Optimizing QoS of the LTE network using a machine-learning-based spatio-temporal distribution and Tabu search metaheuristic

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***Abstract*—Network traffic congestion is a crucial issue facing mobile operators at various locations depending on the time of day and year. Traffic congestion generally occurs at peak times in urban or suburban areas. This is because the eNBs' maximum capacity is very quickly exceeded by the number of users since the resource blocks (RBs) and the bandwith are limited. To best manage network congestion, it is necessary to optimize the allocation of the network resources. The resource allocation problem, which is known to be NP-hard, is commonly formulated as an optimisation problem under constraints. The objective is to minimise the number of uncovered users for a service required on an eNB in a given scenario.**

The territory under study is the city of Lomé, the data used for the analysis come from the geographical data of the OSM database. We propose an approach allowing the dynamic configuration of the network based on a model for predicting users mobility and a heuristic for optimising LTE network resources. A Greedy algorithm and a Tabu Search algorithm have been implemented and tested. The results showed the potential of the Tabu Search algorithm to outperform the Greedy algorithm.

***Index Terms*—QoS, optimization, mobility, Tabu Search, ground characterization, spatio-temporal distribution, NP-Hard problem**

I. INTRODUCTION

The escalating number of mobile network users poses an ongoing challenge for mobile operators striving to improve traffic availability and flow. Long Term Evolution (LTE) networks have significantly boosted throughput, blending performance, flexibility, and cost-effective Quality of Service (QoS) metrics. Introduced in Togo in 2018, LTE technology has encountered congestion issues primarily during peak hours in urban, suburban, and occasionally rural areas due to rapid users growth surpassing antenna capacity.

In response, optimising resource management in LTE networks becomes crucial for ensuring efficient and reliable services. Several works are conducted to address specific challenges and propose innovative solutions in LTE resource optimisation.

Several heuristics are used by the scientific community to address the network resource allocation problem. The Adaptive Iterated Local Search (AILS) algorithm is introduced to address the NP-completeness of capacity allocation in LTE networks by optimising the distribution of capacity from the Evolved Packet Core (EPC) to evolved NodeB (eNB) base stations [1]. Cognitive radio techniques is used to enhance cellular coverage and capacity, focusing on multi-objective resource allocation with the NSGA II algorithm [2].

In the domain of 4G-LTE network planning, a metaheuristic algorithm based on swarm intelligence was proposed to optimise base station placement considering the variation of user density across subareas [3]. Another approach was proposed to leverage big data analytics for resource allocation in cellular networks [4].

Further contributions include the development of the Multiuser Resource Allocation Process (MURAP) algorithm for optimising resource usage in LTE-A uplink systems, as well as the exploration of self-optimisation methodologies in LTE radio access networks [5].

In this research, we devise an approach to optimize LTE network resource allocation that takes advantage of a spatio-temporal ground characterization and population distribution, using the Tabu Search algorithm.

Our main contributions are summarised as follows:

- We defined an optimisation model allowing the dynamic configuration of LTE Network.
- We defined a mono-objective function to minimise the LTE users in outage.

- We implemented a Greedy algorithm and a Tabu Search to optimise QoS LTE network resources, and we compared their results.

The rest of this paper is organized as follows. Section II provides an overview of the related works on the mobile network quality of service and optimisation problem. Section III describes the problem modelling and provides the formulation of the optimisation problem. Section IV provides the datasets description and the methodology approach. Section V describes the experimental results along with their analysis. Section VI concludes the paper and provides perspectives for further research.

II. Related Works

In the study conducted by Moses et al. [6], the focus is on resource allocation in LTE (Long Term Evolution) network's uplink. Specifically, the research examines the distribution of resource blocks (RB) among equipped users (UE) within the LTE network, where the uplink employs the SC-FDMA scheme. This scheme imposes an adjacency constraint on the RB allocated to each UE, adding complexity to the scheduler's task. To address this challenge, the stochastic genetic algorithm (StGA) is used, employing genetic operations of selection, crossing, and mutation to produce new solutions while respecting RB contiguity constraints and minimizing discontinuities caused by hybrid automatic repeat request (HARQ) transmissions. The study's results demonstrate that the StGA algorithm outperforms alternative methods in terms of throughput, delay, PSNR, and meeting users' RB needs.

Kalaycıoglu et al. [7] present a heuristic approach using simulated annealing to regulate femtocellular base station transmission power in LTE heterogeneous networks, aiming to minimise co-canal interference and maintain a minimal signal-to-interference-plus-Noise-Ratio (SINR) for femtocell users. Simulation outcomes demonstrate the method's effectiveness in reducing femtocell power consumption without significant SINR compromise, offering a feasible solution for interference mitigation in LTE environments.

Qatab et al. [2] address resource allocation in LTE/LTE-A femtocell networks, aiming to enhance coverage and capacity using cognitive radio techniques. Their multi-objective optimisation approach, using the NSGA II evolutionary algorithm, yields Pareto-optimal solutions, resulting in an 8% improvement in network performance and multi-objective function score, highlighting its efficacy in managing resources within cognitive femtocell networks.

Ghazzai et al. [3] present an efficient method for 4G-LTE network planning, using swarm intelligence-based meta-heuristic algorithms to deploy base stations while meeting coverage and capacity constraints. Monte Carlo simulations verify its effectiveness in maintaining low failure rates and ensuring desired quality of service.

Kiran et al. [4] propose an innovative approach to address radio resource allocation in modern cellular networks by leveraging big data analytics. Their method involves compressing raw data into binary form for faster processing, followed by pattern recognition to identify resource groups based on user demand patterns. Simulation outcomes highlight the method's efficiency in identifying physical resource blocks (PRBs) and its ability to adapt to diverse network conditions based on key performance indicators (KPIs) and user-related parameters.

Additionally, Khdhir et al. [8] introduce the Multi-user Resource Allocation Process (MURAP) algorithm for LTE-A uplink systems, aiming to optimize resource utilization, maximize system throughput, and ensure equitable resource sharing among users. The MURAP algorithm employs Tabu optimisation-based carrier selection to allocate carriers effectively, resulting in improved network performance in terms of packet loss rate, throughput, and fairness compared to existing methods.

Lastly, Lixiang Xu et al. [5] discuss methods for implementing self-optimisation within LTE radio access networks, a crucial aspect of the Self-Organizing Network (SON) concept aimed at reducing operational complexities. They propose adaptive methods to control the transmission of domestic cells (H(e)NB) based on user presence to minimize energy consumption and interference with macro cells, contributing to simplified network deployment and sustainable development.

This review of the state-of-art highlights various approaches and methodologies employed in optimizing quality of service within LTE networks, showcasing the effectiveness of meta-heuristic algorithms in resource allocation, interference mitigation, and network planning to enhance overall performance and user satisfaction. In our research, we exploit the potential of learning techniques and combine them with optimization algorithms, including meta-heuristics.

III. Problem Modelling

This section presents the formulation of the optimisation problem, it includes three subsections: Subsection III-A defines the decision variables of the problem, Subsection III-B describes the steps to define the fitness function, and Subsection III-C presents the problem constraints.

In this research work, we address the frequency allocation problem to multiple antennas deployed at a site. The frequency allocation depends on the frequency reuse pattern and the characteristics of the antennas. Given a significant number of sites, the potential combinations for frequency allocation increase exponentially. This combinatorial problem represents a computational challenge which is known to be an NP-hard problem [2].

According to the frequency allocated to a sector, our focus shifts to optimise the coverage for users. Within our research scope, the minimal QoS required entails a signal strength robust enough for users to sustain network connectivity. A users who successfully maintains a quality call through the network is considered to have good network coverage.

The Signal-to-Interference-plus-Noise-Ratio (SINR) is an important performance indicator to estimate the achievable throughput provided by cellular networks. The estimation and optimization of the SINR are well-known problems in radio communication systems such as LTE networks. In our research context, the minimum QoS we need is guaranteed by sufficient signal power for a users to hold a communication through the network.

$$SINR^{C}_{b,s} \geq SINR^{MIN} \quad \forall b \in B,\ \forall s \in S \tag{1}$$

where $SINR^{C}_{b,s}$ is the SINR received by the user and issued from the eNB b in scenario s, and the $SINR^{MIN}$ is the SINR threshold required for the user to establish a communication. Below this value, the users within the given area are considered as non-covered users. In our context, we do not take into account requests for specific types of service. Only the possibility of establishing a call is considered, this is why a minimum threshold for establishing a communication is defined.

A. Decision variables

The network manager acts on the antenna parameters (transmitting power of the base stations, mechanical tilt, electric tilt...) to tune the network. These parameters are called 1st level decision variables of the problem. Setting the network is to determine the values of the decision variables. As this is a combinatorial optimization problem, the decision variables are determined in order to provide the best sub-optimal solution of the problem. In our context, three decision variables are considered:

1) The tilt t_b, the vertical orientation of the eNB b : The inclination or tilt of the antenna reduces or increases the area covered by an antenna. In this way, the number of potential users that could be covered by the antenna can be increased to optimise the number of users that will be covered.
2) the transmitted power p_b of the eNB b : The higher the power emitted by an antenna, the more it can be received by distant telephones within the antenna's coverage area. It also improves the quality of communication, because the signal strength is higher.
3) the frequency $f_{b,n}$, the frequency n assigned to the eNB b : The frequency allocated and the bandwidth allocated to an antenna define the number of block resources available for communication with the antenna. This number has a direct impact on the number of users covered.

B. Fitness function

The frequency used by an antenna determines the number of users that can be connected to that antenna, and which is varying according to the time of day. This is what we call a scenario. So the objective is to minimise the number n of users non-covered C for the service required on the eNB b in a scenario s.

The number of users in a given zone can be divided into two categories. Active users are users who are communicating, or using equipment to access a given service on the network; and inactive users are present in the zone but are not attempting to access any service in the scenario under consideration. The number of users considered is the number of active users in the scenario under consideration.

C. Constraints

However, there are constraints related to LTE technology. Three constraints are considered in the problem formulation below:

i An eNB b has a maximum number of neighbors V_b defined according to the frequency reuse pattern: The frequency reuse pattern on a cell limits the maximum number of neighbouring cells that can surround that cell to avoid interference.

ii An eNB b uses one and only one carrier n: Only one carrier is allocated to an antenna at any given time. This means that an antenna cannot simultaneously manage several carriers or frequencies.

iii A mesh m is associated to 0 or 1 eNB b at most: A mesh can be covered by one or more antennas. But in our context, a mesh represents an aggregated point of the number of users present in a given zone. For this reason, it can only be attached to one antenna at most.

Finally, the overall formulation of our optimisation problem results in a mono-objective function subject to constraints as defined below:

$$\begin{cases} min & n^{C}_{b,s} = \sum n^{C}_{m} & \forall b \in B,\ \forall m \in M,\ \forall s \in S \\ s.t. & v_b^{MIN} \leq |V_b| \leq v_b^{MAX} & \forall b \in B \quad (i) \\ & \sum_{n \in N} f_{b,n} = 1 & \forall b \in B \quad (ii) \\ & \sum_{b \in B} u_{b,m} \leq 1 & \forall m \in M \quad (iii) \end{cases} \tag{2}$$

IV. Dataset and Methodology

This section is dedicated to the description of the datasets used in our experiments. It covers the study area, the structure of the data collected, and the methodology of data collection. It also presents the methodology of the study area meshing, and the spatio-temporal distribution of the LTE users. The area under study focuses on the city of Lomé, capital of Togo. It has a total area of 90 km^2. It contains **69** districts, grouped into **5** boroughs and former district.

A. Mobile Traffic Data

For the needs of our research, we approached mobile network operators to request anonymised data on the 4G network. The data we were interested in focused on incoming and outgoing call records, incoming and outgoing sms, presence data, handovers and call pick-up probabilities for all the stations in Lomé during a specified period. The call pick-up probability corresponds, for a covered area by one or more antennas, to the probability that a communication is routed by an antenna from this area. The data collected include antennas locations, and represents **153 sites**. Antenna locations are structured as follows:

- **Longitude:** Refers to the longitude on which the antenna is located
- **Latitude:** Refers to the latitude on which the antenna is located
- **Sitename:** Refers to the name given to the antenna by the operator

- **Region:** Specifies the region in which the antenna is located.

B. Study area meshing

The study area is equally divided into 25 m x 25 m meshes. Our goal is to optimise mesh coverage in an area covered by one or more antennas, in other words, each mesh is associated to the antenna providing it with the best signal. This coverage, depicted in Fig 1, is calculated using the propagation formula based on the COST 231 variant of the Hata model [9] defined below:

$$\begin{aligned} PL_{b,t} &= 46.3 + 33.9\ log_{10}(f_0) - 13.82\ log_{10}(z_b) - a(z_t) \\ &\quad + (44.9 - 6.55\ log_{10}(z_b))\ log_{10}(d_{b,t}) + C_m \end{aligned} \tag{3}$$

with :

$$a(z_t) = 0.8 + (1.1\ log_{10}(f_0) - 0.7)z_t - 1.56\ log_{10}(f_0) \tag{4}$$

where $PL_{b,t}$ is the attenuation of the signal between the eNB b and the mobile's antenna t in dB, f_0 is the frequency used in MHz, $a(z_t)$ is the mobile's antenna height correction factor, $d_{b,t}$ the distance between the eNB b and the mobile's antenna t in km, z_b and z_t are respectively the height of the eNB b and the mobile's antenna t in meter (m) and C_m is a constant equal to 0 for small and medium city and equal to 3 for large metropolitan area. In our case, C_m is equal to 3.

However a mesh is attached to only one eNB that offers the highest SINR. A mesh is represented by the notation $m_i(i, x, y)$ where i is the index identifying the mesh, and x, y the geographic projected coordinates of the mesh center.

TABLE I
CRITICAL SITES

GOUVERNEUR	KODJOVIAKOPE	KODJOVIAKOPE2
COLOMBE	NYEKONAKPOE	BASSADJI
NYEKONAKPOE2	TAMAGNI	AMOUTIEVE
ABLOGAME	GBENYEDJI	AGUIAKOME
OLYMPIA	KODOME	PROTESTANT
ANFAME	SOLIDARITE	TOKOINCENTRE
ENTTP	DOUMASSESSE	CASSABLANCA
NUKAFU	AEROPORT	AKODESSEWA2
KANYIKOPE	HOUNTIGOME	SITO
KPONOU	DJIFAKPOTA	ZOROBAR
FUCEC	LOMEGAN	CERFER
FOIRE2000	HEDZRANAWOE	RADIOMARIA
ADAKPAME	TOTSI	LOME2000
ATIEGOU	ATIEGOU2	EVENTFOIRE
TOGO2000	AGBALEPEDO	GBLINKOME
TOTSIVI	TAMAGNI	AKODESSEWA
LCT	LOMEPLAGE	KLIKAME
NETADI	AGBALEPEDOGAN	

C. Spatio-temporal user's distribution

LTE users are spread across the study area depending on their profile, the time of the day, and the move from one mesh to another. Fig 3 illustrates the fluctuation in the distribution of users from one area to another in a territory. The study area is meshed, each mesh represents the number of users c at a time t present in that geographical area. On each mesh, the number of users is distributed per hour using our distribution model based on the ground characterization. The total number of users associated with an antenna is the sum of users on all the meshes associated with the antenna.

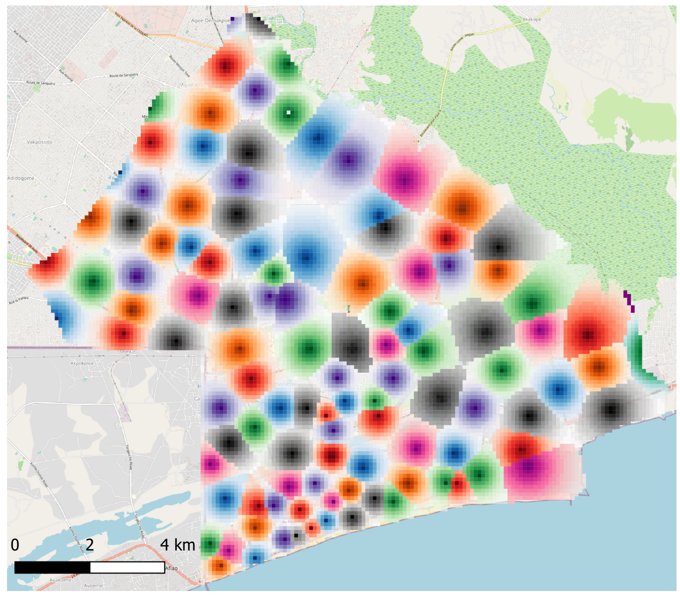

Fig. 1. Simulated antenna's coverage

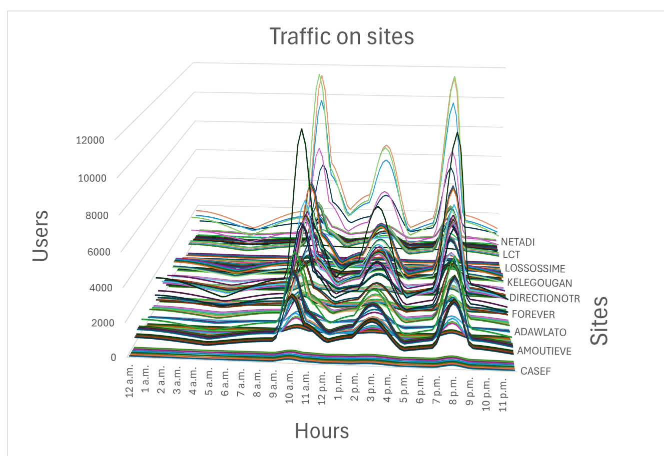

Fig. 2. Number of users per sites and hours

The spatio-temporal distribution identifies the meshes with a high number of users at given times of the day. A critical site is a site to which these meshes are attached, and which counts more than **2000** users. The periods with such a high traffic are considered to be peak hours. There are **53 critical**

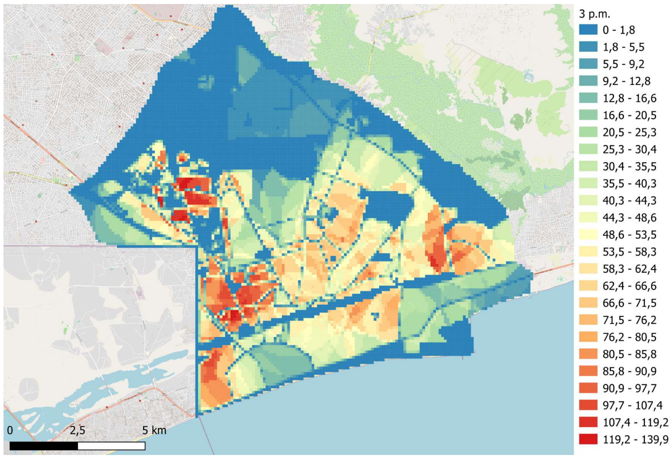

Fig. 3. LTE users distribution at 3 p.m. in the agglomeration of Lomé.

sites as listed in Table I. Fig 2 highlights traffic peaks, and in particular three peak hours, namely **10 a.m.**, **3 p.m.** and **8 p.m.**. For instance, Fig 3 depicts users distribution at **3 p.m.**.

V. Experiments and results

This section describe the experiment setup and the results provided by both approaches. Subsection V-A presents the data-preprocessing methodology, Subsection V-B describes the implementation of the Greedy algorithm along with the obtained results, Subsection V-C describes the implementation of the Tabu Search algorithm along with the obtained results, and finally Subsection V-D presents the results analysis.

A. Data preprocessing

The chosen frequency reuse pattern is 1x3x3 where the frequency band is divided into 3 sub-bands each assigned to one of the 3 co-site sectors. The input data used are the number of active users on a mesh m covered by the eNB b. This number is obtained via our ground characterization-based distribution model. users are distributed by hour. Optimisation is performed during hour slots where traffic peaks are observed (*10 a.m., 3 p.m. and 8 p.m.*). We generate plausible traffic dataset based on census data, antenna positions of an operator network, and the ground characterization in the city of Lomé. The experiments are conducted using a network composed of 153 eNB. The number of critical sites is 53. The list of considered frequency is [700Mhz, 900Mhz, 1800 Mhz], the tilt degree range [$0°$, $12°$] and the emitted power range [39 dBm, 46 dBm]. The number of an eNB neighbors = 6 and the minimum SINR = $0,9dB$.

B. Greedy Algorithm

The implementation of the Greedy algorithm is as follows:

1) Randomly allocate a frequency to each sector for all sites
2) Perform frequency permutations across the different sectors of all sites
3) For each permutation, calculate the fitness to verify users coverage
4) If the fitness is smaller than the previous one, then this frequency plan becomes the best solution
5) Return to step 2) until the fitness is not smaller than the best solution
6) The termination condition is reached when there is no further improvement

The Greedy algorithm is run on all 53 critical sites and stops after 30 minutes of execution, when there is no more improvement of the fitness function. Fig 4 represents the eight most critical sites having more than 10 non-covered users.

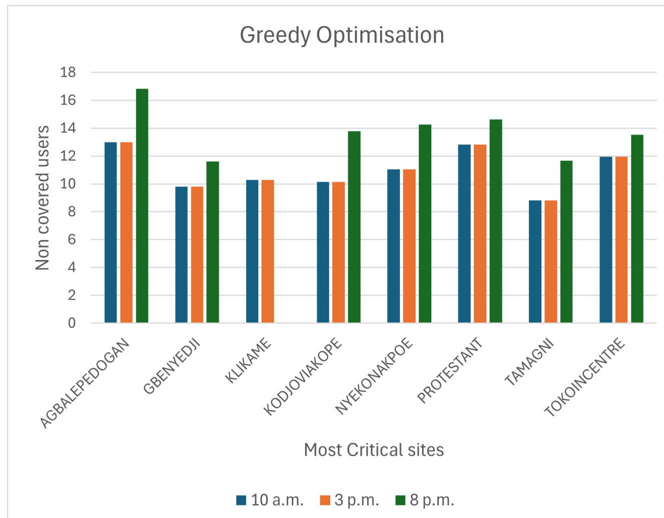

Fig. 4. Non-covered LTE users with Greedy algorithm

C. Tabu Search Algorithm

The implementation of the Tabu Search algorithm is as follows:

1) Randomly allocate a frequency to each sector
2) Randomly select a site s, perform frequency permutations on site s
3) For each permutation, calculate the fitness to verify users coverage
4) The site s is updated with the permutation having the smallest fitness
5) Add site s to the Tabu list
6) Find randomly a site s' in the list of neighbors of site s, and excluding Tabu sites
7) Perform frequency permutations on the site s' until we find the best coverage
8) Evaluate the fitness of site s' compared to site s:
   a If it is better, we add site s' to the Tabu list, and s' becomes the best configuration for the site s'. The network is updated, and we return to step 7
   b Otherwise, we randomly select another site that is not in the neighbors list, and we return to step 3
9) The stop condition is the execution time which is fixed to 10 min.

To determine the size of the Tabu list, we used the following formula $[0.5 \times \sqrt{n}, 1.5 \times \sqrt{n}]$ with n being the number of critical sites. Thus, the size of the Tabu list varies within a range of $[4, 11]$. Fig 5 represents the eight most critical sites having more than 10 non-covered user, which are the same sites as in Fig 4.

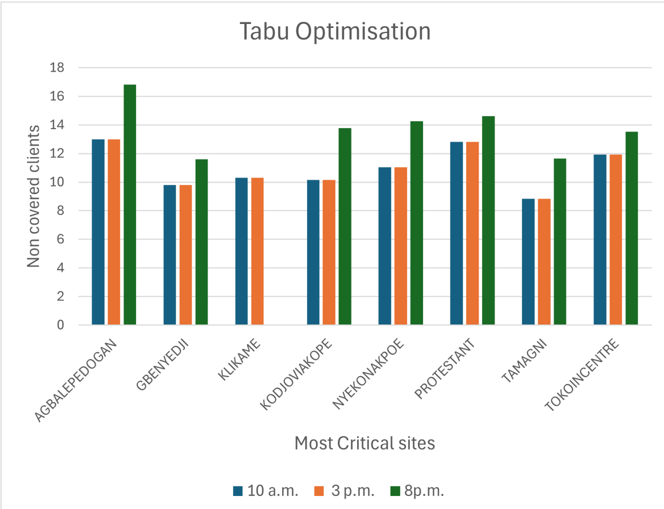

Fig. 5. Non-covered LTE users with Tabu algorithm

D. Results analysis

At the end of the execution of the Greedy algorithm, all critical sites were visited, and then optimized. While the Tabu algorithm provides the same results in less time (10 minutes) without visiting all critical sites. We observe from Fig 4 and 5 that the same eight sites remain critical. At **8 p.m.**, the critical site **KLIKAME** has all users covered. Based on the ground characterisation, the spatio-temporal distribution reveals a low number of users present on meshes attached to KLIKAME eNBs at **8 p.m.**. Whereas site **AGBALEPEDOGAN** has the highest number of non-covered users and would need targeted optimisation in a future step. Also, these results demonstrate that the most critical hour across all critical sites is **8 p.m.**.

Both algorithms produced good quality solutions. To optimise all critical sites, Greedy algorithm required three times more execution time than Tabu Search to achieve identical outcomes for the same eight critical sites, while Tabu search does not run through all sites to obtain the same quality solution. As a matter of fact, Tabu Search outperforms Greedy algorithm, and is promising for better results.

VI. Conclusion

Network congestion is a critical challenge for mobile operators, particularly during peak hour in urban area when user numbers surpass eNB capacity due to resource limitations. Indeed, managing congestion necessitates optimising resource allocation of the network. In our research work, an innovative hybrid approach is proposed and works in two stages: first, a spatio-temporal characterization of the study area is carried out using learning techniques and multi-source data. Then, the characterization of the study area is exploited to achieve scenario-based optimization. In this paper, we proposed a dynamic network configuration approach based on users mobility prediction using mobile data, census data, OSM data, and a heuristic for LTE resource allocation optimisation. To solve the optimisation problem of the network resource allocation, we considered two algorithms: a Greedy algorithm that builds a solution satisfying the constraints but without guarantee on the quality of the solution in terms of optimality, and a Tabu Search algorithm that provides the same quality of solution relative to the number of users covered, but with better execution time performance. By conducting experiments based on spatio-temporal scenarios in the city of Lomé, we demonstrated that Tabu Search algorithm outperforms Greedy algorithm in alleviating congestion, and optimising the network resource allocation thus improving the LTE network QoS.

To solve our resource allocation problem, we used simple algorithmic approaches, namely a Greedy algorithm and a simple Tabu Search. In perspective, we can combine Greedy algorithm and Tabu Search, or use variants of Tabu Search with degradation control. We can also explore other meta-heuristics such as genetic algorithms and compare their performance against Tabu Search in optimizing solutions for similar problems.

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