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RANKING OF LTE CELLS BASED ON KEY PERFORMANCE INDICATORS USING MCDM METHODS

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Abstract

The growth in worldwide data traffic and user subscriptions in mobile telecommunication networks makes it increasingly difficult to manage network performance in an environment already containing multiple radio access technologies. Despite the rise of 5G, LTE remains the dominant technology, and new cells are installed daily to support traffic growth and new services such as voice over LTE. Detecting faulty cells in the network is one of the main concerns of operators. Self-organizing networks have been introduced to deal with this problem, and their self-healing functionality has improved cell fault management. Nonetheless, faulty cell detection remains challenging, and most of the tasks involved are still done manually. This paper introduces a new method of faulty cell detection in an LTE radio access network, applying multiple criteria methods to this problem. The cells are ranked based on selected key performance indicators, using the multi-attribute utility theory to construct a utility function. The analytic hierarchy process is used to define weights for the criteria.

Keywords: long-term evolution, multiple criteria methods, radio access network performance management, self-organizing networks.

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1 Introduction

Despite the uncertainty caused by the COVID-19 pandemic, mobile subscriptions continue to grow globally, bolstered by the new 5G NR (5th Generation New Radio) radio access technology (RAT). Nonetheless, 4G LTE (4th Generation Long Term Evolution) remains the dominant RAT by subscription, and voice over LTE (VoLTE) service enables interoperable voice and communication services on 4G and 5G devices. VoLTE adoption also accelerates the decommissioning of 2G and 3G networks, freeing frequencies for use by new LTE bands. Meanwhile, the year-on-year mobile network data traffic growth remains at around 50%, driven by the rising number of smartphone subscriptions and an increasing average data volume per subscription (Jejdling, 2020).

While the data traffic continues to grow and VoLTE service continues to expand, new technologies, such as dynamic spectrum sharing (DSS), allow LTE and 5G to share the same carrier (Nory, 2019). Carrier aggregation between the two RATs is driving operators to expand their LTE access network capacity even more, adding more layers and, in the end, more cells to the existing network. The complexity of managing and operating such networks is forcing operators to auto-mate many operational processes to remain competitive. Self-organizing networks (SONs) were introduced to reduce the operating expenditures associated with managing the increased number of cells by reducing the need for manual network planning, configuration, and optimization (3GPP TS 32.500, 2020). SON functionalities (described in the next section) can be classified as self--configuration, self-optimization, or self-healing.

Barco, Lazaro, and Munoz (2012) point out that there are few studies on self--healing (Sallent et al., 2011; Hu et al., 2010), and emphasize the complexity of cell fault detection problems. They are usually revealed not through a highly anomalous value of one key performance indicator (KPI) but through slightly abnormal values of several KPIs. Szilagyi and Novaczki (2012) further point out that self-healing studies focus mainly on simple use cases, such as detecting complete cell outages. This paper proposes a new decision process to contribute to the literature on the self-healing of networks.

This process weighs multiple indicators and ranks the cells by their performance, filtering the most degrading ones to facilitate network operation and management. It is based on the Multiple Criteria Decision Methods (MCDM), defined by Obayiuwana and Falowo (2017) as an advanced technique of optimization research for resolving decision problems with multiple criteria using a more robust, explicit, rational, and efficient decision-making process.

According to Obayiuwana and Falowo (2017), MCDM methods have been used primarily for network selection decisions in situations where different RATs coexist. MCDM methods have rarely been applied to other RAT-related problems. Moreover, MCDM methods have been used in cases with a limited number of alternatives, such as RATs or small groups of cells. They have not been used for detecting fault cells while considering the complete network as an alternative.

This paper proposes a new application of MCDM methods in an LTE radio access network to detect and rank faulty cells based on key performance indicators (KPIs), considering all the cells of a given network.

The paper is organized as follows. Section 2 introduces the concepts and theories used, outlining the current decision methods used in radio access networks. Section 3 presents the proposed approach, highlighting its novelty and contributions to multiple criteria decision problems. Section 4 presents some results from applying the proposed method in an actual LTE network. Finally, Section 5 summarizes the contributions of this paper.

2 Theoretical and conceptual background

This section provides the background for the concepts and theories used in the paper. The idea of self-organizing networks is described, with particular attention to self-healing. Cell fault detection and key performance indicators are also discussed.

2.1 Self-organizing network concepts

In 2008, the Next Generation Mobile Networks (NGMN) Alliance, an open forum founded by major mobile network operators, defined the requirements and recommendations for implementing self-organizing networks (Next generation, 2008). This allowed the automation of some network planning, configuration, and optimization processes through SON functionalities (3GPP TS 32.500, 2020). The functionalities indicated by NGMN were self-configuration, self-optimization, fault management, and fault correction (subsequently renamed self-healing). Later, the 3rd Generation Partnership Project (3GPP), which provides reports and specifications for cellular telecommunications technologies, introduced SON in its standards as a fundamental element for LTE deployment (Barco, Lazaro, and Munoz, 2012) and defined the main SON functionalities based on the NGMN requirements (3GPP TS 32.500, 2020). The main SON functionalities are summarized by Barco, Lazaro, and Munoz (2012):

1. Self-configuration: includes functions for network deployment and configuration of its parameters. Thanks to autoconfiguration, network elements can start autonomously, run setup routines, and configure initial parameters.

2. Self-optimization: responsible for auto-tuning parameters, which should be dynamically recalculated when traffic and network conditions change. Self--optimization includes tuning parameters related to the list of neighboring cells, traffic balance, handover, and coverage.
3. Self-healing: includes functions to cope with service degradations or outages, including fault detection and diagnosis and mechanisms for outage compensation.

The first two functionalities are well-documented, and some functions, such as automatic neighbor relation (ANR) and node auto-connectivity, were even used in the first LTE deployments. Self-configuration reduces costs and accelerates cell deployment in the network, while self-optimization provides operational cost savings through energy saving or load-balancing optimization. On the other hand, studies on self-healing are scarce, as it is the most complex of the three domains due to the variety of vendors, software versions, and hardware types coexisting in a single network (Szilagyi and Novaczki, 2012). The existing studies on self-healing are incomplete, dealing only with certain straightforward self--healing aspects in specific scenarios, such as detecting complete cell outages (Barco, Lazaro, and Munoz, 2012). However, new studies on automatic fault detection and diagnosis can also reduce the cost of managing networks.

2.2 Self-healing concepts

As described by 3GPP, self-healing aims to solve or mitigate the faults that can be translated automatically by triggering appropriate recovery actions. The self--healing function consists of two parts: the monitoring part and the healing process part (3GPP TS 32.541, 2020). In the first part (shown in Figure 1), the trigger condition of self-healing (TCoSH), which could be either an alarm or a key performance indicator, is monitored; when the TCoSH is reached, a particular action is triggered to prevent or mitigate the specific fault. This article focuses on detecting a cell fault during the monitoring phase of the self-healing process.

Detecting and solving cell faults is one of the main concerns for network operators and vendors. Self-healing is required when a cell degrades, impacting the rest of the network. This kind of cell is called a problematic cell, and each operator and vendor uses a different indicator to identify the cell fault symptoms. A symptom is a measurement whose observed value helps identify a fault. Symptoms include key performance indicators, alarms, online measurements, and drive tests (Barco, Lazaro, and Munoz, 2012).

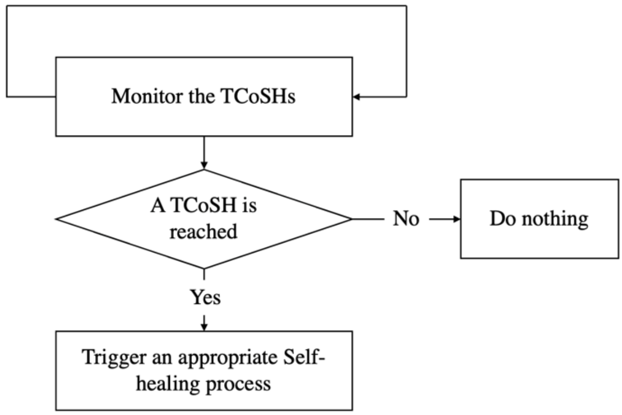

Figure 1: The monitoring part of the self-healing function

Source: Adapted from: 3GPP TS 32.541 (2020).

2.3 Cell fault detection

In general, alarms can identify a cell fault only in critical cases, i.e., software and hardware failures, transmission problems, or downtimes. A single fault may generate multiple alarms, and several different faults can trigger a single alarm. Furthermore, alarm messages cannot always be transmitted when a cell loses connectivity or stops sending information. Also, on many occasions, a cell fault does not generate any alarm. This can be caused by poor radio conditions, i.e., inadequate coverage, shadowing, or external interference (Barco, Lazaro, and Munoz, 2012), or else by incorrect configuration. Therefore, key performance indicators are the main inputs used by RAT experts to detect a cell fault and are used as criteria for the decision process proposed in this paper.

Barco, Lazaro, and Munoz (2012) propose a self-healing reference model, which is the basis for this paper's cell fault detection process. According to them, fault detection is responsible for identifying the problematic cells to be healed, including cells with service outage (cell outage detection) and cells with service degradation (cell degradation detection). A possible simple method of detecting a cell fault consists of setting thresholds for some KPIs. However, gradual degradations cannot be detected simply by a threshold, especially if proactive rather than reactive detection is carried out. Therefore, the authors state that an algorithm should be developed that considers all relevant KPIs and uses appropriate decision logic to determine whether an outage or degradation has occurred.

2.4 Key performance indicators

For managing purposes, to monitor the network's overall performance and compare the performance in different areas or periods, an operator needs to measure the statistical network performance periodically. Statistical data sampling can be performed regularly, i.e., daily, weekly, or monthly (3GPP TS 32.421, 2015). Performance data are collected and recorded by network elements, following a schedule established by the network element manager. These data are used to evaluate performance in five areas: network traffic, configuration, resource access, resource availability, and quality of service (QoS) (3GPP TS 32.401, 2018). QoS indicators measure the network performance the end user is expected to experience. These are the measurements considered in this paper.

Data performance is measured through specific parameters, or performance indicators (PIs), defined by each equipment vendor and used to monitor the current network status and performance. This enables prompt action to control, when necessary, the performance and resources of the network and services. A radio access network can have hundreds of PIs. Often measurements are taken simply because they are available, not because they are meaningful. It should be noted that the complete range of network status information and PIs is not necessary to manage the network. One of the challenges of managing networks is understanding which data are critical for supporting specific objectives (ITU-T Recommendation E.419, 2006). PIs representing the essential network performance measurements are called key performance indicators (KPIs).

For an LTE RAT, 3GPP defines six categories of KPIs (3GPP TS 32.450, 2019). All except for the last one can be used to measure the QoS. The categories are the following:

1. Accessibility KPIs: used to measure the availability of service within specified tolerances and other given conditions when requested by the user (ITU-T Recommendation E.800, 2008).
2. Retainability KPIs: used to measure the abnormal interruptions of service (ITU-T Recommendation E.800, 2008).
3. Mobility KPIs: used to measure how LTE mobility functionality is working.
4. Integrity KPIs: used to measure the data integrity, ensuring that data have not been altered in an unauthorized manner (ITU-T Recommendation E.800, 2008).
5. Energy efficiency KPIs: used to measure data energy efficiency in LTE network elements.
6. Availability KPIs: used to measure the percentage of times when the cell is considered available.

2.5 Multiple Criteria Decision Methods

Multiple Criteria Decision Methods have a relatively short history as a discipline. Their foundations were laid between 1950 and 1960, and they became the dominant paradigm in decision analysis and decision support in the presence of multiple evaluation dimensions (Zavadskas, Turskis and Kildienė, 2014). MCDM has been one of the fastest-growing problem areas in many disciplines, where a set of alternatives needs to be evaluated in terms of several criteria (Triantaphyllou, 2010). Nonetheless, there is no single well-defined methodology that one could follow from the beginning to the end of a decision-making process. When dealing with objects that can only be described and compared using multiple characteristics, aggregating them is a significant problem. The aggregation aims to synthesize the (usually contradictory) features of the objects to achieve a goal, such as choosing among the objects, rank-ordering them, sorting them into categories, and so on (Bouyssou et al., 2006).

MCDM methods use a wide range of approaches to solving the problems mentioned above. They can be broadly classified into two categories (cf. Figure 2): discrete MCDM or discrete MADM (multi-attribute decision-making) and continuous MODM (multi-objective decision-making) methods. MODM methods are associated with problems where alternatives are not predetermined. The goal is to design the best/optimal choice considering a set of well-defined design constraints and a set of quantifiable objectives. Thus, MODM methods deal with the design process, and the number of alternatives is infinite (continuous). On the other hand, discrete MCDM/MADM methods deal with discrete and predetermined options described by discrete determined criteria sets (Zavadskas, Turskis and Kildienė, 2014).

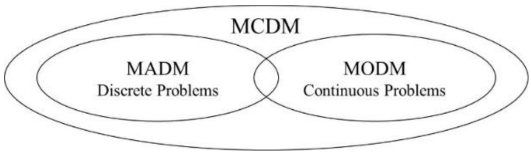

Figure 2: Broad classification of MCDM methods

Source: Zavadskas, Turskis and Kildienė (2014).

MCDM methods have been primarily used in radio access networks to address discrete problems of network selection in heterogeneous wireless networks (HWN). Decision-making problems have become more complex since the advent of the third-generation (3G) radio access technology WCDMA (wideband code division multiple access), specified in Release 99 by 3GPP in 1999, which allowed higher data rates and facilitated the significant increase in the number of mobile devices. Furthermore, mobile devices with advanced capabilities saw a massive proliferation with the evolution to 4G and the LTE RAT, specified in Release 8 by 3GPP in 2008. The imminent deployment of 5G will introduce yet another new RAT, which will coexist with the current RATs. Hence, the selection of the best network becomes essentially an MCDM process (Paul and Falowo, 2017). Obayiuwana and Falowo (2017) review and classify the most significant MCDM algorithms used to solve the network decision-making problems for HWNs.

On the other hand, Yeryomin and Seitz (2016) evaluated different algorithms used in the multiple criteria network selection problem, including simple additive weighting (SAW), weighted product model (WPM), elimination and choice expressing reality (ELECTRE), the technique for order of preference by similarity to ideal solution (TOPSIS), grey relational analysis (GRA), optimization and compromise solution (VIKOR), and the analytic hierarchy process (AHP). Some other critical applications of MCDM methods in those problems can be found in Pervaiz (2010), Sasirekha and Ilanzkumaran (2013), and Nguyen-Vuong et al. (2013). At the same time, Alhabo and Zhang (2018) predict that the introduction of 5G and the increasing demand for mobile data will lead to a selection scheme that considers different users with different priorities and preferences.

LTE evolution and increased data traffic have also introduced new decision-making problems that MCDM methods could address. While network selection can be considered a vertical handover, LTE is designed to support user mobility, even at high speed, moving from one cell to another during active service sessions (Nathaniel et al., 2014), which is considered a horizontal handover. Horizontal handover can also contribute to an effective load balancing for the optimum use of network resources. Recognizing this, Nathaniel et al. (2014) used a new MCDM approach to create a framework with a decision algorithm to solve the load-balancing problem in LTE. Furthermore, Dudnikova et al. (2015) introduced another innovative approach for MCDM while considering the problem generated by densely deployed heterogeneous networks with significant network energy consumption increments. To deal with this situation, they proposed using grey relational analysis and the analytic hierarchy process (MCDM tools) to find the number of base stations to switch off to maximize energy savings.

Therefore, different MCDM methods have been long applied in cellular networks and RATs, primarily for the network selection problem. However, the increasing complexity generated by new technologies, the colossal data traffic, the growing number of mobile subscriptions, and the cumulative number of cells installed in the network over the years make this scenario a fertile ground for new applications of MCDM methods to solve new decision problems.

The present study proposes a new application of the MCDM methods MAUT and AHP to solve the decision problem where faulty LTE cells need to be detected and ranked in a self-healing system in a network with non-predetermined alternatives and a vast number of options.

2.6 The Analytic Hierarchy Process

The AHP, first introduced by Saaty (2013; 1990), is a decision-making process based on the innate human ability to use information and experience to estimate relative magnitudes through paired comparisons. These comparisons are used to construct ratio scales of various dimensions, arranged in a hierarchic structure that allows for a systematic procedure to organize basic reasoning and intuition by breaking a problem down into smaller constituent parts. Thus, the AHP leads from superficial pairwise comparison judgments to the priorities in the hierarchy (Saaty, 2013).

2.7 The utility function

The utility function is a way of measuring the desirability of preferring different objects called alternatives. The utility score is the degree of well-being each of those alternatives provides to the decision-maker. The utility function comprises various criteria that assess an alternative's global utility. For each criterion, the decision-maker assigns a marginal utility score. One advantage to defining utility functions is that the options of the decision problem receive a global score. The marginal utility scores of the criteria are aggregated to yield the global utility score. This score makes it possible to compare all options and rank them from best to worst, with equal rankings permitted. A bad score on one criterion can be compensated by a good score on another (Ishizaka and Nemery, 2013). This approach is called the whole aggregation approach.

Ishizaka and Nemery state that if the utility function for each criterion (a representation of the perceived utility given the performance of the option on a specific criterion) is known, then the multi-attribute utility theory (MAUT) is recommended (Ishizaka and Nemery, 2013).

2.8 The Multi-Attribute Utility Theory

One of the most readily understandable approaches to decision analysis is multi-attribute utility analysis (MAUT) by Keeney and Raiffa (Keeney and Raiffa, 1993; Rupprecht et al., 2017). MAUT is based on the hypothesis that every decision-maker tries to optimize, consciously or implicitly, a function that aggregates all their points of view. It means that the decision maker's preferences can be represented by a function called the utility function *U*. Each alternative of set *A* is evaluated based on function *U* and receives a utility score *U*(*a*) (an example is shown in Figure 3). This utility score allows all alternatives to be ranked from best to worst (Ishizaka and Nemery, 2013). The preference and indifference relations among the other options of *A* are thus defined as follows:

$$\forall\, a, b\ \in A\colon a\ \mathrm{P}\ b\ \Leftrightarrow U(a) > U(b)\colon a\ is\ preferred\ to\ b \tag{1}$$

$$\forall\, a, b\ \in A\colon a\ \mathrm{P}\ b\ \Leftrightarrow U(a) = U(b)\colon a\ and\ b\ are\ indifferent \tag{2}$$

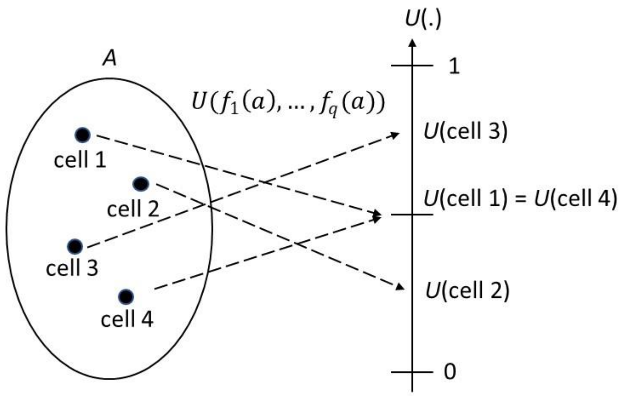

Figure 3: Representation of the set *A* ranking of the MAUT model

Source: Adapted from: Ishizaka and Nemery (2013, p. 82).

The utility function is defined using the additive model, the most popular and widely used model. In this model, the simple weighted sum is a particular case where U_j are all linear functions (Ishizaka and Nemery, 2013). The utility score corresponds to the following:

$$\forall\, a_i \in A\colon U(a_i) = U(f_1(a_i), \dots, f_q(a_i)) = \sum\nolimits_{j=1}^{q} U_j(f_j(a_i)) \cdot \omega_j \tag{3}$$

where q is the number of criteria, ω_j is the weight of criterion f_j, and $U_j(f_j) \geq 0$. In general, they satisfy the normalization constraint (Ishizaka and Nemery, 2013):

$$\sum\nolimits_{j=1}^{q} \omega_j = 1 \tag{4}$$

The marginal utility function has the property that the best alternative on a specific criterion has a marginal utility score of 1, and the worst option has a score of 0 on the same criterion.

3 The proposed cell ranking method

We propose an algorithm to rank the LTE cells of a given RTA on the basis of their general performance, measured through the most relevant KPIs. The cells are ranked from the lowest-performing ones to a predefined threshold to facilitate cell fault management and self-healing processes by reducing the number of cells to be managed and healed. The main difficulty with ranking all the cells in a network is the vast number of alternatives (thousands of LTE cells). Thus, we propose using discrete MCDM methods to solve a problem where the other options are numerous and non-predetermined (faulty cells) with a set of quantifiable objectives (selected KPIs) that could be classified as a continuous MODM problem. Therefore, based on the broad classification of MCDM methods presented by Zavadskas (Zavadskas, Turskis and Kildienė, 2014), the present problem could be associated with a new category of problems, which Zavadskas had not considered, at the intersection of discrete and continuous problems (see Figure 4).

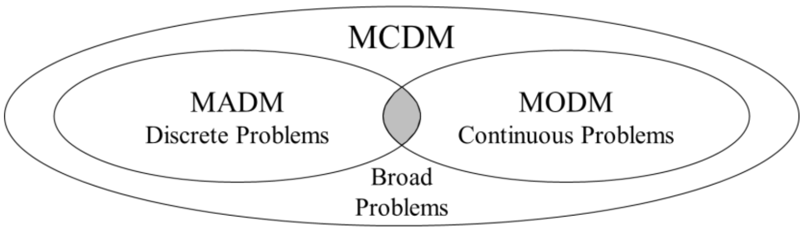

Figure 4: New proposed classification of MCDM methods

Source: Adapted from: Zavadskas, Turskis and Kildienė (2014).

The proposed method involves three steps, which are described below.

3.1 KPI selection

This first step is to select the RAT KPIs with the most significant impact on the end-user experience, considering both data and voice indicators. Selection is based on two factors: the motivation to improve the user experience (3GPP TS 28.404, 2020) and the difficulty of expressing it objectively and mathematically. To make this selection, it is essential to establish a relationship between user expectations and the QoS KPIs (Vaser and Forconi, 2015). Therefore, from the five categories of KPIs defined in (3GPP TS 32.450, 2019) and classified as QoS KPIs in this article, eight individual KPIs were selected from the three categories with the most significant impact on the end user: accessibility, retainability, and mobility. The Telemanagement Forum (TMF) Wireless Services Measurement Handbook GB923 (The Open Group, 2004) states that voice and data networks have been provisioned separately, and KPIs have been considered independently for each service. All the KPIs included in the proposed method are calculated as the ratio of two or more performance counters, so they are all normalized, ranging from 0 to 1. The KPIs selected and their formulas are described below.

Accessibility KPIs

E-RAB accessibility is a measurement showing the probability that an end user would be provided with an E-RAB (evolved UTRAN radio access bearer) on request (ITU-T Recommendation E.419, 2006). This type of KPI is perceived by the end user in data service as a connection delay and has a high impact on voice service, as it is perceived as service unavailability. Therefore, two KPIs of this type were selected:

1. Data E-RAB accessibility: a KPI that shows the probability success rate for E-RAB establishment:

$$ACC\_ERAB\_DATA = \frac{Number\ of\ successful\ data\ ERAB\ establishments}{Number\ of\ received\ data\ ERAB\ establishments\ attempts} \quad (5)$$

2. Data VoLTE E-RAB accessibility: a KPI that shows the probability success rate for VoLTE E-RAB establishment:

$$ACC\_ERAB\_VoLTE = \frac{Number\ of\ successful\ VoLTE\ ERAB\ establishments}{Number\ of\ received\ VoLTE\ ERAB\ establishments\ attempts} \quad (6)$$

Retainability KPIs

E-RAB retainability is a measurement that shows how often an end user loses an E-RAB in an abnormal way when the E-RAB is used (ITU-T Recommendation E.419, 2006). The end user in data service also perceives this type of KPI as a connection delay since the service needs to be re-established. It also seriously affects voice service, as it interrupts the voice call. 3GPP defines retainability as abnormal E-RAB releases per session time in seconds. However, this paper measures the ratio of normal E-RAB releases to the total number of E-RAB releases to be consistent with the other indicators, ranging from 0 (no success) to 1 (100% success). Therefore, two KPIs of this type are selected:

1. Data E-RAB retainability: a KPI that shows the rate of the number of normally released E-RABs with data in a buffer:

$$RET\_ERAB\_DATA = \frac{Number\ of\ normally\ released\ data\ ERABs}{Number\ of\ total\ released\ data\ ERABs} \tag{7}$$

2. Data VoLTE E-RAB retainability: a KPI that shows the rate of the number of normally released VoLTE E-RABs with data in a buffer:

$$RET\_ERAB\_VoLTE = \frac{Number\ of\ normally\ released\ VoLTE\ ERAB}{Number\ of\ total\ released\ VoLTE\ ERAB} \tag{8}$$

As for defining an abnormal E-RAB release with end-user impact, a release of the E-RAB is only considered abnormal if the eNodeB assumes that data is waiting for transfer in any of the buffers (ITU-T Recommendation E.419, 2006).

Mobility KPIs

LTE mobility is a measurement showing how LTE mobility functionality works (ITU-T Recommendation E.419, 2006). 3GPP includes handovers with both intra- and inter-LTE frequencies in the same KPI. However, in this paper, they are considered separate KPIs since they affect data and VoLTE services differently. Handover failures can cause delays in data transfers and call degradation, affecting the end user's perception. Four KPIs of this type are selected:

1. Intra-frequency handover: a KPI showing how E-UTRAN mobility functionality works within the same LTE frequency:

$$INTRA\_HO\_DATA = \frac{Number\ of\ successful\ intra\ frequency\ HO}{Number\ of\ intra\ frequency\ HO\ attempts} \tag{9}$$

2. Inter-frequency handover: a KPI that shows how E-UTRAN mobility functionality is working between different LTE frequencies:

$$INTER\_HO\_DATA = \frac{Number\ of\ successful\ inter\ frequency\ HO}{Number\ of\ inter\ frequency\ HO\ attempts} \tag{10}$$

Another process considered when evaluating problems related to mobility is the single radio voice call continuity (SRVCC), which is the continuity between voice calls in VoLTE and circuit-switched access (WCDMA or GSM RATs) (3GPP TS 23.216, 2020). The SRVCC procedure can be considered a particular case of handover, starting when the coverage or quality of the VoLTE call is poor. The session is transferred to a different RAT to keep the call active.

The SRVCC procedure consists of two steps: SRVCC preparation and SRVCC execution. SRVCC preparation does not directly impact the end user but can indicate a fault scenario. SRVCC execution strongly affects the end user, generating voice call interruptions. Therefore, both KPIs related to SRVCC are selected:

3. SRVCC preparation: a KPI that shows the success rate of the first step of SRVCC, preparing the SRVCC handover, starting when the user device receives the handover command (Qualcomm Technologies Inc., 2012):

$$SRVCC\_PREP = \frac{Number\ of\ successful\ SRVCC\ Preparation}{Number\ of\ SRVCC\ Preparation\ attempts} \tag{11}$$

4. SRVCC execution: a KPI that shows the success rate of the second step, which happens when the user device executes the handover after success in the previous step (Qualcomm Technologies Inc., 2012):

$$SRVCC\_EXE = \frac{Number\ of\ successful\ SRVCC\ Execution}{Number\ of\ SRVCC\ Execution\ attempts} \tag{12}$$

3.2 Weight definition

Weights must be defined for each of the selected KPIs to construct the utility function. AHP was chosen as it relies on simple hierarchic structures to represent decision problems (Saaty, 2013). The weights are found by calculating scores (or priorities, as they are called in AHP) based on the pairwise comparisons provided by the user (Ishizaka and Nemery, 2013).

To define the weights for the selected KPIs, AHP is implemented in three steps, following the procedure described by Dudnikova et al. (2015).

1. The problem is decomposed into its constituent parts, or criteria, which are the KPIs described in the previous subsection (summarized in Table 1).

Table 1: Selected KPIs

Category	Service	KPI
Accessibility	Data	ACC_ERAB_DATA
	Voice	ACC_ERAB_VoLTE
Retainability	Data	RET_ERAB_DATA
	Voice	RET_ERAB_VoLTE
Mobility	Data	INTRA_HO_DATA
	Data	INTER_HO_DATA
	Voice	SRVCC_PREP
	Voice	SRVCC_EXE

2. A relative importance value is assigned to each criterion by pairwise comparison. The fundamental scale, or the Saaty scale, defined in Saaty (2013), is used to rank the judgments introduced in Table 2. In LTE networks, voice is a data service (Voice over LTE − VoLTE). It follows the strictest quality criteria, as voice is susceptible to delay, jitter, and loss (The Open Group, 2004). Hence, the method proposed in this paper assigns higher importance to voice KPIs than to the other KPIs.

Table 2: Fundamental or Saaty Scale

Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one activity over another
5	Strong importance	Experience and judgment strongly favor one activity over another
7	Very strong importance	An activity is favored very strongly over another; its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between adjacent judgments	

Source: Saaty (2013).

The quantified judgments about pairs of criteria are represented by the following $j \times j$ matrix A:

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1j} \\ 1/a_{12} & 1 & \cdots & a_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ 1/a_{j1} & 1/a_{2j} & \cdots & 1 \end{bmatrix} \tag{13}$$

3. The eigenvector w of matrix A is calculated using the geometric mean method (Pervaiz and Bigham, 2009), and the relative weights of the factors (ω_j) are derived from the components of the normalized eigenvector (Dudnikova et al., 2015):

$$w_j = (\Pi a_{jj})^{1/q} \tag{14}$$

$$\omega_j = \frac{w_j}{\sum_{j=1}^{q} w_j} \tag{15}$$

The matrix A, the eigenvector, and the relative weights calculated from the presented formulas are shown in Table 3.

Table 3: Pairwise KPI Comparison, calculated eigenvectors and relative weights for each KPI

	RET_ERAB _VoLTE	ACC_ERAB _VoLTE	RET_ERAB _DATA	ACC_ERAB _DATA	INTER_HO _DATA	INTRA_HO _DATA	SRVCC _PREP	SRVCC _EXE	w	ω
RET_ERAB_ VoLTE	1	3	6	5	9	9	9	9	5.2650	0.4276
ACC_ERAB_ VoLTE	1/3	1	3	7	5	4	6	5	2.8373	0.2304
RET_ERAB_ DATA	1/6	1/5	1	3	6	5	2	2	1.3643	0.1108
ACC_ERAB_ DATA	1/5	1/7	1/3	1	3	3	2	2	0.8748	0.0710
INTER_HO_ DATA	1/9	1/5	1/6	1/3	1	5	2	2	0.6296	0.0511
INTRA_HO_ DATA	1/9	1/4	1/5	1/3	1/5	1	2	2	0.4429	0.0360
SRVCC_ PREP	1/9	1/6	½	1/2	1/2	1/2	1	9	0.5652	0.0459
SRVCC_ EXE	1/9	1/5	½	½	½	1/2	1/9	1	0.3339	0.0271

As expected, voice KPIs have the highest relative weights, and the retainability of VoLTE calls (RET_ERAB_VoLTE) is the most significant weight.

Since comparisons performed in AHP are subjective, judgment errors are inevitable and must be detected by verifying the consistency rate (*CR*) of *A* before selecting the weight values. The *CR* is calculated as follows:

$$CR = \frac{CI}{RI};\ CI = \frac{\lambda_{max} - q}{q-1} \tag{16}$$

where *CI* is a consistency index, representing the deviation of the maximum eigenvalue of matrix A (λ_{max}) from the number of criteria used in the comparison process (q). *RI* is a random index, the average *CI* of a randomly generated reciprocal matrix. All *RI* values for different matrix dimensions are provided in Saaty (2013). If *CR* = 0, the matrix is perfectly consistent. If *CR* ≤ 0.1, the evaluated weight values are acceptable (Dudnikova et al., 2015). The λ_{max} is calculated as follows:

$$\lambda_{max} = \left[\sum_{j=1}^{q} a_{j1} \quad \cdots \quad \sum_{j=1}^{q} a_{jq}\right] \cdot \begin{bmatrix} \omega_1 \\ \cdots \\ \omega_j \end{bmatrix} \tag{17}$$

In the present problem, λ_{max}= 8.9276, *CI* = 0.1325, *RI* = 1.41, and *CR* = = 0.0940. Therefore, *CR* ≤ 0.1, and the obtained relative weights are consistent.

3.3 Utility function construction

As explained in Section 2, when the utility function for each criterion is known, the multi-attribute utility theory (MAUT) is recommended (Ishizaka and Nemery, 2013). It is the case for the present problem, where the criteria are the selected KPIs, each having a defined function. As all selected KPIs are ratios from the interval [0,1]. Hence, the MCDM method MAUT can construct the utility function.

The proposed method uses the simple weighted sum to construct the utility function for each LTE cell, considering the eight KPIs selected as criteria a_i, the relative weights obtained using the AHP method, and the number of fails for each KPI. The number of fails is necessary to avoid assigning a high score to a cell with degraded KPIs, but a low number of fails due to low traffic.

The function is then normalized by dividing the weighted sum by the sum of weights multiplied by the fails for each KPI, as shown below:

$$\forall a_i \in A: U(a_i) = \frac{\sum_{j=1}^{q} U_j(f_j(a_i)) \cdot \omega_j \cdot Fails_j}{\sum_{j=1}^{q} \omega_j \cdot Fails_j} \tag{18}$$

The number of fails of each KPI is calculated as a difference between the number of attempts and the number of successes for each indicator:

$$Fails_j = Number\ of\ attempts_j - Number\ of\ successes_j \tag{19}$$

4 Results

The proposed method has been applied in a real LTE network from a Brazilian telecommunications operator. 4925 cells from different equipment vendors covering a region of west-central Brazil were selected to verify the results. First, statistical data sampling of the eight selected KPIs was performed, aggregating the counters in a 24-hour base, and the utility function U (Formula 18) was applied to the cells. Then, the cells' utility functions were ranked in reverse order, from worst to best, to quickly identify the most degraded cells. The results are presented in a dashboard, with the cells labeled, starting with Cell 0 to Cell 4925.

The KPIs values in the dashboard are classified into three ranges for easier visual monitoring:

1) critical: from 0 to 0.50, indicating the most critical values;
2) alarming: from 0.50 to 0.99, indicating intermediate values;
3) OK: from 0.99 to 1, indicating the highest values.

The utility values follow the same classification, ranging from 0 to 1, with critical values between 0 and 0.50.

As an example of the results obtained, Table 5 reproduces the dashboard for a specific day, showing the first 12 results. The utility function allows the eight KPIs of the cells to be aggregated into a single indicator, facilitating ranking of the cells. Furthermore, only 0.20% of the cells have values below 0.50, significantly reducing the number of critical cells from the selected universe that need to be managed and healed, and highlighting the worst cells in terms of QoS, which are the main objectives of the proposed model.

On the analysis day, Cell 3083 was ranked as the worst cell, as SRVCC preparation performed very poorly, followed by SRVCC execution and handover KPIs. However, the cell had no active alarms or other operational problems and was not identified by traditional fault management. Crucially, although Cell 3083 was not the one with the most fails, its impact on the network was huge, as the fails were concentrated in VoLTE mobility, which the end user would have perceived as voice quality degradation. Table 4 shows all Cell 3083 measurements used to calculate its utility function, as detailed in Formula (20):

$$U(3083) = \frac{\sum_{j=1}^{q} U_j(f_j(3083)) \cdot \omega_j \cdot Fails_j}{\sum_{j=1}^{q} \omega_j \cdot Fails_j} \tag{20}$$

where:

$\sum_{j=1}^{q} U_j(f_j(3083)) \cdot \omega_j \cdot Fails_j = 0.9923 \cdot 0.4276 \cdot 1 + 1 \cdot 0.2304 \cdot 0 + 0.9996 \cdot$
$\cdot\ 0.1108 \cdot 10 + 0.9998 \cdot 0.0710 \cdot 3 + 0.9870 \cdot 0.0511 \cdot 76 + 0.9852 \cdot 0.0360 \cdot 119 +$
$+\ 0.0026 \cdot 0.0459 \cdot 2267 + 0.8333 \cdot 0.0271 \cdot 1$

and:

$\sum_{j=1}^{q} \omega_j \cdot Fails_j = 0.4276 \cdot 1 + 0.2304 \cdot 0 + 0.1108 \cdot 10 + 0.0710 \cdot 3 + 0.0511 \cdot$
$\cdot\ 76 + 0.0360 \cdot 119 + 0.0459 \cdot 2267 + 0.0271 \cdot 1$

Table 4: Measurements from Cell 3083 used to calculate its utility function

KPI	Success	Attempts	Fails	Value	Weights
VoLTE_RET	129	130	1	0.9923	0.4276
VoLTE_ACC	130	130	0	1.0000	0.2304
RET_ERAB	25776	25786	10	0.9996	0.1108
ACC_ERAB	19505	19508	3	0.9998	0.0710
HO_INTRA	7912	8031	76	0.9870	0.0511
HO_INTER	5762	5838	119	0.9852	0.0360
SRVCC_PREP	6	2273	2267	0.0026	0.0459
SRVCC_EXE	5	6	1	0.8333	0.0271

Another significant result from applying the proposed model is shown by the analysis of Cells 0574 and 0573. They are neighbor cells and present a value of zero in VoLTE KPIs. However, they did not have VoLTE fails, which indicates no traffic on that service, even if the KPIs impacting their utility function were from data handover. However, the lack of VoLTE traffic can also indicate a configuration failure and should be investigated by cell performance managers.

An overall analysis of the results for the worst cells of the network can give engineers valuable insight into its health, as it aggregates the most relevant LTE radio KPIs. For example, the KPIs values of the worst cells from Table 5 show that the network problems are concentrated in handover and SRVCC indicators, meaning that mobility is the key issue to address.

Table 5: Utility function results (U) and ranking applied in cells of an actual LTE network

Cell	U	Fails	RET_ERAB _VoLTE	ACC_ERAB _VoLTE	RET_ERAB _DATA	ACC_ERAB _DATA	INTER_HO _DATA	INTRA_HO _DATA	SRVCC _PREP	SRVCC _EXE
Cell 3083	0.0886	2477	0.9923	1.0000	0.9996	0.9998	0.9870	0.9852	0.0026	0.8333
Cell 2806	0.1190	3056	0.9967	0.9882	0.9995	0.9972	0.9876	0.9815	0.0029	1.0000
Cell 1411	0.2465	7761	0.9957	1.0000	0.9979	0.9963	0.1931	0.9863	1.0000	1.0000
Cell 1802	0.3054	14905	0.9883	0.9881	0.9991	0.9993	0.2823	0.9426	1.0000	1.0000
Cell 2217	0.3072	14822	0.9952	1.0000	0.9994	0.9993	0.9860	0.2809	0.0000	0.0000
Cell 1834	0.3161	1735	0.9985	0.9977	0.9996	0.9985	0.9793	0.9895	0.0061	1.0000
Cell 0574	39.7838	506	0.0000	0.0000	0.9993	0.9997	0.5068	0.3742	0.0000	0.0000
Cell 0862	40.3638	124	0.9969	0.9973	0.9986	0.9997	0.9971	0.9311	0.0829	0.9810
Cell 0573	41.8881	204	0.0000	0.0000	0.9987	0.9992	0.7213	0.3468	0.0000	0.0000
Cell 1417	42.4690	420	1.0000	0.9939	0.9994	0.9986	0.3808	0.9668	1.0000	1.0000
Cell 4501	44.2235	362	1.0000	0.9951	0.9994	0.9925	0.9916	0.3857	0.0000	0.0000
Cell 1349	45.9742	586	0.9931	0.9946	0.9992	0.9964	0.3743	0.9870	1.0000	1.0000

5 Conclusion

This paper proposes using an innovative application of MCDM methods for radio access network analysis and cell failure management by ranking the worst-performing LTE cells. This is the first attempt to use discrete MCDM methods to solve problems with quantifiable objectives where the alternatives are numerous and not predetermined.

As shown in the previous section, we could identify very poorly performing cells with no active operational alarms that could not be identified through traditional fault management. By ranking cells based on a utility function U that aggregates the main radio QoS KPIs, the proposed method automatically indicates the global worst cells to be repaired, improving network quality more efficiently. Furthermore, the utility function U can filter cells based on performance objectives to be analyzed and repaired by network engineers. This approach may reduce the time consumed in identifying faulty cells that affect the end-user performance, improving the perceived LTE network performance.

Repairing the most critical performance cells quickly and efficiently helps operators and cell optimization service providers with network performance management. It satisfies quality requirements set by the government or by other inspection agencies. The weights defined by the AHP method can also be adapted to the operators' needs − for example, by switching priorities from voice to data or mobility − making the method customizable.

The proposed method may also be used to rank a group of cells (e.g., clusters or cities), aggregating the selected KPIs and calculating the utility function for each defined group, helping to identify performance variations in that group. Furthermore, the method can be adapted to rank cells of other radio access technologies, such as 3G (WCDMA) and 5G NR (New Radio), selecting the most important KPIs for each technology and applying the weights and the utility function. Hence, the method described in this paper is a framework that can be adapted to different performance management systems.

The above advantages could be verified in a live LTE network. The time to detect a failing cell and the number of non-detected failing cells in the network were significantly reduced. Furthermore, the weights and KPIs prioritization can be changed according to the customer's priorities, being a flexible framework that fits network management. Some disadvantages of the method were also perceived during the tests, as sleeping cells, cells hanging resources, and low--traffic cells could not be well-detected. Cells off also become unreachable and undetected by the method, which doesn't replace traditional faulty cell detection systems.

The proposed approach can contribute significantly to cell performance management in radio access networks. We have presented a new method of KPI aggregation to rank the worst-performing LTE cells based on MCDM methods. This paper also contributes to the MCDM literature, introducing its methods to SON functionalities and applying them to a large set of non-predetermined options.

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