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***Abstract*—Resilience is defined as the ability of a network to resist, adapt to and quickly bounce back from disruptions, to continue keeping an acceptable level of service from users' perspective. To characterize and analyse the resilience of a 5G Radio Access Network, it is vital to be able to measure current and prospective resiliency levels using relevant metrics. In this work, we perform an analysis and a quantification of 5G-RAN resilience based on radio coverage indicator and one of the Quality of Service indicators, namely the service integrity. They are considered as the main performance indicators for network planners and operators. In this objective, we model network states using the performance indicators, Reference Signal Received Power and Received User Equipment Throughput. Then, we use them to build Markovian models and to define resilience metrics. By means of simulations, we evaluate the ability of our analytical model to accurately capture network resiliency levels. We discuss numerical results from multiple usage scenarios to show how the resilience metrics can be used to identify potential outages and to help network planners or operators deciding on which adequate adaptive resilient mechanisms to deploy.**

***Index Terms*—Resilience, Coverage, QoS, CTMCs, Quantification, Outage prediction, 5G RAN, RSRP, throughput**

I. Introduction

Most RAN resilient mechanisms (e.g. Cell Outage Compensation (COC) or Self-Healing as a function of Self Organizing Networks (SON) [1, 2]) don't quantify the improvements observed within the network. As a consequence, the majority of resilience solutions in the RAN domain purely qualitative. Thus, current efforts are not enough to protect totally the radio environment from failures, service blackout and bad Quality of Service (QoS). In fact, according to the Regulatory Authority for Electronic Communications, Posts and Press Distribution (ARCEP), an average repair time of 46 hours was recorded in 2021 for 85% of quickly detected anomalies [3]. For the sake of effective resilience management, the first and crucial step to be done is resilience analysis [4]. Frequently, the resilience of systems is analyzed using historical data and provide resilience measurements using quantitative methods before site deployment [5]. In this work, we extend this concept to manage resilience in RAN with a proactive strategy, during service delivery based on real time data collection. We assume that in the future, network providers or operators will need to define the network resilience requirements in Service Level Agreement (SLA) contracts based on target attributes.

Analysing and measuring the global network resilience in RAN is related to the analysis of relevant network Key Performance Indicators (KPIs) like coverage and QoS. In fact, any downtime in the network can be noticeable on the service indicators and the users experience. In the continuity of [6], we propose a quantitative analysis method of resilience using Continuous Time Markov Chains (CTMCs) to model network states with coverage and QoS. Coverage is an initial indicator that an operator considers when commercializing cellular communication networks due to its direct impact on service [7]. In this work, we focus, in addition to coverage indicator, on the throughput since it is a crucial indicator to check the integrity of data services and thus it helps us to determine as a first step the QoS [8], especially for Enhanced Mobile Broadband (eMBB) services like high-speed internet access or streaming videos 4k, 8k, or live Virtual Reality (VR).

To study the network resilience, we investigate two types of Markov chains numerically to assess both radio coverage and service integrity over a service area. For that, we rely on the Reference Signal Received Power ($RSRP$) [9] and the received User Equipment (UE) throughput measurements. We validate the models over realistic simulated scenarios of wireless transmission within a 5G RAN. Moreover, we propose two resilience metrics to characterize the network's resiliency in terms of coverage and QoS and try to predict the network status and risks of outage. Studying different resilient metrics based on distinct indicators would help engineers or automatic healing mechanisms understanding what is happening on the network layout, assessing precisely the impact of the failures and providing the most appropriate solutions according to the operator's policy. This analysis represents a first step towards global resilience management that can be enabled via a resilience framework in a 5G-RAN architecture (Fig. 1). The framework was discussed in [6], and will be briefly reviewed to demonstrate the usability of our work. The rest of the paper is structured as follows. Section II discusses related work about resilience analysis in the RAN domain. Section III describes briefly resilience overview in RAN domain and presents the performance indicators. In Section IV we present resilience analysis using Markov processes for modelling network states to obtain relevant resilience metrics for our quantitative analysis. In Section V, we validate our analysis method using simulations in different scenarios, quantify the outage risk, predict the network resiliency and discuss the results. Conclusions are given in Section VII.

II. Related Work

Resilience is not a simple binary view of the system, but it is always a matter of degree [10]. In RAN, there is no common and well-defined resilience metrics and analysis method. Early work in this area [11] defined resilience in terms of nodes disconnection probability. [5] and [12] extract resilience metrics directly from data and express them in terms of reliability or availability over a period of time. However, the methods proposed are not flexible and reproducible (require to store data to recompute metrics). Furthermore, they give resilience only at time t without prediction. In the literature, modeling is a widely used tool to characterize the behaviour of repairable systems. CTMCs were used in [13] to capture high level status of Base Stations (BS), but without checking practically the status with KPIs and [6] provides a theoretical study based on the coverage indicator only. In this work, we extend our previous study [6] to both coverage and throughput indicators and provide a simulation based CTMC evaluation. This analysis method is reproducible (store only the model to recompute metrics) and can be combined with failure mitigation mechanisms (e.g. COC) using our framework.

III. RAN Resilience Context

In this section, we give an overview of the resilience management scheme deployment in a 5G architecture while focusing on the resilience analysis part of coverage and QoS.

A. 5G cellular network architecture: Resilience Framework

Consider a 5G network architecture comprising multiple macro cells (MCs) and a large number of small BSs that handles multiple heterogeneous devices. User Equipments (UEs) are connected to Radio Units (RUs), which send information to the 5G network via the Distributed Unit (DU) and then to the Control Unit (CU) (Figure 1). The management plan of the radio system is executed by the Network Management System (NMS). This module can integrate a resilience management framework that performs proactive resilience analysis of a group of cells, a geographical area or a slice [6]. Using network performance indicators and data logs collected from BSs, the analysis module allows predicting outages and quantifying their impact. Afterwards, the estimation process is responsible for decision making on the suitable actions that improve the network resilience. We focus on the analysis module.

B. Coverage and service KPIs: $RSRP$ and throughput

A geographical area is considered as covered when the UE is able to connect to its mobile network, establish and maintain a session for a minimum period of time. In the one hand, the UE connection to network requires to receive a signal strength from BS above an acceptable threshold. In the other hand, to maintain a good connection and access a service, the UE should achieve a specific data transmission speed (i.e. throughput or data rate) over the connection established. For 5G, the Channel State Information (CSI) - radio received signal $RSRP$ is a valuable layer 1 measurement to provide an information about the signal strength received by users and the radio coverage within a service area. It is defined as a linear average over the power contributions (in Watts) of a single Reference Signal (RS) resource element (in dBm) [9]. Besides, throughput (in Kbps) gives indication about QoS of the user session. It depends on the bandwidth, channel quality and the Resource Blocks (RBs) allocated.

	Classification	$RSRP$ **(dBm)**
RF Conditions	Good (or excellent) Fair (Mid cell) Poor(Cell Edge)	-90 to -44 -126 to -91 -140 to -127

TABLE I: Radio RF condition configuration ($RSRP$)

For $RSRP$, we assume a set of UEs are randomly distributed within a coverage area. We split users into 3 categories according to their levels of $RSRP$. Figure 1 shows UE positions for each $RSRP$ level category. We denote by $x = x(t)$, $y = y(t)$ and $z = z(t)$ the percentage of users that has *Good, Fair* and *Poor* levels of $RSRP$ respectively at t, where the sum of all percentages is equal to 100%. We investigate one possible configuration type of $RSRP$ levels, which radio conditions are given in Table I. For throughput, we denote by D the requested data rate for a given service, and by Th the throughput achieved per UE. Let $d = d(t)$ be the percentage of users receiving at least the requested data rate. Both $RSRP$ and Th are used in the Markov models.

IV. Network Resilience Analysis

In this section, we present the analysis of the network resilience using CTMCs. They are based on stochastic processes allowing to characterize and predict network status.

Methodology for resilience analysis and quantification

(A) Definition of Markov models (states and transitions) to characterize coverage and QoS status evolution.
(B) Markov models analysis: Transition rates computation from data logs, state probabilities distributions analysis, and models validation over simple metrics.
(C) Quantification of network resilience and analysis of radio coverage and service integrity using resilient metrics.

A. Model Development

We propose two CTMC models to represent the different network states of L 5G cells in a given geographical area. Let $X_{RSRP}(t)$ and $X_{Th}(t)$ be the CTMC models that capture radio coverage and service integrity states using $RSRP$ and Th of all users, respectively. Both models have 5 states with full transitions. Due to their similarities, we define the generic CTMC model $X(t)$ (see Figure 2) with finite state space $S = \{G = “Good'', F = “Fine'', A = “Acceptable'', P = “Poor'', O = “Outage''\}$. We call G, A and O the “main states” and F and P the “intermediate states”. This classification allows having a fine grained observation for a better anticipation of outages. The states are defined differently for each indicator ((a) and (b)) as follows:

(a) Radio coverage: We define each state in terms of the tuple (x, y, z) previously described within the coverage area of a gNodeB. We set out to 5% the admissible percentage of users, that receive an $RSRP$ below the threshold associated with poor $RSRP$. The model considers the radio system to be resilient when the majority of users within a service area

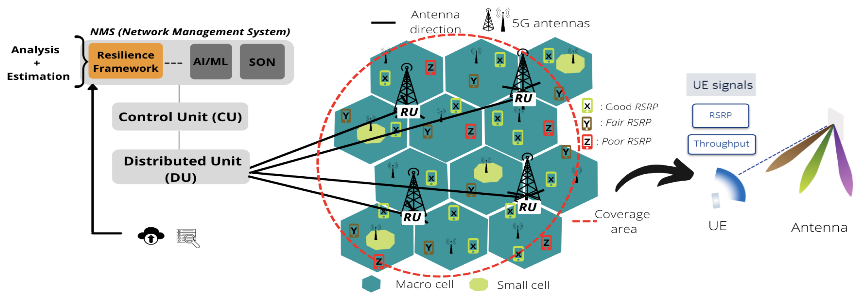

Fig. 1: Coverage area and architecture of 5G cellular sites

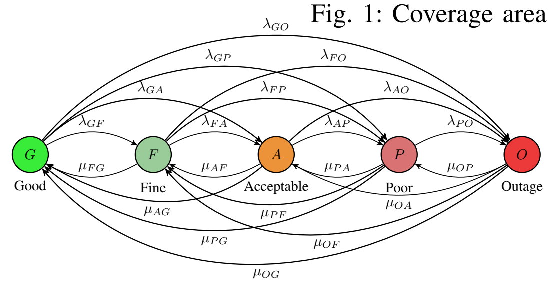

Fig. 2: Markov model of coverage status

enjoy a minimum acceptable coverage threshold specified with $RSRP$ levels given in Table I. This implies that the operator network guarantees a minimal radio coverage of 95% to be resilient. It is directly inspired from assumptions of mobile network radio planning [14]. Thus the states definition:

1) $X_{RSRP}(t) = G$ for *"Good"* if $x > y$, $x \geq z$, $x > y + z$ and if the percentage of users with poor $RSRP$ verifies $z < 5\%$.
2) $X_{RSRP}(t) = F$ for *"Fine"* if $x > y$, $x \geq z$ and the percentage of users with poor $RSRP$ verifies $z < 5\%$ but $x \leq y + z$.
3) $X_{RSRP}(t) = A$ for *"Acceptable"* if $y > x$, $y \geq z$ and the percentage of users with poor $RSRP$ verifies $0 \leq z < 4\%$.
4) $X_{RSRP}(t) = P$ for *"Poor"* if $y > x$, $y \geq z$ and the users percentage with poor $RSRP$ verifies $4 \leq z < 5\%$.
5) $X_{RSRP}(t) = O$ for *"Outage"* if the percentage of users having poor $RSRP$ verifies $z \geq 5\%$.

This means that cells carry traffic with best (resp. fine, acceptable) performances in state G (resp. F, A). In P, they carry some traffic, but with poor performance, and in O, the coverage is at least severely degraded, and possibly with no traffic carried. The reader can verify that all states are fulfilled by the tuple (x, y, z) where all percentage sum is 100%, and the coverage status of the service area can only have one state at a time.

(b) Service integrity: We define each state in terms of users' percentage d that receives at least the requested data rate D, namely $Th \geq D$. The states are defined as follows:

(1) $X_{Th}(t) = G$ if $d \geq 80\%$. **(2)** $X_{Th}(t) = F$ if $65\% \leq d < 80\%$. **(3)** $X_{Th}(t) = A$ if $50\% \leq d < 65\%$. **(4)** $X_{Th}(t) = P$ if $30\% \leq d < 50\%$. **(5)** $X_{Th}(t) = O$ if $d < 30\%$.

Models properties: We use the generic model $X(t)$ for describing both $X_{RSRP}(t)$ and $X_{Th}(t)$. In the proposed Markov models, we classify transitions into failure transitions with rates λ_* and recovery transitions with rates μ_*. The former are perturbations that can degrade the status of coverage (e.g. interference, sleeping cells, disasters) and the latter restore the coverage to optimal states (e.g. coverage enhancement techniques, self-healing, redundancy, compensation or mitigation functions,...). The infinitesimal generator matrix $\mathbf{Q}$ of $X(t)$ is:

$$\mathbf{Q} = \begin{pmatrix} -\alpha & \lambda_{GF} & \lambda_{GA} & \lambda_{GP} & \lambda_{GO} \\ \mu_{FG} & -\beta & \lambda_{FA} & \lambda_{FP} & \lambda_{FO} \\ \mu_{AG} & \mu_{AF} & -\gamma & \lambda_{AP} & \lambda_{AO} \\ \mu_{PG} & \mu_{PF} & \mu_{PA} & -\delta & \lambda_{PG} \\ \mu_{OG} & \mu_{OF} & \mu_{OA} & \mu_{OP} & -\theta \end{pmatrix}, \qquad (1)$$

$$\text{where} \begin{cases} \alpha = \lambda_{GF} + \lambda_{GA} + \lambda_{GP} + \lambda_{GO}, \\ \beta = \mu_{FG} + \lambda_{FA} + \lambda_{FP} + \lambda_{FO}, \\ \gamma = \mu_{AG} + \mu_{AF} + \lambda_{AP} + \lambda_{AO}, \\ \delta = \mu_{PG} + \mu_{PF} + \mu_{PA} + \lambda_{PO}, \\ \theta = \mu_{OG} + \mu_{OF} + \mu_{OA} + \mu_{OP}. \end{cases}$$

B. Markov chain analysis

Compute failure and recovery transitions: To compute the transition rates, we retrieve data logs of $RSRP$ and Th of all users within a service area from the network (in our work from a simulation run). Using the data logs and the states definition, we compute a time series of multiple network states history (a model's trajectory) of coverage or service indicators. Then, the transitions λ_* (or μ_*) from i to j are estimated as follows:

$$\lambda_{ij} = \frac{P_{ij}}{T_i} \quad \text{where} \quad P_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}. \qquad (2)$$

Here, T_i is the total time spent in state i and P_{ij} is the probability to switch from i to j, estimated computing the ratio between the number n_{ij} of transitions that go from i to j and the total number of transitions that exit state i.

Transient and steady state analysis: Using the generator matrix $\mathbf{Q}$, we can obtain the transient states probability vector $P(t) = (P_G(t), P_F(t), P_A(t), P_P(t), P_O(t))$ of the Markov models by solving the Ordinary Differential Equation (ODE) system $P'(t) = P(t) * Q$, and obtain the steady state probability vector $\pi = (\pi_G, \pi_F, \pi_A, \pi_P, \pi_O)$, by solving the linear equation system $\pi * Q = 0$ in the stationary regime.

Markov model validation: To check if the model reflects the input system behaviour and captures the underlying characteristics of data logs and network states, we compare the distributions and the statistical characteristics of the network states delivered from data logs with the states sequences generated and computed from the CTMCs. We compare the distributions using the similarity distance measure Kullback-Leibleir Divergence (KLD), D_{KL} [15]. A measure of entropy between two probability distributions $p(x)$ and $q(x)$:

$$D_{KL}\ (p(x) \mid\mid q(x)) = \sum_{x \in X} p(x) \ln \frac{p(x)}{q(x)}. \tag{3}$$

Moreover, we compute the statistical characteristics of the network states sequences using two reliability basic metrics: Mean time to Repair ($MTTR$) and Mean Time To Failure ($MTTF$) [13]. The former is expressed as the sum of all downtime (i.e. time spent in outage state) over the total number of failures in eq. 4), and the latter is measured as the sum of all uptime (i.e. time spent in operational states) frames over the total number of uptime periods eq. 4). In practice, these metrics are estimated using a standard confidence interval. We choose a confidence interval of 95%.

$$MTTR = \frac{\sum_{i=1}^{n} downtime(i)}{n}\ \ ;\ MTTF = \frac{\sum_{i=1}^{n} uptime(i)}{n} \tag{4}$$

C. Resilience metrics of coverage and service indicators

We propose two different metrics to quantify and estimate the evolution of network resilience within a geographical zone or a service area at the levels of:

- Radio coverage, using the Markov model transient state probabilities $P(t)$ of $X_{RSRP}(t)$
- Service integrity, using the Markov model transient state probabilities $P(t)$ of $X_{Th}(t)$.

– **Radio coverage:** the resilience metric *Global Stochastic Mean* $RSRP$ (GSMR), denoted $\mathcal{M}(t)$, is defined as the mean value of $RSRP$ medians at time t, [6]:

$$\begin{aligned}\mathcal{M}(t) = {} & med_{G_{RSRP}}(t)P_G(t) + med_{(F)_{RSRP}}(t)P_F(t) \\ & + med_{A_{RSRP}}(t)P_A(t) + med_{(P)_{RSRP}}(t)P_P(t) \\ & + med_{O_{RSRP}}(t)P_O(t).\end{aligned} \tag{5}$$

The value of $med_{i_{RSRP}}(t)$ where $i \in S$ is the $RSRP$ median over all UEs distributed between tuple percentage (x, y, z) at each state i, observed between 0 and t. These percentages are associated with $RSRP$ medians of Good, Fair and Poor levels described in Table I. Thus for each statet i, $med_{i_{RSRP}}(t) = med_{Good_{RSRP}}(t) * x + med_{Fair_{RSRP}}(t) * y + med_{Poor_{RSRP}}(t) * z$ and $P_i(t)$ are the state probabilities. In practice, it is preferable to look at lower and upper average bounds of $\mathcal{M}(t)$ where (x, y, z) takes respectively, the lowest and highest percentages at each state configuration.

– **Service integrity:** Based on [12], we propose a resilience metric that measures the network probability of providing at least an acceptable service integrity state over a given period T_c. In other words, where the majority of UEs receives an average throughput greater than the requested data rate D for a given service. It is referred as the *Probability of Achieving the Requested Throughput* (PART) and is expressed as:

$$\mathcal{P}R_{T_c}(t) = \frac{1}{T_c} \int_{t-T_c/2}^{t+T_c/2} \sum_{i \in S_R} \mathbb{P}_i(t)\,\mathrm{d}t, \tag{6}$$

where T_c is a sliding period considered to track the requested throughput availability D using Th of all users, and S_R is the set of states $\{G, F, A\}$ where $d \geq 50\%$.

Remark about the methodology: Once the transition rates in the model are available (derived), the analyst can define and evaluate any kind of new metric (e.g the time spent at set of main states $\{G, F, A\}$) using standard Markov properties.

V. Simulations: Results and discussions

In this section, we will evaluate numerically our resilience analysis strategy detailed in Section IV on two realistic simulation scenarios that contain failures. The simulations are done using SONTool simulator [16], developed and maintained up-to-date on Matlab. The downlink principles of the simulator are presented in [17] and uplink modeling aspects in [18]. We track coverage and service states evolution based on data logs of measured $RSRP$ and Th of all users. Tracking is done over a given area covering 21 cells and during 7 days. For each scenario and using the CTMCs defined in section IV-A, we compute the transition rates of the coverage and service models over the 6 first days data logs using eq.2. Following the analysis detailed in section IV-B, we solve the ODE system to obtain state probabilities $P(t)$. Then, we validate of the Markov models. Finally, we provide results discussion on the prediction of the network resilience using the metrics given in section IV-C. To this end, we compare the resilience metric GSMR that estimates the evolution of mean $RSRP$ with the mean $RSRP$ measured on the 7th day from data logs. In addition, the resilience metric PART will be compared to the *asymptotic availability* of D measured on the 7th day simulation logs to assess the correctness of the prediction. PART gives insights about the availability of the requested throughput for the majority of users within a service area.

Parameter	Value	Parameter	Value
Network type	Hexagonal	Indoor/Outdoor users number	800 / 200
Number of cells	21	Indoor users speed	3-10 KM/h
Inter site distance	200 m	Outdoor users speed	40 Km/h
Number of users	1000	UEs Requested data rate (**D**)	512 Kbps

TABLE II: Network configuration on simulator

(A) Layout, scenarios and network states: We consider a regular hexagonal network layout with the configuration described in Table II. A total of 1000 UEs are uniformly dropped into the whole area. We track the evolution of measured $RSRP$ and Th for UEs moving in the network during one 7 days with SONTool. We collect their traces with a granularity of a 20s time-step for two scenarios $S1$ and $S2$. $S1$ corresponds to a network configuration where outage is more likely to occur and persists for hours. $S2$ is more resilient where outage may occur, but the network can recover

Original x 6 days	**Scenario 1**		**Scenario 2**	
Metric / Indicators	Coverage	Service	Coverage	Service
MTTF(Hours)±	3.36±1.9	2.93±1.9	4.70±2.3	5.08±2.9
MTTR(Hours)±	2.75±1.8	2.10±1.4	0.65±0.2	0.70±0.3
Generated 10 x 6 days	**Scenario 1**		**Scenario 2**	
MTTF(Hours)±	3.67±1.9	3.18±2.2	4.63±2.1	5.35±2.7
MTTR(Hours)±	2.78±1.3	2.09±0.8	0.62±0.4	0.68±0.4
KLD	0.002	0.005	0.003	0.005

TABLE III: Network states characteristics comparison

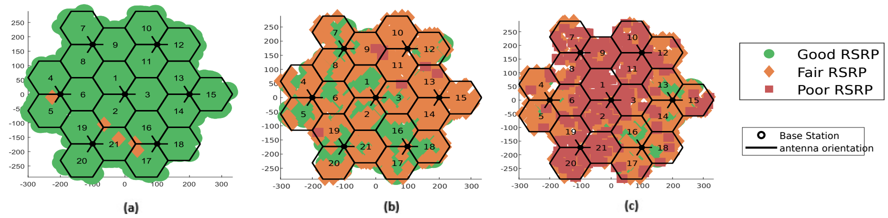

Fig. 3: Snapshots of radio Coverage maps based on UE $RSRP$ values from left to right: (a) Good, (b) Acceptable, (c) Outage

quickly. Failures are simulated using random tuning of antenna sites transmit power (TxPower, P0). Figures 4 and 5 depict the evolution of average $RSRP$ and Th. In $S1$ network is subject to two major failures over a longer time period (around 40h and 120h), whereas $S2$ is subject to multiple downtimes over shorter periods. In the Figures, failure occurrences correspond to poor overall $RSRP$ or Th levels, and their duration includes the time taken to detect, analyse and repair the outage. Using the CTMCs states definition in IV-A, we compute the sequences of average network states each 5 time steps for both radio coverage and service integrity. They are given in Figures 4 and 5 for S1 and S2, and we refer to them as the original state sequences. In each scenario, the coverage state can differ a bit from the service state (e.g. in S1, at 50h, $RSRP$ state is $'A'$ vs. Th state is $'F'$). In fact, outages may have different impact on performance indicators. Thus, studying different indicators helps engineers assessing the overall network resilience according to operator policy. Moreover, to visualise what is happening on the network layout, we show in Figure 3 some snapshots of coverage maps of multiple radio coverage states based on $RSRP$ values.

(B) Transitions computation and Markov models validation: The network states time series of the 6 first days are used to compute failure and recovery transitions (λ_*, μ_*) of S1 & S2 using eq. 2. Some transitions between two states may not be observed and their rates are set to 0. Then, we obtain the 5 states probabilities $P(t)$ for each of the four Markov models (S1, S2) x ($RSRP$, Th), by solving their corresponding ODE systems. For solving the equations, we assume that the network state condition starts at best state 'G'. Before analysing the resilience of network, we first check if the CTMCs capture accurately the behaviour of the network. To do so, we generate 10 times 6 days of network states sequences evolution using the computed $P(t)$ and extract their average statistical characteristics. To this end, we compute the MTTR and the MTTF of equation 4, on original states delivered from simulations and on the generated states computed from the CTMCs. The results are given in Table III for each metric with a confidence level 95%. The one-to-one comparison of each metric reveals that MTTR and MTTF are similar between the original and generated states sequences. It also indicates that MTTR confirms that S2 is more resilient than S1 (i.e. less than 1h vs. 2h average outage duration, respectively). Besides, we derive in Table III the KLD between the distribution of the original states sequences and the distribution of the generated states sequences, $D_{KL}(original, generated)$ in eq. 3. The low value of this metric indicates high similarity between the distributions. From the comparison of these basic metrics, we assume that we have checked that the CTMCs are producing valid output information that corresponds to the behaviour of the network original data input, which is a preliminary validation for the CTMC based resilience quantification.

(C) Quantitative outage estimation: The states probabilities $P(t)$ allow to quantify the risk of outage at time t and predict the network states. Figure 6 shows the evolution of coverage states probabilities for S1 and S2. The curve predicts that S1 has higher outage risk (40-45%) compared to S2 (2-3%). At the same time, S2 has better chances to provide good performances ($P_G(t)$ drops to ∼90%) than S1 ($P_G(t)$ drops to ∼50%) after 3 days. Besides, Figure 7 shows coverage vs. service states probabilities evolution for S1. The engineer can conclude that outage on antennas (failure scenario considered in this work), has more impact on coverage $RSRP$ than on service integrity Th. The same conclusions are driven for S2.

(D) Network resiliency prediction: To get better insights

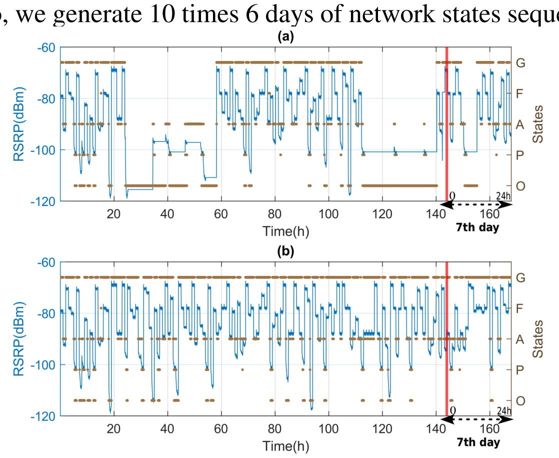

Fig. 4: Average evolution of $RSRP$ and its corresponding radio coverage states sequences: (a) S1, (b) S2.

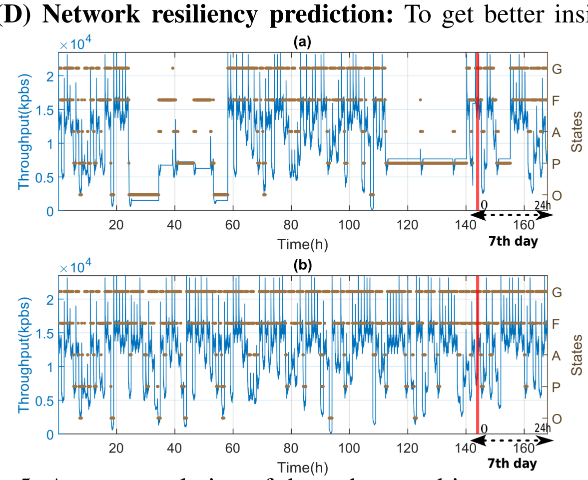

Fig. 5: Average evolution of throughput and its corresponding service integrity states sequences: (a) S1, (b) S2.

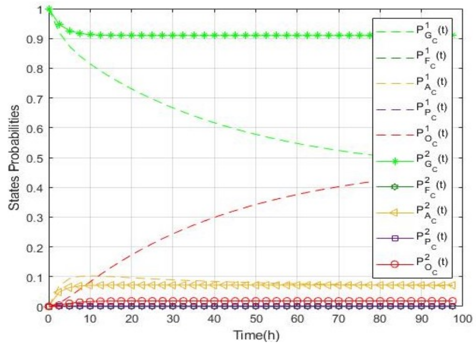

Fig. 6: Evolution of radio coverage states probabilities (S1, S2): $P^1_{i_C}$ and $P^2_{i_C}$ stand for probability of state $i \in S$ of coverage indicator in S1 and in S2 scenarios, respectively.

on the network resilience, engineers can rely on meaningful resilience metrics (expressed in eq.5 and in eq.6) instead of states probabilities. In fact, Figure 8 shows the evolution of resilience metrics GSMR from eq.5 (shaded areas) and PART from eq.6 (lines). The GSMR helps to identify the potential range where the value of mean $RSRP$ is likely to evolve. These stochastic average bounds are given as indicators and not as absolute maximum and minimum values. In Figure 8, we observe that in S1, the GSMR may drop to -95 dBm 12h later. We compare it to the mean $RSRP$ measured at 12h on the 7th day from $RSRP$ data logs. Indeed, this measurement is taken at 156h in Fig.4.a, precisely at 12h after the 6 first days. We observe that, at this time and for S1, the mean measured $RSRP$ drops to -100 dBm. For S2, the GSMR may drop to -92 dBm after 20h. Similarly, when looking on the 7th day of simulation scenario and at 20h after the 6 first days, namely at 164h in Figure 4.b, we observe that, at this time, the mean measured $RSRP$ drops to -90 dBm. We note that, at 16h after the 6 first days, precisely at 160h in Figure 4.b the mean measured $RSRP$ is equal to -100 dBm which is slightly lower than the value given by GSMR that predicts -95 dBm at the same time. The second metric PART gives insights about the availability of the requested data rate D for at least 50% of users during a sliding period of 24h. We take the value of PART metric at t=24h, where it drops to 73% for S1 and to 97% for S2. This prediction is compared with the *asymptotic availability* of the requested throughput D for at least 50% of simulated users measured on the last day. This metric corresponds to the frequency of occurrences of the set of network service states $\{G, F, A\}$. The measured *asymptotic availability* is equal to 73% and 95% for S1 and S2, respectively. Therefore, GSMR and PART metrics help engineers to get a good estimation on the network resilience. Depending on the starting state, the analysis can output different resilience level values.

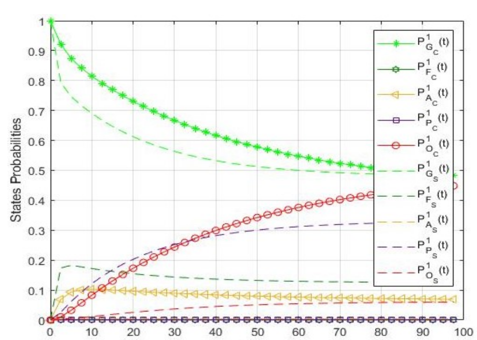

Fig. 7: Evolution of coverage vs. service states probabilities (S1): $P^1_{i_C}$ and $P^1_{i_S}$ stand for probability of state $i \in S$ of coverage and service indicators, respectively in S1 scenario.

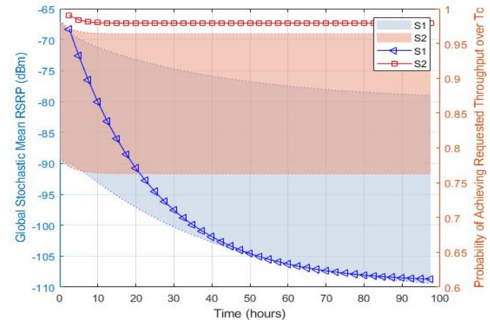

Fig. 8: Estimation of GSMR lower and upper bounds (shaded area) and PART metric (line) over a period of 24h in S1 (blue) and S2 (red) scenarios.

(E) Outcome discussion: CTMCs are a powerful tool to provide a characterization and prediction of the average network behaviour over short term delay. The operator can compare the estimated resilience metric value with a specific threshold to react on time and mitigate the outages. For instance, if there is a high risk of outage, engineers have to trigger the antenna tilt or increase its power to maintain coverage using the estimator module. More details on the actionable knowledge were provided in [6]. Coupling this approach with methods of Anomaly Detection or Root Cause Analysis can help in better decision making of the adaptive resilient mechanisms. This method requires to keep track of coverage and service indicators. No additional traffic is required because our CTMC uses existing 3GPP radio data collected inside RAN. But, it induces to repeat the resilience computation and analysis periodically due to the stationarity property of the Markovian models. The challenge resides in storage of historical data and computational cost.

VI. Conclusion

This paper provides a proactive quantitative resilience analysis for 5G-RAN. The analysis uses Markov processes for modelling network status using $RSRP$ and Throughput data. Based on two models, we predict radio coverage and service integrity states, and propose metrics to quantify the level of network resilience. To show the usability of our approach, we conduct a numerical analysis through simulations in two different failure scenarios. According to numerical results, the proactive approach can help to efficiently forecast the average behaviour of mobile network states, at the level of outages and resilience, in short or mid-term duration. Besides, quantifying network resilience with multiple metrics for each performance indicator allows to determine the impact on each indicator separately and take suitable anticipated decisions to improve the network by activating resilience mechanisms. A resilience management scheme is briefly discussed in order to apply this approach on 5G and beyond networks architecture. For future work, the proposed predictive model can be extended to support other UE signals like Signal to Interference and Noise Ratio (SINR), Reference Signal Received Quality (RSRQ) or to include latency indicator for ultra-reliable low latency communications (URLLC) services where the core network can be involved since it creates higher latency than RAN. Finally, Machine Learning methods can be considered to help in decision making for resource management.

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