Accessibility Degradation Prediction on LTE/SAE Network Using Discrete Time Markov Chain (DTMC) Model

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Abstract. In this paper, an algorithm for predicting accessibility performance on an LTE/SAE network based on relevant historical key performance indicator (KPI) data is proposed. Since there are three KPIs related to accessibility, each representing different segments, a method to map these three KPI values onto the status of accessibility performance is proposed. The network conditions are categorized as *high*, *acceptable* or *low* for each time interval of observation. The first state shows that the system is running optimally, while the second state shows that the system has deteriorated and needs full attention, and the third state indicates that the system has gone into degraded conditions that cannot be tolerated. After the state sequence has been obtained, a transition probability matrix can be derived, which can be used to predict future conditions using a DTMC model. The results obtained are system predictions in terms of probability values for each state for a specific future time. These prediction values are required for proactive health monitoring and fault management. Accessibility degradation prediction is then conducted by using measurement data derived from an eNodeB in the LTE network for a period of one month.

1   Introduction

Over the past decades, enormous progress has been achieved in serving the rapidly increased traffic volume and high bandwidth demand in mobile networks for improving network performance. This is reflected in the evolution of the mobile network standard from 1G to the current generation of LTE/4G and 5G, which will soon become available. The subsequent generations will fulfill new demands, have new features and will be faster than the previous generations. Nevertheless, this evolution must also provide easy network operation and maintenance, because the future generation of mobile networks will be increasingly complex, in terms of troubleshooting, configuration and network optimization, considering that more devices are connected, including applications for machine-to-machine communications. Therefore, the concept of

self-organizing networks (SONs) has been introduced [1] and was developed as a requirement that was integrated in the 3G standard and was appended by telecommunications standard development organization 3GPP [2]. SONs are designed to automate the functions of network management as much as possible through mechanisms of self-configuration, self-healing and self-optimization. The ability of the system to be able to adjust to the condition of the network, depending on whether it is in a normal state or in a degraded state, is crucial for the SON process to work. For this purpose, a number of monitoring results are gathered from various network elements (NEs), whether in the form of log events, counters, or the key performance index (KPI). The KPI is a performance indicator that is calculated based on the results of monitoring a number of network elements.

A set of relevant KPIs deals with accessibility issues. This type of KPI provides a measure of how successful users are in accessing the network. These KPIs are expressed in a percentage that indicates the ratio between the number of successful accesses compared to the total access attempts by users on various segments of the network.

In this research, long-term accessibility performance based on discrete-time Markov chains (DTMCs) and three accessibility KPIs was predicted. The three KPIs used were S1_Connection_Signaling_Success_Rate, ERAB_setup _success_rate and RRC_setup_success_rate. Based on the value of each KPI, a rule is proposed to determine the accessibility condition of the system, whether it is in a *high*, *acceptable* or *low* (degraded) state. Given a set of accessibility performance indicators based on historical data, the probability that the system will enter a degraded condition at a certain future time can be determined. Likewise, the long-term probability of the accessibility performance can be calculated for each possible state. The prediction values can be utilized for proactive health monitoring and fault management.

Detection and diagnosis of degradation conditions in a mobile network are the main components in the conventional processes of fault management and troubleshooting (Figure 1). However, this alone is not enough for future generations of mobile networks. Foresight about future network conditions is also needed to be able to deal with increasingly complex networks [3]. Therefore, detection also has to be more proactive, where possible future problems can be estimated from available historical data with probabilistic estimation analysis. By having a prediction of future network conditions, maintenance and preventive actions can be scheduled and used as the basis for root cause analysis [3,4].
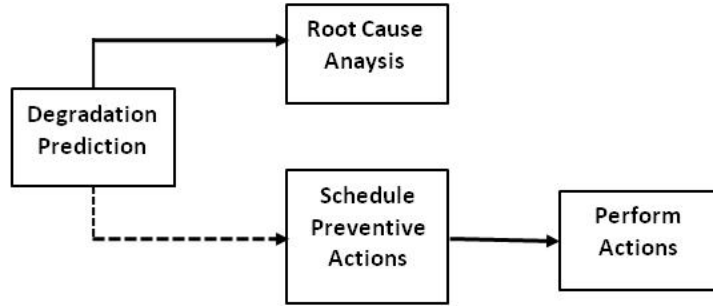
Figure 1 Block diagram of proactive fault management [3].

The KPI data used in this study were calculated from the results of an eNodeB measurement that employed 3 cells/sectors in an LTE/SAE network for a period of 1 month on an hourly basis. The hourly accessibility data collected over one month provided time series data for each KPI. From these three time series data, the state of the system was determined for each hour interval, whether the system is in a *high* (H), *acceptable* (A) or *low* (L) state.

The observations resulted in 739 sequences of hourly cell accessibility data in the form of a series of states H, A or L for each of the cells observed. This sequence of states also describes the transition from one state to another for every one-hour step. From these sequences a transition probability matrix was made. In a Discrete Time Markov Chain (DTMC) model, the transition probability among all possible states is the basis for calculating the probability that the system will be in a particular condition for a given specific period of time ahead. The model can also predict the probability of long-run accessibility conditions of the system or steady state probability of the system.

2   Related Research Work

From the literature survey, SON research can be categorized into the following three state-of-the-art areas, namely self-configuration, self-optimization, and self-healing. This last category is the automated mechanism of detection, diagnosis and compensation of fault. Accessibility degradation prediction, which was the focus of this research, can be categorized under self-healing problems, especially detection issues. Several methods related to degradation detection have been proposed, including [5] and [6], which propose methods for implementation on cellular networks. In the first paper, a proactive approach of detecting degradation in cells is presented that utilizes the correlation between two cells as a means of identifying degraded cells and to reduce the possibility of false alarms. In the second paper [6], a method to detect deterioration in cells

through the analysis of the time evolution of several metrics is introduced. Other degradation detections applied to radio channel degradation and diagnosis based on statistical analysis are proposed in [7].

Furthermore, some papers have proposed methods for fault detection and diagnostics instead of degradation detection. For example [8], which discusses an algorithm for cell outage detection using neighbor cell list reports, while a sleeping-cell detection algorithm is proposed in [9] using N-gram analysis in LTE networks. Also, some papers discuss anomaly detection as a stage in the process of fault detection and diagnosis. Reference [10] proposes probabilistic anomaly detection based on system calls analysis, while [11] introduces sophisticated profiling and capabilities to detect anomalies and a diagnosis framework for mobile network operators from a live 3G network. Another approach is reported in [12], which proposes an adaptive ensemble method framework for modeling cell behavior to detect cell anomalies in terms of partial and complete degradation in cell-service performance. Reference [13] introduced a data mining framework for anomaly detection algorithms for sleeping-cell detection caused by RACH failure in LTE networks.

In contrast to degradation detection, anomaly detection and diagnostics, little research has been done that discusses degradation or fault prediction on cellular networks, more specifically on LTE networks. This is also in contrast with software fault prediction, a field that is very bountiful and mature. However, by having a prediction of future network conditions, maintenance and preventive actions can be scheduled and used as the basis for root cause analysis. Fault detection and prediction are proposed in [14], which introduced a stochastic model to predict user throughput in mobile networks by taking into account the uncertainty of such random phenomena (e.g. fast fading) or inexact information (e.g. user location). Meanwhile, [15] predicts outages in mobile networks based on recorded data logs. Another approach to accessibility degradation prediction uses the value of one of the accessibility KPIs instead of three KPIs, as proposed in this paper, utilizing the Markov model that has been reported in [16].

3   Theoretical Background

3.1   LTE Architecture

The common architecture of a mobile radio telecommunications network such as 3G consists of three main parts, namely user equipment (UE), radio network subsystem (RNS), and core network (CN). The UE relates to devices on the user side such as mobile phones or other mobile devices. RNS consists of two main components, namely Node B and RNC. Node B relates to the interface between

the UE and the network side or the network provider and is controlled by a radio network controller (RNC). Meanwhile, CN deals with centralized processing and system management. However, 4G/LTE, the next generation after 3G, has a flattened architecture. The simplified network architecture of LTE consists of the following three main network components: user equipment (UE), the evolved UMTS terrestrial radio access network (E-UTRAN) and the evolved packet core (EPC). E-UTRAN contains only one network element, namely the Evolved Node B (eNodeB), which has its own control functionality. EPC, which is the CN of an LTE/SAE network, has the main function of routing/forwarding, user authentication and mobility management, which are done by MME, S-GW/P-GW and HSS respectively. The simplified architecture of LTE/SAE is shown in Figure 2.
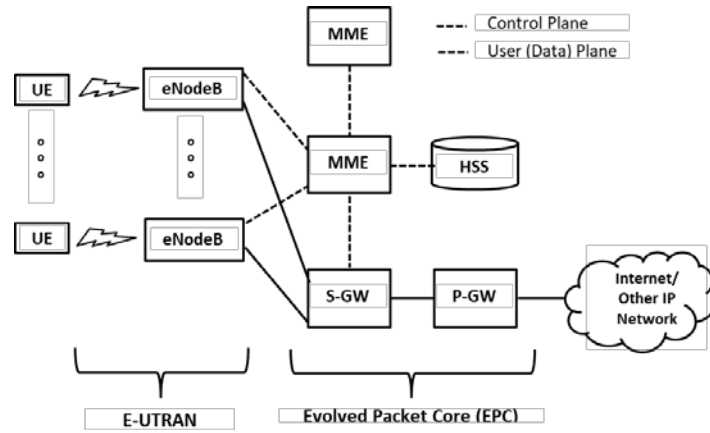

Figure 2 LTE/SAE network architecture.

We should keep in mind, however, that the architecture above only describes the main network elements that exist in a 4G network system. In the realization of network implementation, the service provider must deploy many network elements, especially eNodeBs, which can reach thousands in number. The health of the individual network elements and the system as a whole must always be maintained to provide adequate service level agreement (SLA) for customers.

3.2   Accessibility Key Performance Indicators (KPIs)

The huge number of NEs produces enormous amounts of raw data on a daily, hourly and even minutely basis. These raw data can be grouped into a number of key performance indicators (KPIs). The results can then be used to determine if the condition and network performance indicators are within a desired target

or they can be used for further troubleshooting analysis. If a large amount of data have to be analyzed, it will be too laborious to process them manually to determine the condition of the system accurately, let alone predict future states of the system.

The key performance indicators can be categorized into RF (radio frequency) KPI, Service KPI and Operation KPI. Each KPI category has its own objectives for different purposes of use. RF KPI is required during the phases of network planning, network rollout and initial optimization to measure actual values against planned values. On the other hand, Service KPI is used to evaluate the quality of service expected to be seen by the users for different services and is utilized during the phases of optimization and commercial introduction, and for debugging specific problems. Lastly, Operation KPI is continuously collected and analyzed to set the network performance and behavior for further optimization processes during all network optimization stages [17].

The 3GPP standard categorizes the Service and Operation KPIs related into 5 requirements [18]: accessibility, retainability, integrity, availability and mobility. Applicable individual KPIs for each group are shown in Figure 3, while a strict definition of each KPI can be found in [19].
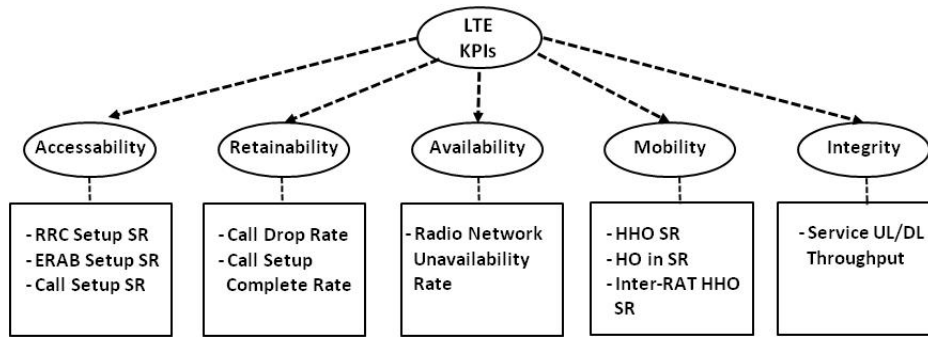

Figure 3 3GPP EUTRAN KPI categorization.

PIs relating to operations, maintenance and services are collected from the appropriate performance counters of the entire network. A set of KPIs is essential to measure user accessibility performance, which indicates how easy or difficult it is for users to access the network to meet the desired service. As shown in Figure 3, the Accessibility KPI can be divided into three parts: RRC_Setup_Success_Rate, S1_Connection_Signalling_Success_Rate and ERAB_Setup_Success_Rate. For convenience each is abbreviated as RRC_{SR}, $S1ConnSig_{SR}$ and $ERABSetup_{SR}$.

RRC_{SR} denotes the ratio between the two types of RRC connections that occur between the EU and the eNodeB, where the dividend is the number of successful connections and the divisor is the total number of connection attempts, which can be written as in following Eq. (1):

$$RRC_{SR} = \frac{RRC\ Connection\ Success}{RRC\ Connection\ Attempt} \times 100\% \tag{1}$$

As shown in Figure 4, the RRC connection setup includes the process of sending *Random_Access_Preamble*, *RRC_Connection_Request* and *RRC_Connection_Setup_Complete* from the EU and the *Random_Access_Recponse* and RRC_Connection_Setup responses from eNodeB. The RRC Connection success counter is triggered when *RRC_Connection_Request* has successfully been received, while the RRC Connection Attempt counter increases when *RRC_Connection_Setup* has successfully been received [20].
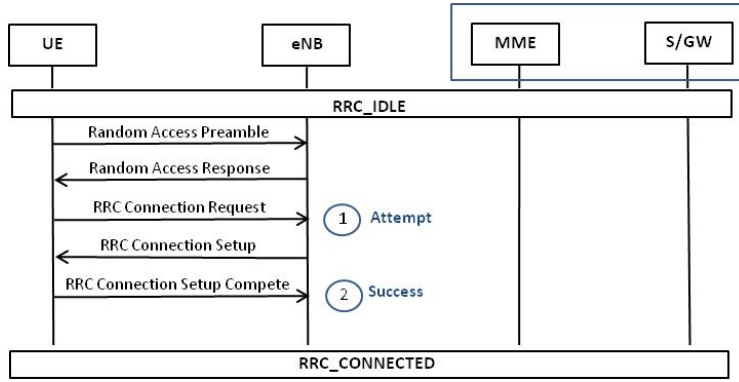

Figure 4 RRC connection setup success rate.

The second KPI, $S1ConnSig_{SR}$, measures the success ratio of sending *Initial_UE_Message* messages and their response between eNodeB and MME, as shown in Figure 5, which can be written as in following Eq. (3):

$$S1\ ConnSig_{SR} = \frac{S1\ SIGConnectionEstablish\ Connection\ Success}{S1\ SIGConnectionEstablish\ Connection\ Attempt} \times 100\% \tag{2}$$

The third KPI, $ERABSetup_{SR}$ measures the probability success rate of overall service access for all types of traffic in a cell or network. This KPI is determined based on an ERAB connection setup counter and successful ERAB setup as shown in Figure 6, which can be formulated as in following Eq. (3):

$$ERAB\ Setup_{SR} = \frac{ERAB\ Setup\ Success}{ERAB\ Setup\ Attempt} \times 100\% \tag{3}$$
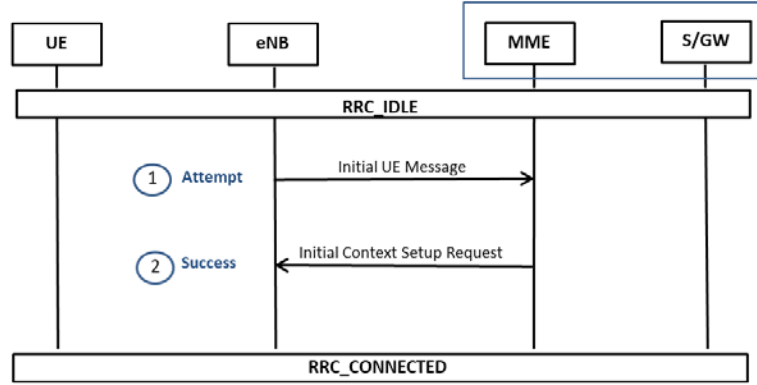
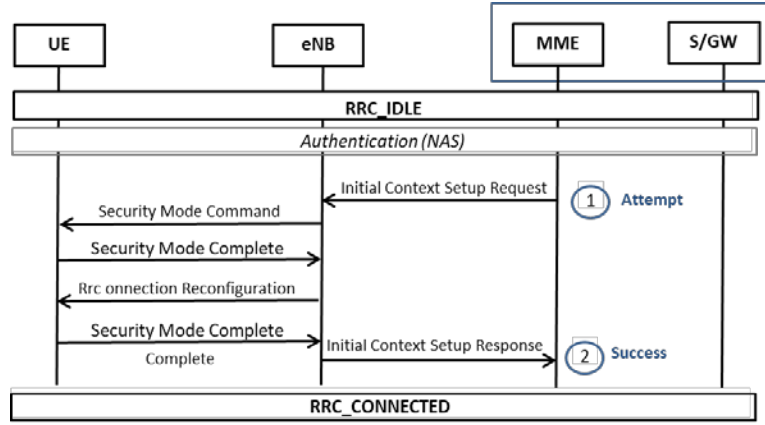**Figure 5** S1 Connection setup success rate.

Figure 6 ERAB setup success rate.

3.3   Markov Chain Analysis

A stochastic process $\{X_t : t \in T\}$ constitutes a Markov process if for all $0 = t_0 < t_1 < \ldots < t_n < t_{n+1}$ and all $s_i \in S$, the conditional probability distribution CDF of $X_{t_{n+1}}$ depends only on the previous value, X_{t_n}, and not on the earlier values, $X_{t_0}, X_{t_1}, \ldots X_{t_{n-1}}$ [21]. By implementing the time parameters and the state space, both having discrete values in the general definition above, a special form of Markov process is obtained, known as discrete-time Markov chain (DTMC). Meanwhile, if the time parameters are continuous instead of discrete, a continuous-time Markov chain (CTMC) can be acquired. The formal definition of a DTMC, which is the model that was used in this study, can be

formulated as follows [21]: a given stochastic process $\{X_0, X_1, \ldots, X_{n+1}, \ldots\}$ at consecutive points of observation *0, 1, ..., n+1* constitutes a DTMC if the following relation in the conditional *pmf*, i.e. the Markov property (Eq. (4), holds for all $n \in N_0$ and all $s_i \in S$:

$$P(X_{n+1} = s_{n+1} \mid X_n = s_n, X_{n-1} = s_{n-1}, \ldots, X_0 = s_0) =$$
$$P(X_{n+1} = s_{n+1} \mid X_n = s_n) \tag{4}$$

Given initial state s_o and its initial probability, the probability of being present in state s_n after *n* steps can be calculated given step transition probability P_{ij} in Eq. (5). This probability is a conditional *pmf* for transitions from state s_i at time step *n* to state s_j at time step *(n + 1)* for all *i* and *j*.

$$P_{ij} = P(X_{n+1} = s_j \mid X_n = s_i) \tag{5}$$

Transition probability in a DTMC model can be written in matrix form as in following Eq. (6):

$$P = \begin{bmatrix} p_{0,0} & p_{0,1} & p_{0,2} & \cdots \\ p_{1,0} & p_{1,1} & p_{1,2} & \cdots \\ p_{2,0} & p_{2,1} & p_{2,2} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{6}$$

State probability $\pi_i(n)$ is a measure of the probability at *n* steps ahead that the system will be in state *i*. It can be written as in following Eq. (7):

$$\pi_i(n) = P(X_n = i) \tag{7}$$

For a homogeneous DTMC can be written as in Eqs. (8) and (9):

$$\pi_i(n) = \sum_{j=0}^{\infty} P_{ji}^n \pi_j(0) \tag{8}$$

and

$$P_{ji}^n \approx P(X_n = i \mid X_0 = j) \tag{9}$$

If a Markov chain is ergodic, then stationary probabilities $\{\pi_j, j \in S\}$, where $\pi_j \simeq \lim_{n \to \infty} P_{ij}^n$, can be formulated as in following Eqs. (10) and (11):

$$\pi_j = \sum_{i=0}^{\infty} \pi_i P_{ij}, \quad j = 0,1,\ldots \tag{10}$$

and

$$\pi_j \geq 0, \quad \sum_{j=0}^{\infty} \pi_j = 1 \tag{11}$$

where π_j is the limiting probability distribution of state j or stationary or the steady-state distribution of the Markov chain that denotes the long-run proportion of time that the chain spends in state j. In an irreducible and aperiodic homogeneous Markov chain, limiting state probabilities π_j always exist, independent of the initial state probability distribution $\pi_j(0)$ as in following Eq. (12).

$$\pi_j = \lim_{n \to \infty} \pi_j^{(n)} \tag{12}$$

Several studies have implemented DTMC models in the context of LTE networks [11,12,22]. In the first study, a spatio-temporal representation of LTE uplinks using 2-D DTMC is proposed [11]. The second study developed a mathematical framework to model the scalability of a random access channel (RACH) for IoT traffic [12]. The last research proposed a mechanism for monitoring state of cloud resources [22].

4   Accessibility State Identification

As mentioned above, indicators of accessibility performance on LTE networks are represented by three KPIs, namely RRC_{SR}, $ERAB_{SR}$ and $S1SigConn_{SR}$. Each KPI provides a value for each measurement time, generating a large database of time series data. This historical database is then used for the diagnostic process to assess the performance of the LTE network by calculating its representative value. The representative value can be calculated conservatively using a simple method, for example by calculating the average value of KPI over a particular time period, for example one day [23].

The system is said to experience degradation if the value of this representative value is below a certain threshold. To assess system performance, the system's condition is categorized into three states, namely *high*, *acceptable* or *low* (degrading). In the first state, the system works normally and optimally, in the second state the system's performance is still acceptable but not optimal. The last state indicates that the system is experiencing problems and degradation occurs. For example, in a conventional system based on a single KPI, at a value below 98% the system is categorized as being in the *low* state, between 98% to 99.5% it is in the *acceptable* state and above 99.5% it is in the *high* state. Furthermore, because there are three KPIs related to accessibility, where each shows the performance of different segments, it is necessary to find an

aggregate value that represents the condition of the overall accessibility of the system. This aggregate value also transforms the time series data to a value, for example a mean, that is independent of time. The calculation of aggregate values in this study adopted the approach from [23].

Getting the aggregated value from the three KPIs is done as follows: suppose A = {A_{RRC}, A_{ERAB}, A_{S1}} is the set of Accessibility KPI and S = {H, A, L} is the set of 3 possible states i.e. *high*, *acceptable* and *low*. Next to classifying the system into one of the three conditions, the upper and lower thresholds are specified for the middle range (acceptable state), expressed in set B = {b_{au},b_{al}}, where b_{au} is the upper threshold for the *acceptable* state and b_{al} is the lower threshold. Furthermore, to transform from A to S, the function A $\rightarrow$ S is used. Given a value of vector *a* from set A for a specific time, this function is defined as follows:

$$f(\overline{a}) = \begin{cases} S_H & if\ (\forall a_i \in \overline{a}|a_i > b_{au} \\ S_A & if\ (\exists a_i \in \overline{a}|b_{au} \geq a_i \geq b_{al}) \wedge (\nexists a_i \in \overline{a}|a_i < b_{al}) \\ S_L & if\ (\exists a_i \in \overline{a}|a_i < b_{al}) \end{cases} \qquad (13)$$

Visually, the rule to allocate the measurement result of the three accessibility KPIs into a series of states is shown in Figure 7.
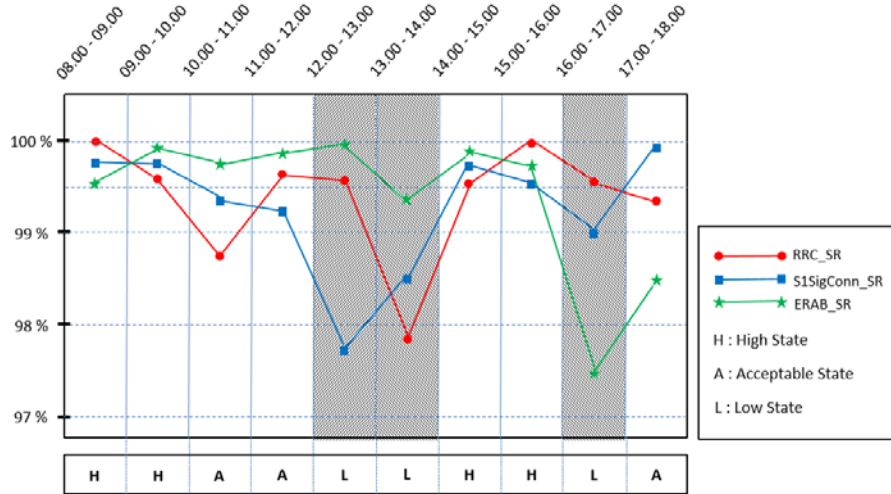

Figure 7 State determination for each time interval.

5   Accessibility Analysis

The method for identifying the system's state using the three accessibility KPIs as described in Chapter 4 above can be applied to the measurement data. The KPI data used were derived from the results of monitoring three cells on an eNodeB for 30 days, resulting in 739 hours of observation for each cell. The total hours of observation were obtained from 24-hour monitoring from 00:00 to 23:00 every day for 30 days between March and April 2017. Furthermore, the system conditions were categorized hourly into one possible state, i.e. *high*, *acceptable* or *low*. From the total of 739 hours of monitoring, the time point where the system was in *low* state can be seen, as shown in Figures 8 to 10, where degraded conditions for cells 1, 2 and 3 occurred for 13, 15 and 26 hours respectively.
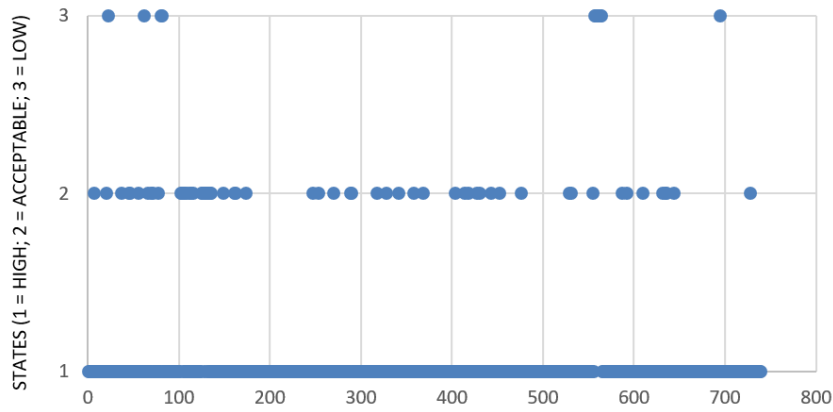
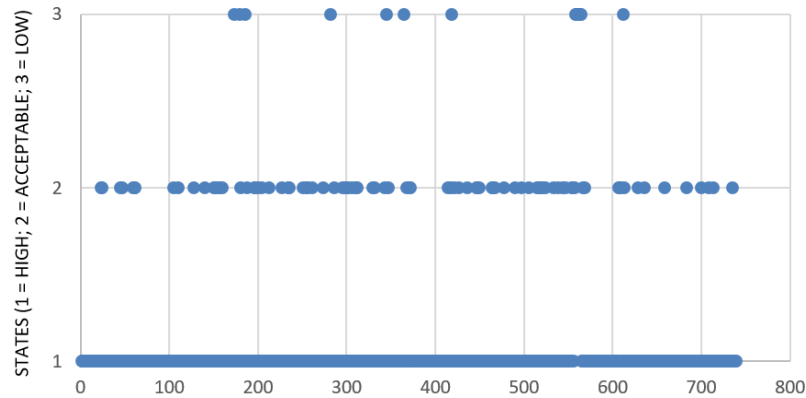**Figure 8**   State mapping of Cell 1 for 30 days on an hourly basis.

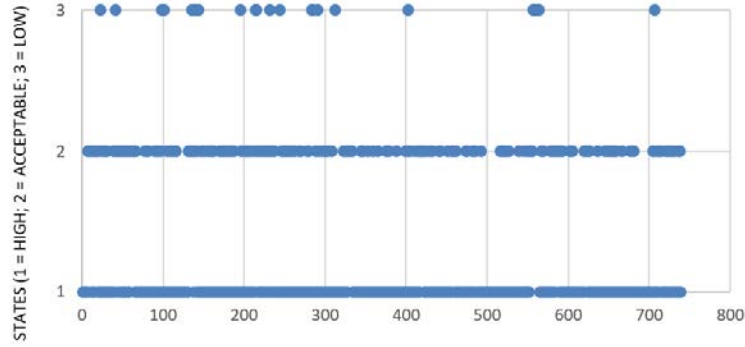**Figure 9**   State mapping of Cell 2 for 30 days on an hourly basis.

Figure 10   State mapping of Cell 3 for 30 days on an hourly basis.

The data that obtained so far were measurement data, but it is also desirable to know future conditions of the network derived from available historical data. To be able to calculate the probability of state and the limiting probability of state to predict the future health of the network, it is necessary to calculate the transition probability matrix of each state first. The former probability measures the possibility of a certain state at a given time while the latter probability states the proportion of long-term time the system will be in a certain condition. The KPI obtained from the observations are subsequently transformed by applying Eq.(13) using b_{au} and b_{al} values of 98.0% and 95.5%, respectively, which yields the state sequence as shown visually in Figure 7. The number of state sequences generated for the one-month hourly measurements was 739 state sequences for each cell. From these state sequences the transition probability matrix could be derived and calculated for each cell, of which the results are depicted in Figure 11.

The contents of the probability transition matrix in the first row and the third column of Cell 1 show that the transition probability value, i.e. the probability of state transition in Cell 1 from being currently in state H (*high*) and in the next period (next hour) moving to state A (*acceptable*), is 0.072. The meaning of the other matrix contents for all locations can be interpreted in the same way. For a clearer visualization of the transition from one state to another, the transition probability matrix can be expressed in the form of a state diagram as shown in Figure 11.

By knowing the transition probability matrix, the accessibility state of the system for a certain future time can be predicted. Hence, $\pi_i(n)$, i.e. the probability that the system will be in i state for the next n period ahead, can be calculated. Using Eq. (8), it can be shown that $\pi_i(n)$ depends on the initial condition at $n = 0$. Tables 1-3 show the state probability of being in state 1, 2 or

3 (corresponding to H, A and L) for the next 1 to 4 periods ahead for each cell for three different initial conditions. As can be seen from these results, for an increasingly large n period, $\pi_i(n)$ will converge to a value and no longer depend on the initial condition. In other words, for large values of n and n approaching infinity, $\pi_i(n)$ is the value of the limiting state probability, which can be obtained using Eq. (10), of which the results are shown in Tables 1-3 for Cell 1 to Cell 3 respectively.

(a) Cell 1

$$P = \begin{bmatrix} 0.920 & 0.072 & 0.008 \\ 0.814 & 0.186 & 0.000 \\ 0.385 & 0.000 & 0.615 \end{bmatrix}$$
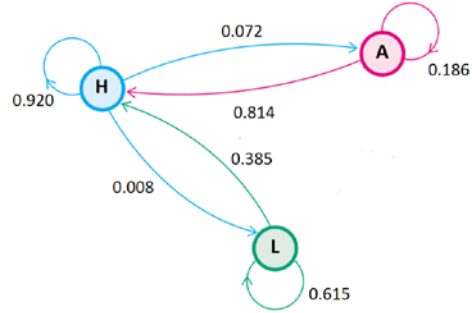
(b) Cell 2

$$P = \begin{bmatrix} 0.874 & 0.113 & 0.013 \\ 0.828 & 0.161 & 0.011 \\ 0.533 & 0.067 & 0.400 \end{bmatrix}$$
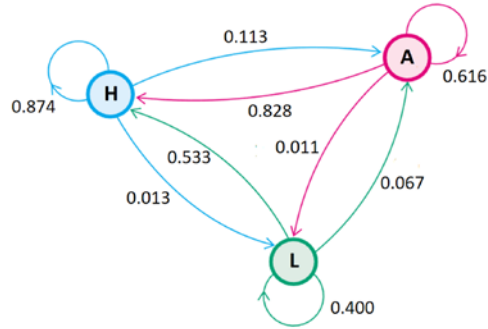
(c) Cell 3

$$P = \begin{bmatrix} 0.745 & 0.235 & 0.020 \\ 0.557 & 0.410 & 0.033 \\ 0.423 & 0.231 & 0.346 \end{bmatrix}$$
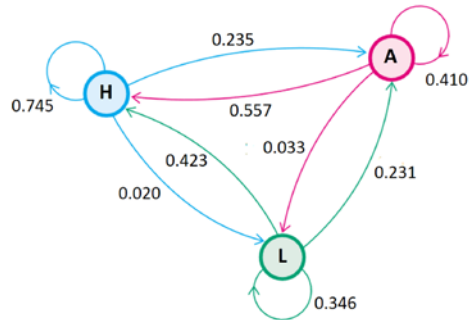
Figure 11 Transition probability matrix and state transition diagram: (a) Cell 1, (b) Cell 2, (c) Cell 3.

Table 1   Probability of state for cell 1 with initial state at 1, 2 and 3.

n	0	1	2	3	4	…….	∞
$\pi_1^{(n)}$	1	0.920420	0.908696	0.905718	0.904376		0.912329
$\pi_2^{(n)}$	0	0.072072	0.079774	0.080365	0.072493		0.080822
$\pi_3^{(n)}$	0	0.007508	0.011530	0.013917	0.015364		0.006849
$\pi_1^{(n)}$	0	0.813559	0.900497	0.907168	0.905988		0.912329
$\pi_2^{(n)}$	1	0.186441	0.093395	0.082313	0.080728		0.080822
$\pi_3^{(n)}$	0	0.000000	0.006108	0.010519	0.013284		0.006849
$\pi_1^{(n)}$	0	0.384615	0.590694	0.713003	0.787124		0.912329
$\pi_2^{(n)}$	0	0.000000	0.027720	0.047741	0.060288		0.080822
$\pi_3^{(n)}$	1	0.615385	0.381586	0.239257	0.152588		0.006849

Table 2   Probability of state for cell 1 with initial state at 1, 2 and 3.

n	0	1	2	3	4	…….	∞
$\pi_1^{(n)}$	1	0.874214	0.864647	0.862804	0.862178		0.870041
$\pi_2^{(n)}$	0	0.113208	0.118023	0.118032	0.102073		0.119015
$\pi_3^{(n)}$	0	0.012579	0.017329	0.019164	0.019875		0.010944
$\pi_1^{(n)}$	0	0.827586	0.862792	0.862856	0.862235		0.870041
$\pi_2^{(n)}$	1	0.160920	0.120350	0.118165	0.117962		0.119015
$\pi_3^{(n)}$	0	0.011494	0.016857	0.018979	0.019803		0.010944
$\pi_1^{(n)}$	0	0.533333	0.734753	0.812566	0.842712		0.870041
$\pi_2^{(n)}$	0	0.066667	0.097772	0.110078	0.114859		0.119015
$\pi_3^{(n)}$	1	0.400000	0.167475	0.077356	0.042429		0.010944

Table 3   Probability of state for cell 1 with initial state at 1, 2 and 3.

n	0	1	2	3	4	…….	∞
$\pi_1^{(n)}$	1	0.745020	0.694444	0.683648	0.681124		0.693567
$\pi_2^{(n)}$	0	0.235060	0.275984	0.283082	0.192340		0.292617
$\pi_3^{(n)}$	0	0.019920	0.029572	0.033269	0.034571		0.013816
$\pi_1^{(n)}$	0	0.557143	0.657348	0.675779	0.679297		0.693567
$\pi_2^{(n)}$	1	0.409524	0.306364	0.288354	0.285213		0.292617
$\pi_3^{(n)}$	0	0.033333	0.036288	0.035868	0.035489		0.013816
$\pi_1^{(n)}$	0	0.423077	0.590222	0.649807	0.670118		0.693567
$\pi_2^{(n)}$	0	0.230769	0.273836	0.282251	0.284011		0.292617
$\pi_3^{(n)}$	1	0.346154	0.135943	0.067942	0.045871		0.013816

Furthermore, the limiting state probability or steady state probability indicating the long-run performance of the system can be calculated using Eq. (10), of which the results are shown in Table 4.

Table 4   Limiting/steady state probability.

	π_1	π_2	π_3
Cell 1	91.23	8.08	0.70
Cell 2	87.00	11.90	1.09
Cell 3	69.34	29.26	1.38

6   Result and Discussion

From historical time series data of three KPIs derived from one-month measurement, the probability that a system exists in a certain state (*high*, *acceptable*, *low*) in term of accessibility can be calculated. The first condition shows the system running normally and optimally, while the second condition shows that although it is not categorized as being in degraded condition, it needs full attention. Meanwhile, the third condition shows that the system has gone into an intolerable degraded state. The probability values for each possible future state can be used as input for root cause analysis as well as for preparing preventive actions. From the analysis of the three cells under study, it appeared that there was degradation in terms of accessibility of Cell 3. From Table 4 it can be seen that in the long run only 69.34% of the system was in *high* state compared to Cell 1, which had a *high* percentage of 91.23%, and Cell 2, which had a *high* percentage of 87.00%. As for degraded conditions, Cell 3 had a relatively high *low* percentage of about 1.38% compared to 0.70% and 1.09% for Cell 1 and Cell 2. In general, it can be concluded that Cell 3 had poor performance compared to the other 2 cells. Therefore, special attention must be given to Cell 3 as well as anticipation of performance improvement.

7   Conclusion

In this research, a method to predict the accessibility performance of an LTE/SAE network was developed. This method is based on historical values of the three accessibility KPIs, namely RRC_{SR}, $ERAB_{SR}$ and $S1SigConn_{SR}$, which are aggregated and mapped onto the conditions of network accessibility. DTMC is used to predict future accessibility states. The proposed method can predict accessibility conditions for a certain future time or assess overall network health on a long-term basis. The results obtained can be used as part of the self-healing process of an LTE network. The method developed was tested by monitoring of a real LTE/SAE network for one month. The analysis results showed one out of three cells experienced degradation. In this paper, the proposal is limited to how

to transform from large time-dependent databases that are recorded from the measurement of three accessibility KPIs to a representative value in the form of probabilities. Further development is required for further utilization as input for root cause analysis, degradation detection, anomaly detection and scheduling preventive measures.

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