On the Detection and Solution of Coverage Holes in 5G Networks through Relay User Equipment: a combined DBSCAN and Deep-Q Network Approach

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***Abstract*— This paper proposes a model to detect and solve coverage holes in 5G Radio Access Network (RAN) deployments operating with millimeter waves. The proposed model utilizes a DBSCAN-based detector to identify coverage constrained areas and then proposes the use of Relay User Equipment (RUE) capabilities to extend the RAN coverage. To optimize the activation and deactivation of RUEs, a Deep-Q-Network-based algorithm is proposed, aiming to improve spectral efficiency and decrease the outage probability experienced by network users. The obtained results demonstrate the effectiveness of the model in accurately detecting coverage constrained areas and efficiently solving these issues by means of an effective RUE activation, leading to significant improvements in network performance while minimizing the time that RUEs remain in active mode, which implies potential benefits for MNOs and UE holders and significant energy savings.**

Keywords*— *Radio Access Network, Deep-Q Network, 5G coverage holes, UE-to-network relaying, DBSCAN, clustering.

I. Introduction

The growth of mobile network traffic has been substantial and sustained in recent years, according to the Ericsson Mobility Report [1]. It is expected that the average data consumption per smartphone will surpass 19 GB per month in 2023 and will grow to 54 GB by 2028. It is also projected that the number of 5G mobile subscriptions will reach 5 billion by 2028. In general, mobile traffic is expected to increase in the near future. To cope with this demand, mobile network operators (MNOs) must upgrade their radio access network (RAN) infrastructure to handle the expected increase in traffic. In this context, substantial capital expenditures (CAPEX) are required. This becomes especially significant when it comes to 5G operations in high frequency bands like millimeter waves (mmWave), since a higher density of base stations is required to achieve adequate coverage from outdoors-to-indoors.

The use of mmWave in 5G networks allows for increased bandwidth, which translates into faster data transfer rates and lower latency among other benefits. However, these frequencies are also more susceptible to blockage by physical objects such as buildings, trees, and other obstacles, which will reduce the signal strength received by the User Equipment (UE). This can lead to coverage holes, which can impact the quality of service experienced by end-users. Overall, a proper diagnostic of the 5G network is essential for MNOs to effectively cope with coverage issues and consequently enhance end-user's experience. Some of the common coverage issues in mobile networks are overshoot coverage, weak coverage, pilot pollution and coverage holes, among others [2]. A coverage hole refers to an area where the signal level of the serving cell is insufficient to maintain basic service, such as the Signaling Radio Bearer (SRB) and Downlink Shared Channel. Coverage holes can be caused by various factors, including physical obstructions like new buildings or hills, unsuitable antenna parameters, or inadequate RF planning [3].

When a UE is located in a coverage hole, it may experience call drops and radio link failures, which can negatively impact the user experience. In the literature there are several methods for detecting coverage constrained areas in 5G networks, including coverage analysis, performance measurements, drive testing and crowdsourced data [2]. In fact, by means of the Minimization of Drive Tests (MDT) functionality [3], MNOs are able to collect radio network measurements that allows to identify issues such as coverage holes, handover problems, interference, etc. Therefore, this data can be used for network optimization purposes. For instance, the authors in [4] analyzed network performance data to detect weak coverage regions in where to place new base stations. They used a clustering technique known as Density-Based Spatial Clustering of Applications with Noise (DBSCAN). By identifying the coverage constrained areas, MNOs can take steps to mitigate the impact of coverage gaps, such as deploying additional base stations, adjusting the frequency and power of the signals transmitted, or making use of Device-to-Device communication (D2D), among others techniques as stated in survey [2].

In recent years, the evolution of network infrastructure and UEs technologies have been significant, resulting in the availability of UEs with powerful communication and computational capabilities. In that respect, D2D communication technique becomes a feasible option to solve coverage issues. For instance, the study in [5] has shown that the use of Relay UEs (RUEs) can provide significant benefits for MNOs by reducing the number of base stations required. The idea of using relays has been a topic of research for some time (see e.g., [6]). 3GPP has also studied the use of UEs to relay data in [7] and has added it as a connectivity model in [8]. This interest in UE-to-network relaying is reflected not only in standards but also in studies such the recent survey [9]. Different works in the literature have studied the use of relay capabilities to enhance network coverage. For instance, [10] proposed a functional framework for RUE activation based on characterizing potential RUEs using a utility metric that assesses the improvement in network coverage when the RUE is activated. In [11] an underlying D2D multi-hop relay-aided scheme has been proposed to improve the coverage capacity.

In view of the above, this paper focuses on two main objectives. Firstly, the detection of coverage holes in base stations, and secondly, the resolution of these coverage holes by means of the proper activation of relays. The activation of the RUEs must be done according to the potential benefits brought by the activation given the network dynamics. Therefore, a key factor to consider at the time of designing an efficient solution to the coverage holes and RUE activation problem is the space-time traffic distribution of the network. This can be influenced by factors such as the density of UEs, the availability and quality of network coverage. The temporal distribution of traffic is also influenced by the time of day, day of the week or even for occasionally UEs concentrations in sporadic events such as in concerts, meetings, etc. Overall, understanding the space-time traffic distribution is critical for MNOs to effectively manage network resources and optimize network performance. In that respect, we consider all these factors at the time of designing the network coverage enhancement by means of RUE activation. To approach the aforementioned aspects, the paper relies on the use of two main tools: DBSCAN algorithm [12] for the detection of coverage holes and on the Deep-Q Network (DQN) [13] technique for the coverage enhancement by means of activation of RUEs. To the authors' best knowledge, the combination of DBSCAN and DQN techniques to detect coverage holes considering space-time traffic distributions and resolve it by means of RUEs activation has not been previously explored and therefore this constitutes the main novelty of this paper.

The rest of the paper is organised as follows. Section II presents the system model and formulates the considered problem. The proposed DBSCAN-DQN-based solution is presented in Section III and different performance results are provided in Section IV. Finally, Section V summarises the conclusions.

II. System Model and Problem Definition

The scenario under consideration consists of a RAN that includes a Base Station (BS), the Core Network (CN), and the Service Management and Orchestration (SMO) system, which enables the configuration and monitoring of the network's performance, as used for example in the O-RAN architecture [14]. The considered approach can be split into two stages: the coverage hole detection and the solution of this by means of RUE activation as depicted in Fig. 1. Both processes are described in detail in sections III.A and III.B respectively. Once the coverage holes have been detected, the next step is to find a solution to this problem. In this respect, this work considers the option of activating some UEs to act as relays for other UEs. In this manner, a UE can communicate with the Core Network either through a direct connection with the BS or through a RUE, as illustrated in Fig. 1. For a UE to be considered as a candidate RUE that can be activated to act as relay, it must meet certain conditions. For example, it should remain stationary for a long period of time and outside of a coverage hole, have good enough signal quality, and have a battery level above a certain threshold. Additionally, there must be an agreement between the MNO and the UE holder. The latter is outside the scope of this work, but can be based for example on incentivizing strategies for the UE holder as explained in [9].

The SMO system features a Relay Activation Management (RAM) function that decides when, where, and under what circumstances a UE connected to a BS is eligible to be activated as a RUE. The activation of RUEs for a specific BS is performed by the RUE activation controller (RAC) within the RAM function of the SMO. The RAM, in turn, holds a database with a list of candidate RUEs and their associated information, such as position, ID, mode (i.e. active or inactive), and availability probability based on the time of day. This data together with specific performance measurements collected from the network constitute the inputs to the RAC, so that it can decide when to activate the RUEs, as depicted in Fig. 1.

To formally address the problem, let us consider a UE located in the coverage area of a given base station. If the UE has a direct connection with the BS, the spectral efficiency S_D can be calculated using the Shannon formula.

$$S_D = min\left(S_{max}, log_2(1+SINR_{BS\text{-}UE})\right) \quad (1)$$

where S_{max} value represents the highest spectral efficiency achievable by using the Maximum Modulation and Coding Scheme (MSC) defined in 5G NR [15]. Meanwhile, $SINR_{BS\text{-}UE}$ refers to signal to interference and noise ratio (SINR) in the connection between the UE and the BS. In case that the UE is communicating with the BS through an activated RUE, the spectral efficiency S_R is limited by the link with the poorest conditions between both the BS-RUE and RUE-UE links.

$$S_R = min\left(S_{max}, log_2\left(1+min(SINR_{BS\text{-}RUE}, SINR_{RUE\text{-}UE})\right)\right) \quad (2)$$

where $SINR_{BS\text{-}RUE}$ and $SINR_{RUE\text{-}UE}$, denote the SINR in the BS-RUE and RUE-UE links, respectively. A UE is considered in outage when its spectral efficiency falls below a specified minimum threshold (S_{min}). Only in that case ($S_D<S_{min}$) the UE will attempt to connect to an activated RUE. The RUEs with a spectral efficiency less than S_{min} are assumed unavailable for activation.

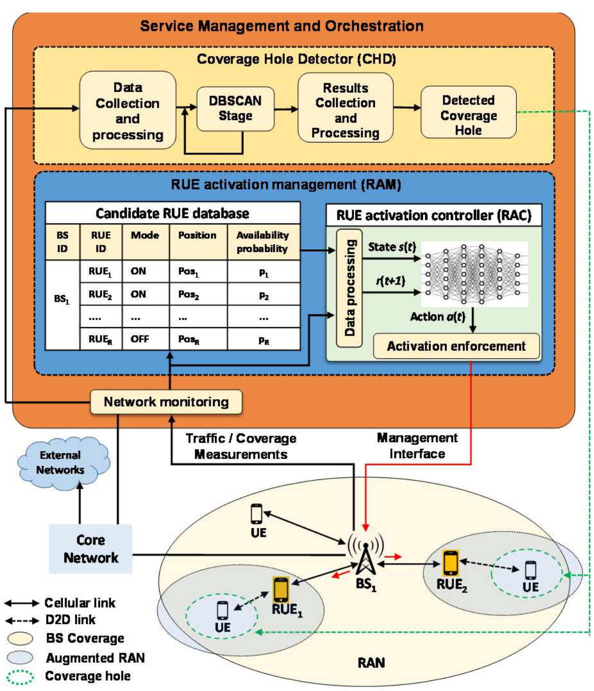

Fig. 1. Architectural components of the considered approach

Regarding the RUE activation problem, let us consider a base station b. Within the coverage area of the base station, there are a number of DBSCAN-detected coverage holes, numbered as z=1,…,Z. To solve them, it is assumed without loss of generality that there is a number of R candidate RUEs to cover each region. These are numbered as r=1,…,R. The r-th candidate RUE of the z-th region has a status mode of $a_{b,z,r}$={0,1} where 0 means that the RUE is deactivated and 1 means it is activated. Therefore, the global status mode configuration associated to BS b can be defined as the $Z{\cdot}R$-length vector $\mathbf{C_b}=\{a_{b,z,r}\}$. The objective of this approach is to find a policy that optimally activates the RUEs, which means to find the optimum configuration $\mathbf{C_b}(t)=\{a_{b,z,r}(t)\}$. It is assumed that these decisions are made in discrete time instants t with granularity ΔT s. These discrete times are denoted as t, t+1,..., t+k,...

The criterion to consider a configuration $\mathbf{C_b}(t)$ as optimum is based on the so-called U_z factor. This metric indicates whether or not it is useful to have a RUE in active mode in a particular zone. It takes a value of 1 when the number of UEs with an active session in a z region is above a given threshold U_{thd} or when the percentage of UEs in outage being served by BS b exceeds an established threshold O_{thd}. Otherwise, U_z=0. This is based on the assumption that the concentration of users in z regions follows a time pattern and is not constant throughout the day and, therefore, the activation of RUEs it only required at particular time periods of the day. Overall, the global efficiency of a given configuration can be computed based on the next criterion: let us define $N_{b,z}(t)$ as the number of RUEs designated to cover a z region that are in active mode given $\mathbf{C_b}(t)$. The RUE activation efficiency of the z-th region can be obtained as follows:

$$E_z\big(a_{b,z,r}(t)\big) = \begin{cases} 1 \;\; if \;\; \begin{cases} N_{b,z}(t)>0 \;\; and \;\; U_z=1 \\ N_{b,z}(t)=0 \;\; and \;\; U_z=0 \end{cases} or \\ 0 \;\; if \;\; \begin{cases} N_{b,z}(t)=0 \;\; and \;\; U_z=1 \\ N_{b,z}(t)>0 \;\; and \;\; U_z=0 \end{cases} or \end{cases} \tag{3}$$

The expression captures different situations. For example, when there is a number of users greater than U_{thd} in a region with limited coverage (U_z=1) and there are RUEs in active mode $N_{b,z}(t)$>0, this combination results beneficial, so the efficiency is 1. In the same way, the function captures non-beneficial combinations, for instance, when there is a concentration of UEs in a z region fewer than U_{thd}, which means that U_z=0 and there are RUEs in active mode. The latter can represent a waste of resources, so the efficiency is 0. In general, (3) intends to measure the pertinence of relay activation given the network dynamics throughout the day. In view of the above, the formal problem to optimize is the maximization of the global efficiency, G_{eff}, given a configuration $\mathbf{C_b}(t)$ while maintaining the system outage probability O_{prb} below a threshold O_{thd}. It is defined as follows:

$$G_{eff} = \frac{1}{Z}\left[\sum_{z=1}^{Z} \frac{1}{R}\sum_{r=1}^{R} E(a_{b,z,r}(t))\right] \qquad s.t. \; O_{prb} < O_{thd} \tag{4}$$

III. Proposed Solution

The proposed solution is based on two main techniques which are described in the following subsections.

A. DBSCAN algorithm

This algorithm works by grouping together points in a dataset that are close to each other and identifying outliers as noise. The inputs of the algorithm consist of two parameters, *db_epsilon* and *min_samples*. *db_epsilon* defines the radius around each point that should be considered as part of a cluster and *min_samples* defines the minimum number of points required to form a cluster. The algorithm starts by selecting an arbitrary point and expanding the cluster by finding all the neighboring points within *db_epsilon* distance. If there are at least *min_samples* points within this radius, a new cluster is formed. Otherwise, the point is marked as noise. Next, the algorithm proceeds to the next point and repeats the process until all points have been assigned to a cluster or marked as noise. Further details on this process can be found in [12].

The proposed solution consists in 4 stages (see Fig. 1). In first stage by making use of, for example MDT procedures [3], data is collected from network users such as, location, received signal level, channel quality indicators (CQI) that is mapped to spectral efficiency, signal-to-noise-ratio (SNR), etc. Then, it is processed this information to filter the information of users experiencing signal quality levels below a certain threshold and to adapt this data to the format required by the DBSCAN algorithm. The second stage consists in applying the DBSCAN algorithm. The result of the algorithm are clusters that contain the users with poor signal quality in a given geographical area, so each cluster represents a coverage hole. Since the area of a cluster can have arbitrary shapes and sizes, it is characterized by the coordinates of a centroid and by an estimated radius from the centroid to the farthest point of the cluster. The second stage is executed different times (C_{ex}) with different source data (e.g. measurements of different days). The third stage involves analyzing the data obtained in the second stage and validating the clusters. To validate the presence of a cluster, it is computed the euclidean distance between the centroids of different executions. Specifically, if the distance between the centroid of the first execution and the centroids of the other executions is less than r_p% of the length of the radius of the first execution, then the cluster is considered valid. In the fourth stage, the data from the detected clusters is stored in a coverage holes database.

B. DQN-based solution for RUEs activation

Designing an effective solution to activate RUEs is a complex task that requires considering several variables, including the current status mode of RUEs, the propagation conditions of RUEs, the changing probability of being available of RUEs, users' concentration at z regions and the traffic dynamics. To tackle this multidimensional challenge, this paper proposes the use of Deep Reinforcement Learning (DRL) as a means of addressing the RUE activation problem. DRL techniques combine deep neural networks (DNN) and reinforcement learning (RL) to assist a software-based agent in making decisions. Specifically, among DRL techniques, the Deep Q-Network (DQN) algorithm in [13] is selected to address the problem at hand.

The proposed DQN approach allows learning the policy π that dynamically activates/deactivates the RUEs in a BS according to the varying conditions in the BS. The learning of this policy is a dynamic process in which the RAC controller containing the DQN-agent (see Fig. 1) makes decisions for the RUEs of the different regions. At time t the DQN-agent performs an action $\boldsymbol{a(t)}$ that represents a RUE configuration $\mathbf{C_b}(t)$ to be applied in the next time window of duration ΔT. The decision of taking a specific action depends on the current state observed at time t, denoted as $\boldsymbol{s(t)}$, as well as the policy π that is available at that particular moment. After applying the chosen

RUE activation configuration, the DQN agent is provided with a reward signal, denoted as $r(t+1)$. This signal evaluates the efficacy of the performed action and is consequently employed over the time to enhance the decision-making policy π. Below are presented the descriptions of the main elements of the DQN-based solution.

The state $\boldsymbol{s}(t)$ is a vector associated with a specific base station b, and consists of the components described in the following:

- $Seff(t)=\{S_{b,z,r}(t)|z=1,...,Z,\ r=1,...,R\}$ represents the spectral efficiency of the RUEs in base station b, computed according to (1).
- $C_b(t)=\{a_{b,z,r}(t)|\ z=1,...,Z,r=1,...,R\}$ denotes the configuration of all RUEs at time t.
- $P_b(t)=\{P_{b,z,r}(t)|z=1,...,Z,r=1,...,R\}$ refers to probability of a RUE of being available at time t.
- $N_b(t)=\{N_{b,1}(t),\ N_{b,2}(t),...,N_{b,Z}(t)\}$ denotes to the number of UEs with active session located inside of the Z regions at time t.

The total number of components of the state is $Z(3R+1)$.

An action $\boldsymbol{a(t)}\in\mathcal{A}$ can be seen as a vector $\mathbf{C_b}(t)=\{a_{b,z,r}(t)\}$ containing the relay activation configuration applied every time window ΔT. The action space $\mathcal{A}$ encompasses all valid activation configurations. Since each RUE can either be activated or deactivated (two modes), the total number of feasible actions in the action space is equal to $2^{Z\cdot R}$.

The reward function $r(t+1)$ assesses the effectiveness of the action $\boldsymbol{a(t)}$ with respect to the optimization goal (3) for the state $\boldsymbol{s}(t)$. It provides a quantitative measure of the quality of the obtained performance, indicating whether it was favourable or unfavourable. The reward is defined as:

$$r(t+1)=\frac{1}{Z}\left[\sum_{z=1}^{Z}\frac{1}{R}\sum_{r=1}^{R}E(a_{b,z,r}(t))\right]\cdot\min(1,\frac{O_{thd}}{O_{prb}}) \quad (5)$$

The function has two terms: the first represents the relay global efficiency for the applied action $\boldsymbol{a(t)}$, while the second acts as a penalty. The second term is only activated if the global outage probability O_{prb} exceeds the established outage threshold O_{thd}. However, if O_{prb}=0, the second term has a fixed value of 1.

The decision-making policy π is dynamically learned by the DQN agent through the rewards received from previous decisions. This is done by implementing the DQN algorithm described in [13], particularised to the state, action, and reward signals mentioned above. The algorithm aims to maximize the expected discounted cumulative reward (i.e., the Q-value) by using a deep neural network (DNN) denoted as $Q(s, a, \theta)$ with weights θ. It approximates the optimal action-value function. The decision-making policy selects the action with the highest Q-value for a given state. The policy is updated based on experiences gathered by the DQN agent, which selects actions with the highest Q-value for a given state. The agent stores information about the state, action, reward, and new state in an experience dataset, which is used to update the evaluation DNN's weights. The detailed process can be found in [13].

IV. PERFORMANCE EVALUATION

This section evaluates the performance of the proposed solution through system-level simulations. The considered scenario is a 200 m x 200 m square area consisting of one 5G NR BS. The traffic generation of UEs assumes a Poisson session arrival process with average generation rate 0.6 sessions/s and exponentially distributed session duration with average 120s. The generated UEs are assumed static for the entire duration of its session. The key parameters of BS are shown in Table I. The scenario considers four candidate RUEs.

TABLE I. BS AND RUES CONFIGURATION PARAMETERS

Parameter	Value	
Type of RAT	5G NR	Relay UEs (RUEs)
Position [x, y] m	[100,100]	[30,130] [33,86] [151,115] [154,93]
Frequency	26 GHz	3.5 GHz
Channel bandwidth	100 MHz	100 MHz
Transmitted power	21 dBm	21 dBm
Transmitter Antenna	26 dB	3 dB
Height	10 m	1.5m
UE antenna gain	10 dB	
Outage threshold	5%	
UE noise figure	9 dB	
UE height	1.5m	
Path loss model	Model of Sec 7.4 of [18]	UE-to-UE propagation model of [19]

A. Performance evaluation of the DBSCAN-based coverage hole detection

The detection of coverage holes is carried out by collecting data from five days of network operation. To that end, the data of the sessions generated between 8:00 a.m. and 20:00 p.m. during these 5 days has been collected and processed in order to find the location of users experiencing $S_D<S_{min}$ where S_{min}=1 (see section III.A). The hyperparameters used for the DBSCAN algorithm were *db_epsilon*=0.3 and *min_samples*=35 which means that along a day there must be as minimum 35 UEs in outage with locations close to each other to be consider that area as a coverage hole. For the validation of clusters, the considered parameters are: C_{ex}=5 and r_p=0.25. Based on the described parameters, the CHD detected two coverage holes (Z=2) with centroid in coordinates [12, 99] and radius of 16 m, and with centroid in [172, 85] a radius of 23 m. Fig.2 depicts the map of spectral efficiency of the base station and the detected coverage holes that satisfied *db_epsilon* and *min_samples*. The model has been developed in Python by using the machine-learning library *scikit-learn* [16].

B. Performance evaluation of the DQN-based strategy

In the following we assess the DQN-based RUE activation strategy. The positions of the four candidate RUEs are shown in Fig. 2b. The availability of each RUE is modeled by a probability that varies between 0.85 and 0.99 depending on the time of the day. The scenario considers the RUE activation in the period between 8:00 a.m. and 20:00 p.m. To model the space-time traffic distribution, each coverage hole z of the scenario has a probability 20% that the generated sessions appear within its area. This probability is applicable during certain time periods of the day according to a specific temporal pattern (e.g. 9:00-11:30 a.m.; 15:30-17:00 p.m., etc.). During the other periods the sessions are uniformly distributed in the whole scenario. It is worth noting that each coverage hole follows a different temporal pattern.

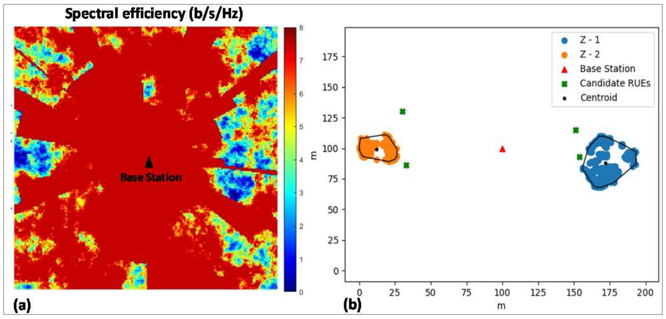

Fig. 2. (a) Map of spectral efficiency; (b) DBSCAN-detected coverage holes.

Based on the described scenario, a training process was conducted. Every 500 training steps, the current policy of the DQN agent was obtained and evaluated in a particular scenario with a given space-time traffic distribution. By conducting evaluations every 500 Training Steps under the same conditions, the results were comparable. The output of each evaluation was an average reward value. This process was repeated until MaxNumberOfTrainingSteps when the average reward values converged. The model has been developed in Python by using *TF-agents* library [17]. The DQN parameters are detailed in Table II. For details of the meaning of these parameters the reader is referred to [13].

TABLE II. DQN ALGORITHM PARAMETERS

Parameter	Value
Initial collect steps	500
MaxNumberOfTrainingSteps	200000
Experience Replay buffer	100e3
Mini-batch size (J)	64
Time window (ΔT)	60 s
DNN updating period (P)	500 Training Steps
Discount factor (τ)	0.9
Learning rate (α)	0.0001
ε value (ε-Greedy)	0.1
DNN architecture	Input layer: 14 nodes Two hidden layers: 100 and 50 nodes Output layer: 16 nodes

Aiming at assessing the obtained policy after the training process, our proposed strategy for RUE activation is evaluated and compared against two reference approaches denoted as *All-RUEs deactivated,* which can be considered as the classical RAN in which no RUE capabilities are exploited, and the *All-time active* strategy, which keeps one RUE active all the time for each *z*-region (except when no RUE is available). The obtained DQN policy along with the two reference strategies have been evaluated during 20 days characterized by different space-time traffic distributions.

Fig. 3 shows the global efficiency of the RUE activation process for each day. The *DQN-based activation* results achieve higher efficiency than the reference approaches, as it activates or deactivates RUEs based on the network dynamics. The efficiency of this strategy is above 90% practically all the time. In fact, on average it achieves 92.5%, while the *All-RUEs inactive* and *All-time active* strategies achieve 42% and 43.7%, respectively. To assess performance in terms of outage, Table III reports the outage efficiency, given by the probability during that the global outage probability O_{prb} is maintained below O_{thd}. It is observed that the *All-time active* strategy achieves the highest efficiency, which is expected since the RUEs are always active. However, the difference with the DQN strategy is only 4.7%. In contrast, with the *All-RUEs inactive* strategy, the outage efficiency is only 44.8%, while *DQN-based activation* strategy reaches a value of 93.7% representing an improvement of slightly more than the double. Regarding the system outage probability, in Table III is shown that, the *All-RUEs inactive* strategy results in an outage probability of 6.4%, while the *DQN-based activation* strategy and the *All-time active* strategy result in 1.3% and 0.4% respectively. The use of relays leads to a significant reduction of 5.1% in the outage probability for UEs, compared to not using relays. Note how there is only a slight performance difference of approximately 1% between maintaining RUEs active all the time and conducting activation based on the DQN strategy.

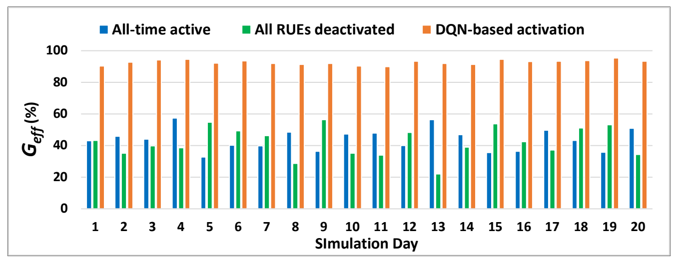

Fig. 3. Comparison of global efficiency for different activation strategies

There is a remarkable reduction in the time that relays remain in active mode when using our proposed strategy in all the evaluated days. Fig. 4 shows that the *All-time active* strategy clearly maintains the relays in active mode for a significantly longer amount of time than the *DQN-based activation* strategy. In fact, *All-time active* strategy uses the relays for an average of 22.7 hours per day, but this value is significantly reduced to 9.75 hours when using *DQN-based activation* strategy, which implies a time reduction of around 57%. Overall, the proposed strategy achieves important reductions in the time that RUEs are active in all evaluated days, also representing a significant reduction in energy consumption.

TABLE IIII. OUTAGE PERFORMANCE OF DIFFERENT STRATEGIES

Activation Strategy	Outage Efficiency Prob($O_{prb} < O_{thd}$)	Outage Probability
All-time active	98.47%	0.4%
DQN-based activation	93.72%	1.3%
All-RUEs deactivated	44.89%	6.4%

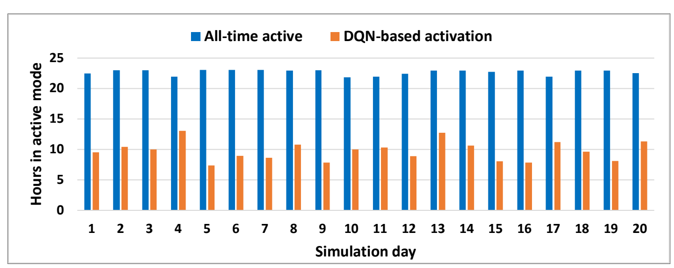

Fig. 4. Number of hours in active mode for different activation strategies

An efficient activation strategy has the potential to impact network performance in terms of spectral efficiency. In that respect, Fig. 5 shows the cumulative distribution function (CDF) of the spectral efficiency values obtained over the 20 days of evaluation. The *All-time active* and *DQN-based activation* strategies exhibit highly similar distributions, achieving minimum spectral efficiency values of 3.98 b/s/Hz and 3.88 b/s/Hz, respectively. In contrast, the *All-RUEs inactive* strategy yields a minimum spectral efficiency value of 2.6 b/s/Hz, which is approximately 33% lower than the *DQN-based activation* strategy. However, the *DQN-based activation* strategy dramatically reduces the time RUEs spend in active mode. Specifically, our proposed strategy achieves similar performance to the *All-time active* strategy in terms of outage probability and average spectral efficiency, but using RUEs an average of 57% less time. This is a remarkable effect that demonstrates the importance of a proper coverage holes detection as well as the efficient use of relays of our strategy.

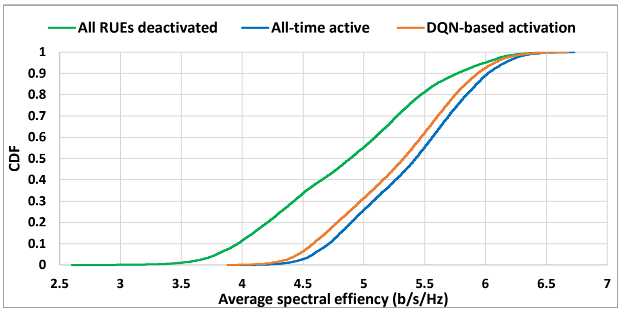

Fig. 5. CDF of spectral efficiency obtained for different activation strategies

V. Conclusions

This paper has proposed a novel approach to detect and solve coverage holes in 5G networks. It is proposed a coverage hole detector (CHD) based on the DBSCAN clustering algorithm, which is able to delimit the regions experiencing lower levels of signal quality by analyzing users' performance and data processing. Once the regions are detected, it is proposed to activate relay capabilities of the User Equipment (UE) to enhance the coverage. The relay activation stage is based on a Deep-Q Network (DQN) algorithm to learn from the network's behavior and develop an efficient RUE activation policy through a training process. The proposed approach has been evaluated by means of system-level simulations and compared to other two reference solutions. Results indicate the capability of the proposed DBSCAN-based approach to efficiently detect the coverage holes, since given the detection combined with the relay activation strategy allowed to reduce the system outage probability and increasing the spectral efficiency experienced by network users. The DQN-based approach uses relays with an average efficiency of 92.57%. In comparison, when RUEs remain inactive all the time the efficiency is 42%, while with RUEs always activated it is 43.7%. This highlights the importance of using or not the RUEs depending on the network dynamics as our solution does. In terms of maintaining the outage probability below an allowed system outage level, our approach achieves to keep it below the 93.7% of the time, achieving more than twice the efficiency with respect to its comparative approach. A remarkable result is the capability of our DQN-based strategy of keeping the RUEs active when it is efficient to do it. In that matter by using our strategy is possible to reduce the time in active mode of the RUEs in average 57% with respect to the *All-time active* case. This brings benefits for MNOs, UE holders and in terms of significant energy savings.

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