An Efficient Strategy with High Availability for Dynamic Provisioning of Access Points in Large-Scale Wireless Networks

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***Abstract*—The dynamical users' association with wireless access points and the requirement for maximum network coverage foster the challenge of providing energy efficiency alongside network availability for large-scale wireless networks. This paper proposes an access-point provisioning strategy based on a multi-objective optimization heuristic. The heuristic purposes are maximizing coverage, ensuring high network availability, and minimizing the number of active access points, while improves energy efficiency. We evaluate our proposal by simulating a connected component of the Universidade Federal Fluminense (UFF - Brazil) wireless network, comprising 363 access points in a university campus. The simulation considers actual flows and features of users' association to the network. The results show that the best performing strategy is a greedy heuristic, which activates access points with the most significant number of potential neighbors that are not active. Our proposal implies 2% of unserved users while activating only 23% of the access points, ensuring high availability and energy efficiency.**

***Index Terms*—Energy Efficiency, Availability, Wireless Network, Smart Campus**

I. Introduction

In 2023 more than 70% of the world's population will have a mobile connection, and the connection bandwidth of mobile devices will triple [1]. Furthermore, according to Cisco's annual report [1], global mobile data traffic for business will grow sixfold from 2017 to 2022, at a yearly growth rate of 42%, with the number of Wi-Fi access points growing fourfold from 2018 to 2023. In parallel, the energy expenditure on data transmission decreases on average by half every two years in developed countries [2]. However, digitalization raises the requirement for greater energy use, which ultimately hampers the effect of energy consumption optimization [3].

Reducing energy waste is an essential factor in the sustainable use of resources. However, this reduction must not affect economic development [3]. The inference of data usage patterns in wireless networks allows defining preventive and energy-saving measures. In this sense, this paper proposes and simulates three different approaches for optimizing access points (AP) usage without loss of quality of service and connectivity. We calculate the wireless network usage patterns to identify the demand of each access point and thus make an optimized usage prediction. The optimization considers network idle time and exploits the usage patterns of the wireless network of the Universidade Federal Fluminense (UFF) in Brazil.

This paper proposes a strategy for optimizing the number of active APs in a large-scale wireless network. We generate a dataset correlating flow statistics, from wireless network users, with features from the APs with which they are associate. From the dataset, it is possible to extract clusters of APs with similar coverage areas to finally identify which APs are essential at every moment of each day of the week in each network's location. To this end, the proposed approach relies on a NetFlow flow statistics data collection, a wireless interface data collection module for the network APs, a data correlation module, and, finally, an AP processing and optimizing module.

We aim to address the Wi-Fi network idleness problem as reported by Apostolo *et al.* [4]. Examples of energy-saving optimization are in the literature. Lyu *et al.* [5] uses load prediction and network usage pattern data to turn off APs for the predicted idle time. Manweiler *et al.* analyze the usage time of each cellular client on the APs using a support vector machine (SVM) [6]. However, these methods are not enough to provide the required quality of service to the users in the network. When considering a large-scale and dynamic wireless network, using only one method would impair the quality of service for the clients [4]. The usage prediction method applied by *Lyu et al.* [5] allows identifying patterns and their variations over time. Additionally, a new procedure for shutting down initially active APs is necessary to optimize network operation, thus ensuring a network with energy efficiency and high connectivity standards.

The remainder of the paper is organized as follows. Section II discusses the related works. Section III presents the method used for data collection. The unsupervised clustering approach is exposed in Sectionr̃efsec:algorithm. The proposal is evaluated in the scenario of a real large-scale wireless network and, the results are discussed in Section V. Section VI concludes the paper.

II. Related Work

Apostolo *et al.* [4] use data collected during six months from the wireless network of the Universidade Federal Fluminense (UFF - Brazil) to predict idle periods of the network. Through machine learning methods, the authors classify and find long periods of idleness in several access points (APs) of the university. The work aims to reduce these idle periods without harming the efficiency of the network.

Manweiler *et al.* propose a system for predicting the permanence time of clients in wireless APs [6]. The central idea of the system is to learn signatures from an initial set of clients on the AP and then infer the dwell time of each client in its vicinity. The prediction uses multiple sensors on the clients' devices, generating a data matrix and passing it to a support vector machine (SVM) classifier that separates the clients into predetermined behavior classes. The system generates these predictions serially. The paper uses an estimation of idle time to disconnect inactive users from the network.

The Internet of Things (IoT), Big Data, and artificial intelligence provide the basis for Smart Cities. This scenario presents no difference at the university level, where the growth of the Smart *Campus* concept has been benefiting universities worldwide, not only in the technological area but also in improving the campus life quality. Uskov *et al.* [7] perform a comparison of a Smart *Campus* with a traditional *campus* demonstrating the need for innovation in this environment. Thus, one of these forms of innovation would be through intelligent systems capable of optimizing the quality of services in university *campi*. Aiming at the smart *campus*, we propose an approach to saving energy in the university wireless network, using a system that monitors the network APs and decides which ones should be activated or deactivated.

Lyu *et al.* [5] propose an intelligent scheme for dynamic controlling of APs in large-scale networks with a focus on energy saving. The adopted strategy uses the prediction of the APs load based on the network's data collected during two months (APs load, data traffic per AP, among others). The proposal performs a prediction every 24h and verifies periods when the network APs are idle without any user connection. If they remain idle for some time greater than or equal to a predefined threshold, these access points are deactivated until the scheduled time for a new user connection.

Chanak *et al.* [8] present a novel green, energy-consumption-aware clustering-based routing algorithm to prevent the premature death of dense, large-scale wireless sensor networks. The proposed scheme classifies deployed nodes into three different categories, and after classifying, organizes sensor nodes into distinct clusters. For this, a distributed clustering algorithm, which maintains the leaders of the clusters, cluster heads (CHs), for a certain time, is used to avoid the frequent CH selection process. A routing algorithm is also applied to calculate the performance load of each CH by dividing the overhead across the routing node.

Ahamad *et al.* [9] propose an approach to extend the lifetime of wireless sensor networks (WSN) using fuzzy logic, based on the selection of cluster heads, which provides a non-probabilistic approach. The approach uses two fuzzy variables: distance from the base station and residual energy of the sensor nodes. It works in scenarios with range overlap and deals with the problem of cluster area selection. The idea of the proposed approach is to divide the whole area into small subareas of equal size, apply fuzzy variables and select the best cluster head for each area. Whenever necessary, the approach performs a new evaluation to select new cluster heads. Similarly, Fermino and Maores propose a physical medium access control protocol that targets energy efficiency by reducing control packet overload in multi-channel and homogeneous sensor wireless networks [10]. Their proposal is a cross-layer approach that decreases the amount of control data in the network while maintaining the quality of data available for structure and route maintenance.

Miranda Jr. *et al.* propose an analysis to classify the best choice of a recurrent neural network (RNN), based on a simplified network simulation and metrics of loss, jitter, latency, and throughput. The authors test the recurrent neural networks Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM) to compare the best efficiency of network usage with network training and prediction. The GRU RNN performed best because it was the simplest and, requiring less memory, converged first to the trained model with the smallest discrepancy [11].

Capanema *et al.* uses a Recurrent Neural Network to forecast network usage [12]. They use an algorithm for collecting and analyzing usage probability at each hour and the type of day in the week. They also perform a routine analysis based on times and weekday types to fill in the sparse data. The data are stored in vectors making up four matrices that form the input of the neural network. The Multi-Factor Attention Recurrent Neural Network (MFA-RNN) is capable of multi-factor learning. It uses the embedding layers, Gated Recurrent Units (GRU), and the Multi-Head Self-Attention (MHSA) layer. The network uses the dropout technique between layers to prevent the model from being tied to the scenario in which it was trained. The vector's density and the layers' order define the model as effective and enable the model to consider multiple factors.

The main contribution of this paper is the energy optimization and utilization of the network without loss of service availability to users. As seen in previous papers, predicting network behavior is important to provide a capacity analysis and guide adopted metrics in the networks.

III. Data Collection and Network Description

The institutional wireless network of the Universidade Federal Fluminense (UFF), located in the *campus* of *Praia Vermelha*, was selected to provide the data on the usage pattern of users [13]. The network counts with 363 access points distributed across the *campus* in a non-uniform manner. In the network, access points constantly remain active, being an ideal environment for applying methods to reduce unnecessary energy expenditures. The collected data aims to provide user's usage patterns at different times of the day and better understand actual demand.

We deploy the NetFlow tool to collect the raw data that compose the dataset concerning the flows in the APs. The generated dataset contains all client flows and associations

TABLE I
FEATURES FROM THE DATASET GENERATED BY THE CAPTURED FLOWS IN THE WIRELESS NETWORK OF THE UNIVERSIDADE FEDERAL FLUMINENSE (UFF, BRAZIL). FEATURES GENERATED BY ENRICHING FLOWS EXTRACTED BY THE NETFLOW APPLICATION WITH NETWORK LOG RECORDS.

Features	**Features' definition**
packets-forward	Number of packets sent by a specific AP.
packets-backward	Number of packets received by a specific AP.
bytes-forward	Number of bytes sent by a specific AP.
bytes-backward	Number of bytes received by a specific AP.
sTime-forward	Moment when a certain client requested a connection with an AP.
dur+msec-forward	Duration of a client connection in seconds.
mac-sta	MAC address of a connected client.
ap	Identifier of the AP.
clients	Number of clients connected to a specific AP.

between clients and APs. We consider data for one week of network monitoring. Table I shows the features of the dataset for the collected data from all APs. The "sTime-forward" feature indicates the time at which the client ordered a flow through the indicated AP ("AP" characteristic). The "dur+msec-forward" feature indicates the number of seconds referring to the flow duration. "Mac-sta" indicates the MAC address of a client device that established the association with the access point, and, "clients", the number of clients associated with the same AP at the time of the flow. The "Packets-forward" and "bytes-forward" characteristics are respectively the number of packets sent and the number of bytes sent, as well as "packets-backward" and "bytes-backward" are the number of packets and bytes received. This dataset enables us to identify patterns of use of access points and characterize the network.

We also developed a simulator using the Python language able to reproduce the network behavior. We perform simulations through the reproduction of the events collected in the network dataset. Each simulation scenario aimed to identify idle access points and the variation of user quantity in the network throughout the day. Data analysis demonstrates a high-demand network usage between $11:00h$ and $15:00h$. It also indicates idleness between $22:00h$ and $5:00h$. These periods coincide with the activity times of the *campus* where hosts the network. Through this result, we can identify long periods in which the APs do not have users associated with, resulting in unnecessary power consumption. Based on this usage pattern, we propose a new model of APs' management, capable of reducing energy consumption in periods with low or no demand.

IV. HIGH AVAILABILITY AND EFFICIENCY STRATEGY

The proposed strategy aims to reduce energy consumption through efficient management of APs activity. Since it is a large-scale network, keeping all access points constantly active results in high energy consumption. The proposed strategy, shown in Figure 1, provides a service capable of minimizing the number of active access points, i.e., powered-on access points.

Initially, all access points on the network are switched off. After this, an initial set of APs that will be activated, called the base APs' set, is selected. The initial set of APs is important because the choice directly impacts the APs that will then be turned on or off. After selecting the initial APs, the system is ready to analyze users' association attempts and identify which AP each user is more likely to associate. The analysis is based on three information: (I) preferred AP, that is, the access point whose user can establish an association with the best possible signal, (II) the APs that are currently connected, and (III) the availability of each AP to receive new users.

After evaluating the associations for a period, the strategy may take two actions concerning the APs. First, it verifies the possibility of relocating clients based on the quality of the association and the availability of active APs without hampering other clients' quality of service. New APs may also be activated to meet the demand for clients that join the network. The second strategy identifies which APs do not have associated clients and shut them down. After this step, the process of analyzing the clients' associations restarts. These steps are detailed following. We divide the strategy into two parts: Selection of the base APs' set, which are the sets of initially active APs; and Management of APs, which decides the access points to activate or deactivate according to the demand of clients' associations to the network.

Algoritmo 1: Activation of only the APs that counts with the maximum number of neighbors in the network.

$graph\_aux \leftarrow sorted(graph, key = lambda\ node : len(node.neighbors))$
$tam \leftarrow len(graph\_aux) - 1$
$greater_qty \leftarrow len(graph\_aux[size - 1].neighbors)$
while $size \geq 0$ *and* $len(graph\_aux[tam].neighbors) = greater_qty$ **do**
  $graph\_aux[size].activateAP()$
  $size -= 1$
end

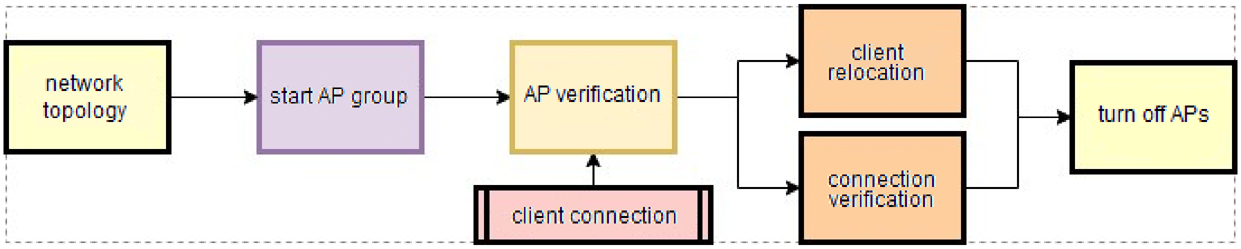


Fig. 1. Flowchart of the proposed strategy. The strategy assumes knowledge of the wireless network topology. The strategy works with an initial base APs' set to turn on, and during network monitoring, as new clients connect to the wireless network, APs are turned on and off on demand.

A. Selection of the base APs' set

In the first step, the strategy selects which access points will compose the base APs set. The strategy considers the prior knowledge of the wireless network target graph. Selection criteria significantly impact the formation of sets, as these sets directly influence how APs' management behaviors while operating the network. Three approaches to the selection of APs are proposed: (I) selection based on APs with the maximum number of neighbors (MNN); (II) selection based on non-neighboring APs, prioritizing number of neighbors (NnAP PNN); and (III) clique-based selection in the wireless network topology graph.

1) APs with the maximum number of neighbors: This approach has the most straightforward logic but presents the most significant number of initially active APs. An auxiliary vector contains all nodes of the graph of the network, and then the vector is ordered according to the number of neighbors of each node. Thus, the last element of this vector has the maximum number of neighbors among the graph nodes. Then, we selected all graph nodes that also have the same maximum number of neighbors. According to the example of Figure 2(a), the AP with the maximum number of neighbors has four neighbors. In this case, all APs that have four neighbors are selected as the base APs' set. The Algorithm 1 presents the selection used within this approach.

2) Non-neighboring APs, prioritizing number of neighbors: In this approach, we create an auxiliary vector containing all the nodes of the graph ordered by the number of neighbors of each node. The vector is then traversed in descending order of the number of neighbors of each node, selecting all nodes that are not neighbors of previously selected nodes. The selected nodes compose the base APs' set. Figure 2(b) presents an example of selection using the approach. The Algorithm 2 describes how the operation.

3) Representing APs from Network Graph Cliques: In this approach, we seek network graph cliques. Then, an AP is selected for each clique. The selected APs have the largest number of neighbors and are not neighbors of a previously selected AP. Figure 2(c) shows the representation of this approach. The graph has three cliques, then three active APs that are not neighbors to each other. The Algorithm 3 presents the clique approach, in which the graph is separated into vectors representing the cliques containing the nodes that make up the corresponding clique. All cliques are checked, and each node goes through a verification.

Algoritmo 2: Activation of APs that do not have current active neighbors, prioritizing those with the more neighbors. We analyze all APs in descending order of the number of neighbors, being activated as long as none of their neighbors has already been activated.

$graph\_aux \leftarrow sorted(graph, key = lambda\ node : len(node.neighbors))$
$size \leftarrow len(graph\_aux) - 1$
while $size > 0$ **do**
  $node \leftarrow graph\_aux[size]$
  $no\_active\_neighbor \leftarrow True$
  for $neighbor \in node.neighbors$ **do**
    if $neighbor.status$ **then**
      $no\_active\_neighbor \leftarrow False$
      $break$
    end
  end
  if $no\_active\_neighbor$ **then**
    $node.activateAP()$
  end
  $size- = 1$
end

The strategy orders the node vector (cliques) relative to the number of neighbors. It traverses the vector verifying that the candidate node is not neighboring any node that is already active. If none of its neighbors are active, the node is a candidate to be activated. Otherwise, the following node with more neighbors is verified. The underlying idea of activating only one node in each clique is that the clique represents a coverage area that overlaps with all those access points. Thus, an active node in the clique tends to cover an approximately equal area to the entire clique.

B. Network Management

To minimize energy expenditure, APs management consists of turning on new APs only whenever it is necessary. The need to activate a new AP is represented when an AP receives an association request of new clients but is already with its maximum capacity. Besides, turning off the APs whenever possible occurs when no user is associated with them, also

Algoritmo 3: Activation of APs that are in graph cliques. One AP of each clique represents the clique present in the network graph and, then, is activated in the base APs' set.

```
Function find_ap_to_activate(list_nodes)
    list_nodes_aux ← sorted(list_nodes, key =
     lambda node : len(node.neighbors))
    size ← len(list_nodes) − 1
    checker ← False
    while size > 0 do
        node ← list_nodes_aux[size]
        for neighbor ∈ node.neighbors do
            if neighbor.status == True then
                checker ← True
            end
        end
        if checker == False then
            returnnode
        end
        else
            size− = 1
            checker ← False
        end
    end
    ret = lista_nodes_aux[len(lista_nodes) − 1]
    return ret
cliques ← seek_cliques(graph)
for nodes ∈ cliques do
    to_activate ← find_ap_to_activate(nodes)
    to_activate.status ← True
end
```

valuing the quality of the signal delivered to the user. We organize the APs management into two cases: activating new APs and shutting down APs.

1) Activating New APs: New access points can be connected in two distinct scenarios: (I) if a client's preferred access point is deactivated and its neighbors unavailable, or (II) if the preferred AP is at maximum capacity and one of its neighbors is disconnected.

If the preferred AP is disconnected, the client must connect to a neighboring AP in the first case. To do this, the client verifies, considering the number of associated users, states, and neighbors on the neighboring APs to find the best option. The approach manages the user association with the network to choose the neighbor with the largest number of associated clients, but without reaching the maximum number of active clients. The client preferred AP[1] is activated if all neighbors have as many associations or are disconnected. The maximum number of associations supported by an access point is considered equal to 15 active clients. Reis *et al.* show that for access points with more than 15 associated and active clients imply a drop in the quality of service experienced by the users [13].

[1]The prefered AP is choosen according to the previous usage pattern of each client in the network.

If the preferred AP is full, its neighboring APs are checked to identify which one has the largest number of neighbors. If all neighbors are unavailable, another check occurs to identify if there are any deactivated neighbors, and from among the deactivated neighbors, which one has more neighbors. Therefore, this neighbor is chosen to be activated.

2) Shutting Down APs: The only situation that an access point can be deactivated is if it has no longer any active user association. Therefore, we adopt a strategy to migrate active users from an underloaded access point, shut down the AP, and keep these users connected to the network. The strategy is to force the distribution of users connected to an AP to others, allowing the underloaded AP to be unassociated and shut down without impairing users' access to the network[2].

The first step to the reorganization is the analysis of all network access points that are active. Then, the strategy checks whether APs have active neighbors in which the total number of clients' associations, added to the number of incoming associations from the underload AP, does not exceed the allowed threshold of associations per AP. When a neighbor with these characteristics is found, the strategy checks whether it or its neighbors are the preferred user in migration; then, the user is relocated. The preferred AP is the one that presents a higher quality signal to a relocated user. If, after these operations, the underloaded AP has no longer any active client association, it shuts down.

V. Experimental Results

In this section, we compare the performances of the three proposed approaches with different metrics. We obtained the data related to the operation of each approach through the use of a simulator developed in Python programming language. The simulator can replicate the behavior of the network in the proposed strategies.

We simulated four scenarios, testing the network in its normal operation to validate the simulator, and the three proposed approaches. The simulation considered the information present in the obtained dataset, which contains the monitored data from 357 APs[3] of the Universidade Federal Fluminense network over approximately 9 days.

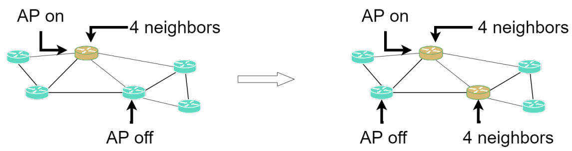
The metrics used in comparing the approaches were: number of activated APs, number of overloaded APs, amount of bytes backward, amount of bytes forward, number of unserved users, and number of valid users in the network.

A. Number of activated APs

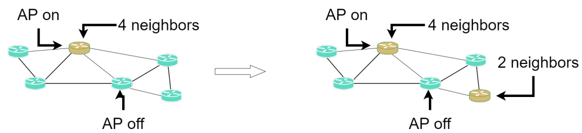
In Figure 3(a) the"Free network" scenario represents the network with no changes. In this scenario, the activated access points are all 357 access points in the network. The data obtained in the"Pure Network" scenario is the baseline for comparison and validation of the simulator. The MNN approach has the least number of activated APs, keeping

[2]The procedure for migrating users between access points is outside the scope of this paper.

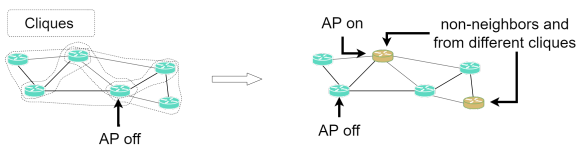
[3]Although the network contains 363 access points, six access points were unavailable at the time of data collection.



(a) APs selection approach with the maximum number of neighbors. APs that have 4 neighbors, the maximum number of neighbors, are connected.



(b) [Non-neighboring APs selection approach, prioritizing those with the highest number of neighbors. APs are connected, one by one, from which they have the largest number of neighbors to the smallest, as long as they are not neighbors of any that have been connected before.



(c) Most representative clique selection approach. Graph cliques we identified, and one AP of each, which is not the neighbor of an AP that is connected, is connected, as long as no other AP within the same clique has ever been connected.

Fig. 2. Examples of each proposed approach to select ing the base Set of APs. Representation of aps connected in green.

approximately 0.6% of activated APs during the simulation period among the compared approaches. Thus, presenting higher energy savings. Meanwhile, the Clique and NnAP PNN scenarios exhibit 19% and 23% of the network APs turned on, respectively. The second-best approach is the Clique approach with approximately 18% less connected access points than the NnAP PNN approach.

B. *Number of overloaded APs*

The average number of overloaded access points in the network is very similar in almost all simulations. The only approach that has a relevant difference in the average is the MNN approach with 0.6 Aps overloaded per hour as shown in Figure 3(b). While the maximum number of overloaded APs in the other simulations is 6, in the MNN simulation, this number decreases to 2.

C. *Amount of bytes backward and bytes forward*

The metric of bytes forward and backward represents the throughput of traffic on the network. A high-throughput means that the network is serving clients efficiently and satisfactorily. A low-throughput, by contrast, represents that too many clients are unable to join the network or that the APs are overloaded.

In the Figures 3(c) and 3(d) one can observe the amount of *bytes* trafficked in the simulated period, both backwards and forwards. These values show similar proportions when compared. For the *bytes* backward, the worst result is in the MNN scenario with 27% of the value compared to the simulation referring to the Free Network scenario with all access points turned on. With slightly better results, approaching the network with all access points on, the cliques scenario presents 53% of the number of bytes backward. Finally, the NnAP PNN scenario with 99% of the number of bytes backward compared to the amount of the Free Network scenario presents the best results among the proposed approaches.

Analogously to the *bytes* backward, the best result obtained for the bytes forward is in the NnAP PNN scenario with 98% of the number of bytes forward in the Free Network. The Cliques and MNN scenarios showed 58% and 27% of the bytes forward, respectively. The MNN scenario presents the most distant values from the Free Network scenario as well as in the comparison of bytes backward, being the worst result among the proposed approaches.

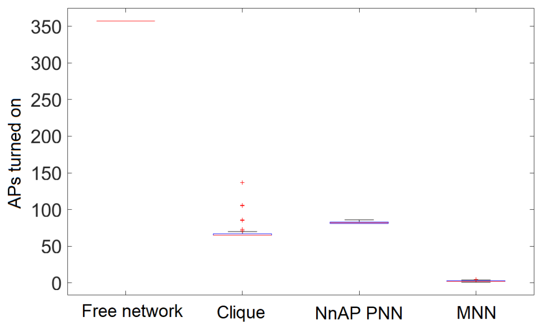
D. *Number of unserved users and valid users in the network*

Along with the number of APs connected, it is important to observe the number of unserved users. This metric allows verifying whether the approach can meet the demand of users trying to associate access points on the network, in addition to performing well in energy efficiency. In Figure 4(a) the MNN scenario presents the worst performance among the proposed approaches with 265 unserved users in the simulated period, considering that the fewer unserved users, the better the network availability. When comparing the other scenarios, Clique and NnAP PNN, it is visible that even though both have much better results than the MNN scenario, there is still a considerable difference between their results. While the Clique scenario presents 126 unserved users, the NnAP PNN scenario presents a total of only 14 unserved users over the simulated period. The NnAP PNN scenario obtained 7x less than the Cliques scenario, making the NnAP PNN scenario present the best results among those compared.

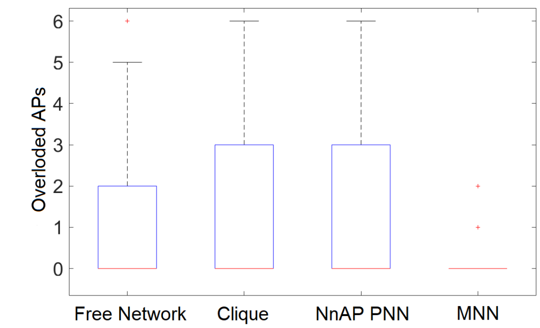
In parallel to the number of unserved users, we can observe this same by comparing the metric of the number of valid users in the network per hour, represented in Figure 4(b). Valid users are those that are active and associated with access points. Thus, as in the previous analysis, the worst results are observed in the MNN scenario, which shows only 25% of users attempting to connect to the network as valid. The best results remain between the cliques and NnAP PNN scenarios, with the Cliques scenario presenting 94% of users and averaging approximately 290.76 users per hour, while the NnAP PNN scenario, which has the best result, showing approximately 98% of users on the network, and averaging 304.5 users per hour.

VI. Conclusion

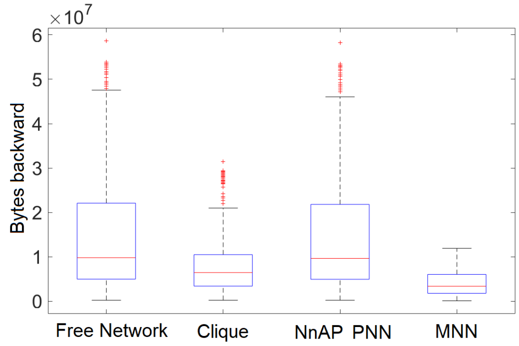
In this paper, we proposed a strategy for managing access points of a large-scale network to maintain the level of network availability and achieving better energy efficiency. The strategy consists of managing the network's access points so that they are turned off when there is no user associated with them. The proposed strategy uses a technique of user relocation,



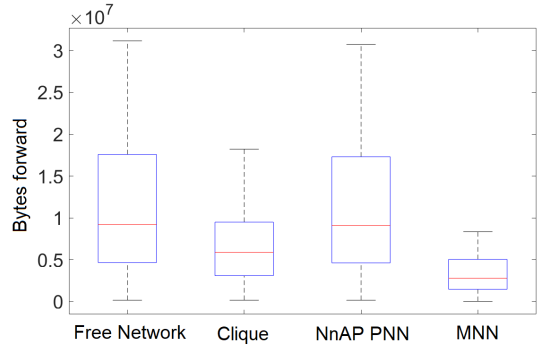
(a) Number of activated APs to the network over the period of approximately 8 days.



(b) Number of overloaded APs in the network over the period of approximately 8 days.

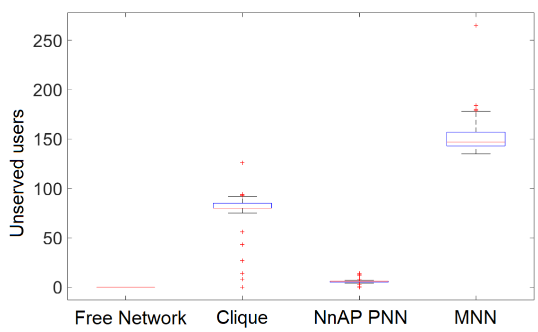


(c) Total amount of bytes backward over time in a period of approximately 8 days.

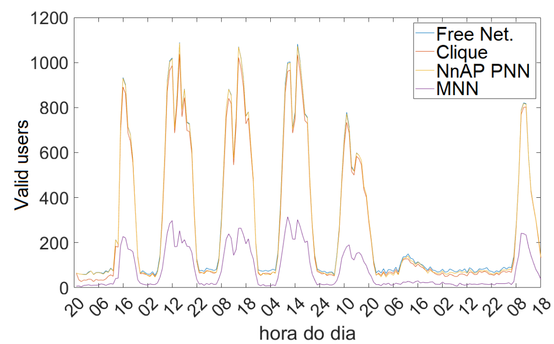


(d) Total amount of bytes forward over time in a period of approximately 8 days.

Fig. 3. Graphical representation of the amount of activated APs, number of overloaded APs, amount of bytes forward, and amount of bytes backward, respectively, of each proposed approach, including the network without the interference of any of the approaches.



(a) Total number of unserved users overtime over a period of approximately 8 days.



(b) Number of valid users in the network over the period of approximately 8 days.

Fig. 4. The NnAP PNN approach introduces the least number of unserved users. The number of valid users is similar between the network without interference and in the Clique and node selection approaches without active neighbors (NnAP PNN).

in which users that are already connected are relocated to other access points to reduce the amount of simultaneously connected access points to obtain a more efficient energy consumption. We tested three approaches for selecting the sets of initially connected access points: activate APs with the maximum number of neighbors, activate non-neighbor APs, prioritizing the number of neighbors, and activate APs representing cliques in the network graph. The proposed approaches showed improvements in the energy efficiency of the network when compared to its normal operation. The approaches showed many valid users in the network exceeding 90% of the users that were attempted to associate to the network. The Cliques approach, kept only 19% APs connected, while the Non-neighbor APs approach, prioritizing to connect APs with the higher number of neighbors, presented a 23% higher number of connected APs than the previous approach, but obtained a better result for the total number of users served, reaching 98% of the total users in the network.

As future work, we intend to explore more energy-saving approaches by reducing the number of unserved users. Among the possible alternatives, explore approaches that use clusters and the use of recurrent neural networks.

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