.17%	52.43%	53.76%	55.05%	62.81%	26.17%	52.43%	53.67%	55.34%	62.80%	6.22%	12.53%	18.90%	25.12%	62.76%
	10000	26.42%	52.95%	54.25%	55.46%	62.89%	26.42%	52.95%	54.23%	55.79%	62.88%	6.20%	12.50%	18.93%	25.08%	62.84%
	5000	26.18%	52.57%	53.94%	55.14%	62.55%	26.18%	52.57%	53.96%	55.48%	62.53%	6.04%	12.59%	19.06%	25.36%	62.42%
	2000	25.5%	51.53%	53.27%	54.43%	61.69%	25.5%	51.53%	53.22%	54.72%	61.65%	6.76%	12.78%	18.19%	24.28%	61.49%
Scenario 2 $\frac{N_M}{N}=15\%$	20000	33.9%	51.72%	53.17%	54.63%	63.59%	33.9%	51.96%	52.84%	54.77%	63.60%	6.25%	12.51%	18.70%	25.06%	63.11%
	10000	33.63%	51.49%	52.93%	54.38%	63.30%	33.63%	51.69%	52.57%	54.47%	63.31%	5.95%	12.45%	18.91%	25.17%	62.79%
	5000	33.85%	51.87%	53.28%	54.69%	63.19%	33.85%	52.19%	53.08%	54.83%	63.19%	6.15%	12.73%	19.27%	25.61%	62.62%
	2000	32.81%	50.86%	52.19%	53.57%	61.98%	32.81%	51.17%	52.04%	53.77%	61.93%	6.54%	12.44%	19.33%	25.10%	61.47%
Scenario 3 $\frac{N_M}{N}=10\%$	20000	48.11%	50.05%	51.88%	53.69%	63.44%	48.11%	49.95%	51.92%	53.17%	63.74%	6.56%	13.25%	19.76%	26.49%	61.79%
	10000	47.64%	49.71%	51.52%	53.31%	62.77%	47.64%	49.64%	51.54%	52.83%	54.98%	6.54%	13.11%	19.46%	26.10%	61.13%
	5000	46.75%	49.00%	50.79%	52.59%	62.40%	46.75%	49.06%	50.81%	52.20%	62.60%	6.49%	12.65%	18.92%	25.41%	60.62%
	2000	46.04%	48.65%	50.41%	52.07%	60.75%	46.04%	48.55%	50.05%	51.55%	60.95%	5.37%	11.83%	18.25%	23.79%	59.00%
Scenario 4 $\frac{N_M}{N}=5\%$	20000	42.87%	45.48%	48.07%	50.31%	57.44%	42.71%	44.21%	46.39%	47.88%	59.15%	6.74%	13.44%	20.17%	26.38%	54.11%
	10000	42.34%	44.95%	47.48%	49.71%	57.05%	42.18%	43.67%	45.82%	47.23%	58.64%	6.55%	13.78%	20.17%	26.40%	53.68%
	5000	41.38%	43.87%	46.36%	48.56%	55.60%	41.34%	42.75%	44.82%	46.31%	57.22%	7.03%	13.13%	19.09%	25.26%	52.35%
	2000	40.47%	42.89%	45.19%	47.36%	54.37%	40.75%	42.13%	44.08%	45.44%	55.82%	6.17%	12.11%	18.44%	24.43%	51.36%
Scenario 5 $\frac{N_M}{N}=2\%$	20000	32.58%	36.62%	39.50%	40.15%	40.36%	30.60%	31.95%	33.43%	34.77%	43.79%	7.07%	13.79%	20.24%	24.54%	37.35%
	10000	31.87%	35.79%	38.59%	39.29%	39.45%	30.15%	31.5%	33.14%	34.43%	42.74%	7.22%	13.73%	19.52%	23.84%	36.61%
	5000	30.62%	34.39%	37.07%	37.74%	37.93%	29.32%	30.56%	31.90%	33.19%	40.86%	6.40%	12.48%	18.07%	22.18%	34.96%
	2000	29.16%	32.70%	35.22%	35.73%	35.92%	28.83%	30.04%	31.21%	32.39%	39.34%	6.21%	11.9%	18.34%	21.16%	33.28%



(a) $N = 5000$, $N_M = 1000$, and $\psi N = 1500$



(b) $N = 10000$, $N_M = 500$, and $\psi N = 1000$

FIGURE 6. Convergence of STAR5 at different network densification levels and many load factors.

increases to 50% and 70%, respectively. Power savings of 22% are also achievable using STAR5 during peak hours. this means that STAR5 achieves significant power savings at any level of traffic and traffic distribution.

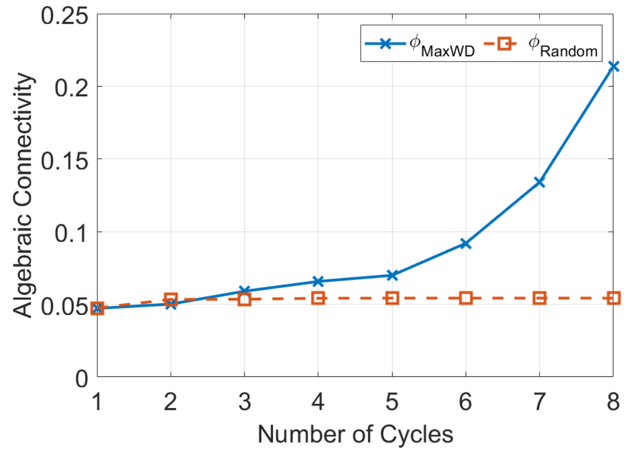
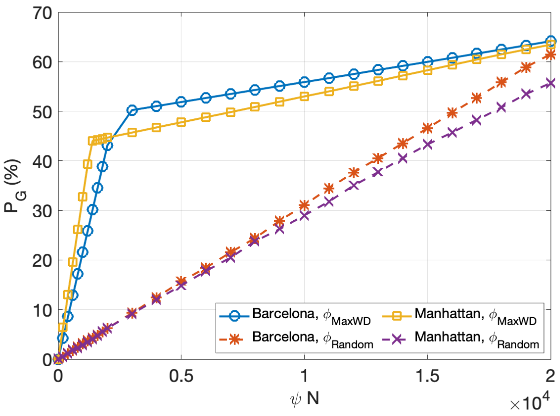


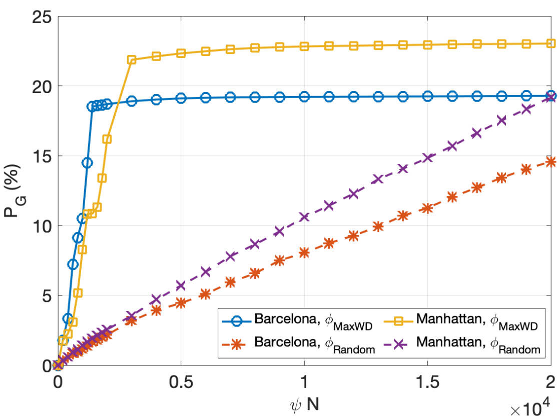
FIGURE 7. Algebraic connectivity for UDN with $N = 5000$ nodes, $N_M = 1000$ MC nodes, and $\psi N = 1500$. Algebraic connectivity of original UDN before applying STAR5 was 0.0334.

D. CONVERGENCE OF STAR5

The performance of STAR5 improves significantly when applied for many iterations (cycles). I.e., order the nodes based on graph theory methods and inspecting the first ψN nodes for power-off/on procedure. Then in the second cycle, reorder the nodes again and apply the power-off/on procedure to the first ψN nodes …etc. In figure 6a, power savings increase by 20% in the second cycle for $\phi_{MaxWD}(G)$ during off-peak ($LF = 30\%$) and up to 90% after 8 cycles. Similar results are obtained during peak hours. In both cases, $\phi_{MaxWD}(G)$ provides more power savings compared to random ordering method $\phi_{Random}(G)$. Similar results are also shown in figure 6b but for different network densification ($N = 10000$). The convergence of STAR5 is evident in both figures during peak and off-peak periods. This is because P_G increases monotonically during the first few cycles until it saturates and converges to a specific power-saving value.

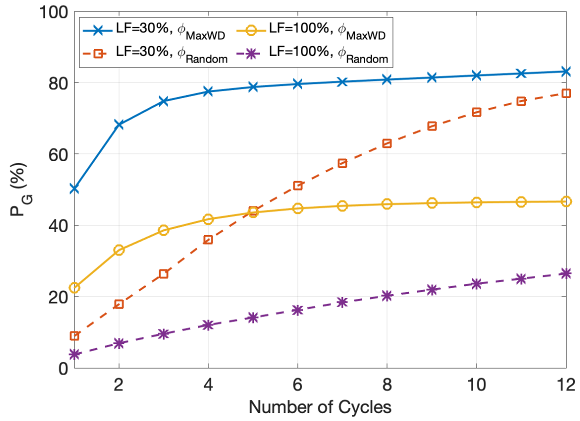


(a) LF = 30%

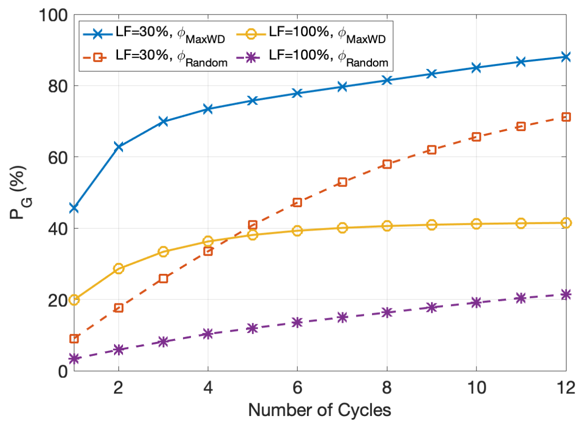


(b) LF = 100%

FIGURE 8. **Power savings of STAR5 for two real-life networks using two selection methods and different load factors. Barcelona with $N = 20700$ and $N_M = 2300$ nodes. Manhattan with $N = 22762$ and $N_M = 1340$ nodes.**



(a) Barcelona, $N = 20700$, $N_M = 2300$, and $\psi N = 3000$



(b) Manhattan, $N = 22762$, $N_M = 1340$, and $\psi N = 3000$

FIGURE 9. **Power savings of STAR5 for two real-life networks at different load factors.**

E. NETWORK CONNECTIVITY

In this subsection, we evaluate the stability and robustness of the UDN network after applying STAR5 by measuring the algebraic connectivity of the graph G'. A network is considered to be more robust if the algebraic connectivity of the graph representing the network increases [30]. The average algebraic connectivity of the network in figure 7 is 0.0344. It increases to 0.047 after applying STAR5 using the $\phi_{MaxWD}(G)$ method. It increases further after applying STAR5 for many cycles. We also observe from the figure that the algebraic connectivity of $\phi_{MaxWD}(G)$ is greater than $\phi_{Random}(G)$. This means that applying STAR5 with $\phi_{MaxWD}(G)$ makes the network more robust compared to $\phi_{Random}(G)$.

F. STAR5 PERFORMANCE OF REAL-LIFE NETWORKS

The power savings performance of STAR5 is also evaluated for two representative dense areas; the City of Barcelona and the Manhattan borough of New York City. We modeled the 5G UDN of these two areas using NEO, and then applied STAR5 to improve power savings of the corresponding networks. According to the 5G transport network blueprint and dimensioning of the city of Barcelona, 22.68 MC nodes per km^2 are needed for such dense urban scenarios [33]. And thus 2300 MC nodes ($N_M = 2300$) are needed to provide coverage for the city of Barcelona with a land area of 101.4 km^2. This is along with 18400 SC nodes ($N_S = 18400$) to provide connection service for a population of 1.4 million inhabitants which corresponds to an average of 8 Small Cell nodes per Macro Cell site [33]. For the Manhattan borough with a land area of 59.1km^2, 1340 MC nodes are needed along with 21422 SC nodes (population of 1.63 million inhabitants) corresponding to an average of 16 Small Cell nodes per Macro Cell site. In figure 8 we show that power savings up to 64% can be achieved for both cities during off-peak when load factor is 30%. This reduces to 22.5% and 19.5% during full load periods for Barcelona and Manhattan, respectively. Applying STAR5 for many iterations (cycles) increases power savings significantly as presented in figure 9. Power saving increases up to 81% and 88% during off-peak periods for Barcelona and Manhattan, respectively. Similar results are attained for both during full load periods.

VI. CONCLUSION

We present an energy management framework for heterogeneous UDG networks based on graph theory. The proposed algorithm aims to reduce power consumption while minimizing control plane signaling due to traffic migration. And thus it is well suited for UDN 5G networks and beyond. In this work, we model a UDN network as a graph, then we exploit graph theory methods to minimize power consumption by putting low-loaded nodes into sleep mode. The traffic of these nodes is migrated to active neighboring nodes through proper control plane signaling. We also show that the order at which nodes are examined for sleep mode affects significantly power savings. In this regard, we propose to examine nodes sequentially according to the weighted node degree centrality method of graph theory in descending order (*MaxWD*). The pseudo-code and the parameters of the proposed algorithm are also presented in this work, followed by an extensive performance evaluation of the STAR5 algorithm at different network densification and load scenarios including two real-life networks. Evaluation results show that significant power savings are attained through STAR5 with *MaxWD* as compared to other graph theory and random methods especially if limits are imposed on control plane signaling (only subset of the nodes is examined for sleep mode). Results also show that power savings are achieved at different levels of network densification and for various network traffic profiles. We also leverage on the proposed algorithm so that STAR5 is executed for many cycles on a subset of the nodes. This increased the power saving gains at the expense of an increase in traffic due to control plane signaling. We have also used the algebraic connectivity to show that STAR5 increases the robustness of the network. As an extension of this work, we are planning to integrate the advanced sleep modes of 5G with STAR5.

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