IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 28 September 2024, accepted 23 October 2024, date of publication 1 November 2024,
date of current version 21 November 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3489354

APPLIED RESEARCH

Toward Zero-Touch Cellular Networks via Next-Generation Crowdsourcing

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This work was supported in part by the Campus de Excelencia Internacional Andalucía Tech and Fondo Europeo de Desarrollo Regional (FEDER) funds through the Project Massive User Experience Assessment and Prediction for Mobile Networks (MUSE) under Grant UMA-CEIATECH-15; in part by Spanish Ministry of Economic Affairs and Digital Transformation and European Union—NextGenerationEU within the Framework ''Recuperación, Transformación y Resiliencia y el Mecanismo de Recuperación y Resiliencia'' under the Project Massive AI for the Open RadIo b5G/6G network (MAORI); and in part by Spanish Ministry of Universities through the Program ''Ayudas Para la formación de Profesorado Universitario'' under Grant FPU20/02863.

ABSTRACT Under the Zero-touch network and Service Management (ZSM) paradigm, cellular networks are moving to fully automated schemes in order to minimize human intervention and maximize efficiency. Until now, such management has been based on network metrics and complemented with drive tests. However, this approach is clearly insufficient to achieve Zero Touch since the information available from the network side is limited, aggregated from all the users within a cell, and collected with a frequency of minutes. Also, the complexity and high cost of performing drive tests to collect user-side data are among the main drawbacks. Nevertheless, there is an option between the two aforementioned: Next-Generation Crowdsourcing Metrics (gCMs). In this regard, the present work describes a novel framework for ZSM cellular networks that exploits the advantages of integrating crowdsourcing User Equipment (UE) side metrics to advanced network management. We analyzed the suitability of the proposal by using data acquired from commercial cellular networks. The obtained results state that there is a wide range of applications for gCMs that can benefit network operation, including the detection of coverage holes, mobility issues, and interference problems. Finally, the identified open challenges are disclosed based on the achieved results.

INDEX TERMS Crowdsourcing, KQI, ML, QoE, RAN, UE, zero touch.

I. INTRODUCTION

A. BACKGROUND

An essential role in cellular networks is played by network management mechanisms that are in charge of changing network parameters mainly for optimization and failure management purposes. Given the more demanding requirements they introduce, this aspect becomes critical with each generation, leading to greater complexity.

In this regard, network infrastructures have incorporated a set of new features, including beamforming techniques, mmWave spectrum, and low-layer design changes, as well as new heterogeneous services. This has resulted in multiplying the number of variables that need to be managed simultaneously. Then, it has become technically unfeasible for radio engineers to manage manually.

Therefore, the industry has been automating some specific tasks by incorporating the Self-Organizing Networks (SON) concept in Third Generation Partnership Project (3GPP) standards through Machine Learning (ML) mechanisms [1]. Regarding ML application, the authors in [2] propose anomaly detection and diagnosis in 5G networks. In [3], they investigated the self-healing problem in SON-based ultra-dense cell networks. Moreover, Quality of Experience (QoE) is also considered for autonomous network management in [4].

The associate editor coordinating the review of this manuscript and approving it for publication was Nurul I. Sarkar.

While these solutions improve some specific aspects, the new ZSM paradigm [5] attempts to go one step further, and focuses on eliminating human intervention in all aspects of network management by extending the SON approach. The potential of ZSM is detailed in [6], where a comparison of ML is done in a case study, stating that it is the way for the ZSM to adapt to changing traffic patterns. Also, it reveals that there is much work to be done and refined in this area. To achieve this, the need for large datasets to enable the training of its ML models is even more pressing [7].

The Self-Evolving Networks (SEN) concept was introduced in [8], although it envisages a self-management that spans across multiple operators and ecosystems (e.g., satellite, aerial and terrestrial networks) to avoid conflicts and enable entities coordination. To do this, a steady monitoring and learning process is required. They considered collaborative computing, where computational resources of UEs can be aggregated into clusters.

While the previous works address the specific aspects of SON, or propose the elimination of human intervention (i.e., ZSM) for network management, both with the application of ML, the present work combines the previous with the utilization of UE side data.

Regarding network management, there exist two main sources of useful information. On the one hand, network side provides several types of performance information. On the other hand, UE side is another source of relevant information towards management. UE side has traditionally been involved in network management by the use of Drive Tests (DTs), where a very comprehensive sampling is carried out with specific devices connected to the network while driving through different areas. However, they are costly and can only provide relatively limited information in terms of both space and time. Also, pedestrian or indoor areas are usually excluded from these tests.

B. MOTIVATION

However, in this work, UEs are regarded as a key data source for network management, as they provide useful information about the QoE, the network load, or the scenario, which are essential to understand the dynamics of network usage. In addition, ML, and especially Deep Learning needs huge amounts of data to work. In this context, data collected from UE side may represent a solution in providing data for training cellular network management algorithms. These data is useful due to their quantity, real-time availability, diversity of scenarios, and accurate representation of the network demand. Here, a crowdsourcing platform was developed with the aim of enabling research [9], but they focused on the coverage map creating, ignoring the application of ML for network management.

In this sense, the exploitation localization data is widely studied in the literature. In [10], they propose environment-aware communications, where the Channel Knowledge Map (CKM) is crucial for enhancing the channel estimation algorithms. This is analyzed at the physical layer, from a pure communication perspective, unless the present work, where the focus is on the network management perspective. Nevertheless, in [11], the use of radio maps for wireless resource management is discussed, raising some main challenges regarding the collection and storage of the data.

The rapidly improving development of mobile applications can be a game changer in overcoming this bottleneck. At the application layer, mobile Operating Systems (OSs), provide Application Programming Interfaces (APIs) that can be used by apps to access the cellular modem information in real time, as well as to localization systems (e.g., Global Positioning System (GPS)) and other sensors. Although crowdsourcing data from UEs is not novel, a refined concept (Next-Generation Crowdsourcing Metric (gCM)) is considered in this work, where richer information is achieved at the same cost. They include radio metrics (Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), ...), device details, location information, and experiment results (video streaming, web browsing, ...) directly related to QoE.

Therefore, there are potential advantages in using UEs side information for network management. In the same vein, the current status of the technology allows the integration of UEs side data into the network management framework. However, this integration requires the coordination of different actors, including network operators, application developers, and equipment vendors. Then, it is key to identify and evaluate the potential applications of gCMs in network management for these actors to be interested in the integration.

C. CONTRIBUTION

Thus, the present work aims to evaluate the application of gCMs, i.e., UE side data, for the management to be applied in next-generation ZSM networks. A complete framework, together with processing techniques, is proposed for its application to network management. This framework considers the integration of different sources of information, focusing on the added value of gCMs. The utilization of ML is envisioned for both processing and concrete network management applications. Then, the complete framework is evaluated using real data from commercial cellular networks. So, this work provides a closed-loop evaluation of the exploitation of gCMs towards the ZSM paradigm. In addition, some challenges remain open for efficiently exploiting gCMs in network management. The open challenges identified during this work are also discussed.

In this way, this paper is organized as follows: Section II presents the different sources of network metrics. Section III describes the framework encompassing several applications that exploit gCMs, including results based on real data. Section IV reviews open research lines and how they could be addressed. Finally, Section V draws some conclusions from this work.

II. SOURCES AND CHARACTERIZATION

This section reviews the sources of information, covering their main advantages and disadvantages and how they could complement each other to fit into the ZSM scheme. Here, for the sake of clarity, the Quality of Service (QoS) is defined as the objective quality, measured through different metrics, e.g., packet loss ratio or service delay. In contrast, the QoE is the subjective quality perceived by users, usually obtained through forms under a laboratory environment, and considers the user's expectations and context. The QoE is usually related to the application being used, e.g., freeze frames in video streaming, refers to the delight or annoyance of the user, and it is by definition highly affected by QoS. The QoS comprises the network performance between end devices, but the scope of QoE is broader as it includes the user perception, according to the International Telecommunication Union (ITU) [12].

A. CLASSIC SOURCES

1) NETWORK METRICS

Cellular networks provide performance information classified into events, alarms, counters, Key Performance Indicators (KPIs), and traces.

However, these metrics are usually aggregated per cell, so it is difficult to detect specific problems, e.g., they would detect a cell outage that it is generating connection drops, handovers, and capacity problems. Still, it will likely be much more challenging to detect coverage holes, where users cannot even attach due to lousy coverage conditions at specific locations. Moreover, counters and KPIs are typically aggregated into hourly periods, being difficult to identify problems in a short time.

In addition, the network perspective is not enough to identify QoE problems. Thus, the user perspective, as well as context information, may enhance the problem detection and troubleshooting. Here, a user could be registered to the network and report good signal quality but unable to use the service it demands, e.g., videoconferencing.

However, tracing this specific user is not feasible; even if it is reporting bad performance through a ticket, operators cannot devote resources to trace the user.

2) DRIVE TESTS

DTs have played a key role in classic network management approaches. They only provide outdoor data but are probably the most precise way to analyze and optimize some network problems, since they have access to Radio Resource Control (RRC) layer 3 messages exchange.

Additionally, Minimization of Drive Tests (MDTs) were introduced by 3GPP Rel-10 [13], aimed at collecting radio quality information at UE, and report it to the network [14]. Nevertheless, their drawback is that operators tend to disable them because they may degrade the user's QoS in terms of data rates and battery life.

B. NEXT-GENERATION CROWDSOURCING METRICS (gCM)

The integration of information from gCMs embodies user metrics from lower layers (RSRP, RSRQ, etc) [15] to the application layer (video streaming, web browsing, etc), into the ZSM offers several advantages. It will allow the network to optimize user experience autonomously, as well as to tailor its services automatically according to user demand patterns. Altogether, this will enable in-depth troubleshooting and problem detection, reducing downtime and the need for human intervention. Lastly, real-time, automated resource allocation based on user equipment data will incorporate efficiency into automation.

TABLE 1. Characteristics of sources of information.

Source	Granularity		Cost		Variability
	Temporal	Spatial	Computational	Operational	
Network metrics	$\uparrow$	$\downarrow$	$\uparrow\uparrow$	$\downarrow\downarrow$	$\downarrow\downarrow$
Drive Test	$\uparrow\uparrow$	$\downarrow\downarrow$	$\downarrow$	$\uparrow\uparrow$	$\downarrow$
gCM-M	$\uparrow$	$\uparrow\uparrow$	$\downarrow$	$\downarrow\downarrow$	$\uparrow\uparrow$
gCM-S	$\uparrow\uparrow$	$\downarrow$	$\downarrow$	$\uparrow$	$\downarrow$

Nevertheless, this work focuses on the analysis of both mobile and stationary gCMs obtained from real cellular network users. Figure 1 illustrates a scenario where both UE-side Network-side metrics are collected. They together power the proposed ZSM framework, which is aided by ML techniques over both data types. The components of the classical ZSM architecture are represented in grayscale, while the novel gCMs components and techniques are colored.

1) MOBILE NEXT-GENERATION CROWDSOURCING METRICS (gCM-M)

This information is collected from the application layer; it has access to the OS and thus asks for information from the radio modem. This way, data can contain information about only low-layer metrics or both low-layer metrics and Key Quality Indicator (KQI). Thus, the samples always contain low-layer information: timestamp, radio information (e.g., band, RSRP, RSRQ), and location information. Additionally, these samples comprise device details (brand, model, operating system version, enabled features…), and operator information (e.g., Mobile Country Code (MCC) and Mobile Network Code (MNC)). The collection of this type of data is cost-effective since the metrics are continuously being taken, and it would only require storing them, without triggering extra measurements. The only task needed is to save the data to a file and report it within a specific period. In this sense, these data can be collected with high temporal granularity. Although computing the position for localization needs some processing, it usually takes advantage of other applications that use the location for other purposes. e.g.,

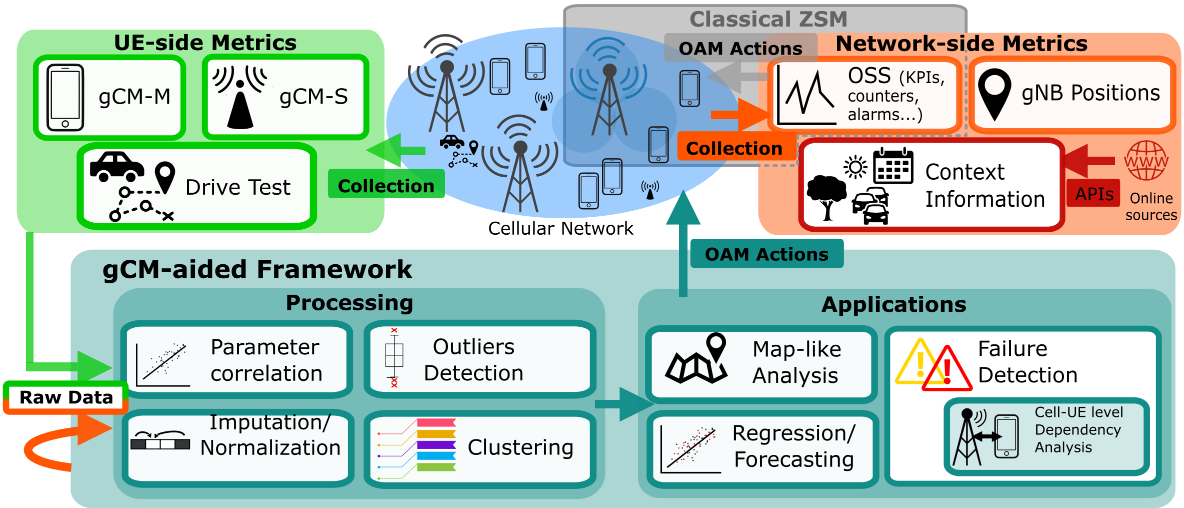

FIGURE 1. UE-driven ZSM management framework.

real-time location sharing with friends. In fact, when the GPS module is being used by any application on the terminal, the temporal granularity could increase at zero cost, e.g., while using navigation to get to a place. In this case, the collected data is comparable to a simplified DT. These data have to be properly anonymized in order to respect privacy laws. Still, it is helpful since it aims to exploit the data to acquire a complete vision of the network performance from the final users' perspective.

On the other side, there is a second type of data that includes service-specific KQI by performing experiment tests. KQIs directly refer to service performance that users experience while using. Experiments consist of performing some short actions that are directly related to what a user may need, e.g., a ping test or a small file download or upload. Triggering these events is less efficient in terms of battery and mobile data usage. Hence, their temporal granularity is typically lower. Two approaches are envisioned here: keeping limited the number of samples with QoE information or using regression techniques to estimate QoE metrics using low-layer metrics as input. This is described in Section III. There are several experiment types configured with different periodicity according to the resources they use. They are designed to be transparent for the users but also to cause the minimum impact on both the device and the network: for the low-layer information, the network burden is zero since radio quality metrics collection does not imply network traffic; for the KQI information, the network burden is reduced, since the amount of traffic that is transferred is minimal, and the experiments are scheduled to be performed while the user is actively using the network for other purposes.

However, the main drawback of these data is the diversity of users. Each user owns a different device, with specific capabilities, radio chipset, and processor, as well as different OS versions. This results in different behaviors in the same data collection application or library on different devices. These differences were appreciated during this work, and some analyses were performed by filtering these characteristics.

2) STATIONARY NEXT-GENERATION CROWDSOURCING METRICS (gCM-S)

An additional source of information is the use of probes (named beacon), that are deployed on specific locations with the aim of acting as UEs that perform typical users' tasks. Beacons are considered in between UE Apps and DTs. They can collect richer information than UE apps since power and data usage is not a constraint, as it happen with DTs equipment. Thus, their temporal granularity is notably higher. On the contrary, they are usually in fixed positions, so their spatial granularity decreases. Their main advantage compared to DTs is their cost, since they do not need and engineer to perform a moving test, as well as the fact that they are usually sited indoors. The indoor coverage estimation is usually challenging because DTs do not commonly include indoors, but UE apps and beacons are potent alternatives to overcome this. Thus, not only department stores or stadiums but also cellular network providers may be interested on deploying beacons on their premises, since it will enable performance analysis from the user's perspective. This approach has also been studied in the literature with different perspectives, e.g., to monitor social events' impact on a network [16]. Moreover, Internet of Things (IoT) devices are also envisioned as a source of network information in [17]. They would show less variability that UE directly measures: on the one hand, due to the fact that the beacons are commonly stationary; on the other hand, the device hardware capabilities of the beacons are almost equal among them. Also, they do not depend on the user's usage as it happen with the UE application data. Parameter correlation findings are also clearer regarding beacon data, as shown in Section III.

In addition, there is another kind of metric that is becoming important for network management: the information from the context, e.g., traffic, social events, weather... By combining contextual information with the rest of metrics, some problems can be detected when unusual behavior is identified over the KPIs [18].

In conclusion, Table 1 summarizes the different sources of information, where advantages and disadvantages are highlighted in green and red, respectively. It shows that each source has negative points, regardless of the effort that is needed to post-process the retrieved information. However, UE apps provide great advantages at low cost, except for the high variability, given the different characteristics of the devices that are used. They can play an important role towards ZSM, as described in the next section.

For the remainder of this paper, UE-side metrics will refer to both UE application metrics and beacon metrics, since drive test data are not deeply treated in this work.

III. ZERO-TOUCH MANAGEMENT FRAMEWORK

The proposed framework for the acquisition of both sides of the network and the exploitation of the data towards ZSM is illustrated in Figure 1, whose components are detailed in the following subsections.

Firstly, although we distinguish between data collected from UE side and non-UE side, the framework is based on the gCMs, being able to benefit also from classical non-UE metrics if they are available. In this sense, Cell-UE level dependency analysis is considered an optional component that could enhance the results. This framework is able to process data from different sources, which implies different formats (Raw data in Fig. 1), so they are formatted and internally stored by following a common structure. This format allows the data retrieval by the different components and applications of the system.

Consequently, these data are then passed to the processing block, where there are different mechanism that can be applied on the data in order to extract relations between parameters, clean the data from anomalies, and prepare them to be used by the network management applications. The applications block is the last step within the framework as it provides information on the past, current and forecasted network states. The use of real-time inputs for the framework is possible since the users will only need to carry their UEs with them. The framework components have been applied on real data, and they are described in detail in the following subsections.

A. DATA PROCESSING

As described above, the data processing block is key within the framework. The UE-side data is noisy by nature, since it comes from different devices and people, which means each sample is likely singular. At the same time, this randomness of conditions where users can report information leads to a wealth of data, which is beneficial while it requires high complexity processing. This block is composed of multiple functionalities: parameter correlation, imputation/normalization, outliers detection, and clustering.

1) PARAMETER CORRELATION

Firstly, classic pre-processing correlation techniques are applied. They provide an initial analysis of the linear and non-linear correlation coefficients. Several insights were obtained from the Pearson correlation coefficient, i.e., a measure of linear dependency between random variables, which is illustrated in Fig. 2. It shows that the QoS metrics with higher correlations are different between Downlink (DL) and Uplink (UL) rates. This means that Signal-to-Noise-Ratio (SNR) is the most important metric for estimating DL rate while RSRP is the most important for the UL rate estimation. In the figure, some observations are direct, such as the incorrelation of the WiFi connection (WifiConnected). But others will need further analysis, for instance, the month when the sample is taken (LocalTime_month), which could be related to the season, but in this case, was then actually related to the number of available samples.

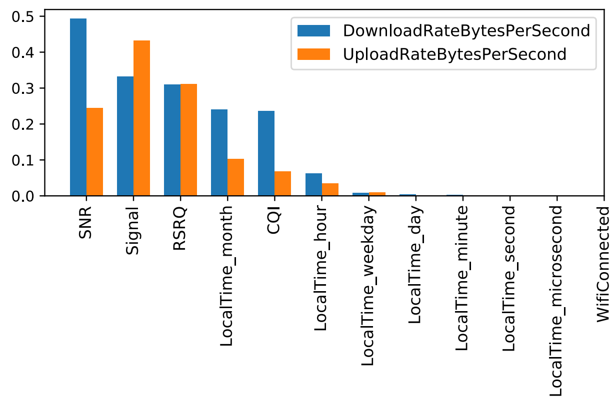

FIGURE 2. Pearson correlation coefficient between QoS metrics and the DL and UL rates.

2) IMPUTATION/NORMALIZATION

Imputation consists on using the existing samples to generate artificial values for missing samples. This is performed on the QoS samples since they are more robust. Here, different techniques have been considered, from computing the mean of the existing samples as baseline to using decision tree estimators. These techniques can increase the size of the dataset. Then, the synthesized QoS samples are also used as input for regression techniques, that are described below.

On the other side, the QoS metrics that are present in the samples are miscellaneous. Here, there are mainly radio metrics and device information, but also other metrics such as the status of the screen or whether some services are enabled or disabled. This implies that normalization of the data is required, given the fact that different metrics use different ranges of values. Figure 3 represents the enhancement in terms of R^2 score (i.e., the predictive performance of the model), when imputing samples using an *Extra-Trees* regressor with different normalization techniques. *Extra-Trees* regressor consists of an ensemble learning algorithm that constructs multiple decision trees and combines their outputs. In the figure, it can be observed, as expected, that some metrics cannot be properly imputed (e.g., battery_level, is_screen_on). However, this is not a problem because they are not the intended metrics for the proposed system.

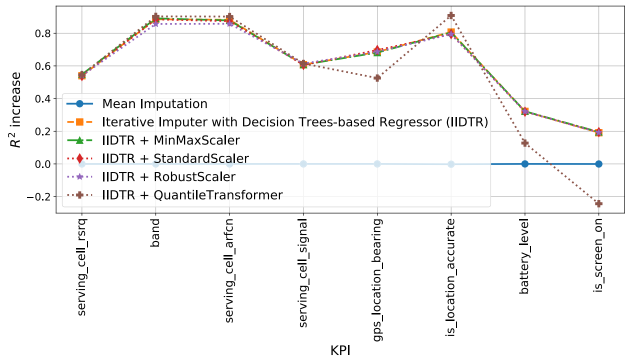

FIGURE 3. R^2 **increase of different imputation techniques in comparison to Mean Imputation technique for different a set of KPIs.**

3) OUTLIERS DETECTION

Here, the data collected through UE application depends on many factors. The brand, device model or operating system version may influence not only the radio indicators (QoS) but also the experiment results. UEs often get frozen, receive calls, or are asked by the users to open an exigent application while they are performing some other tasks, that is, metrics collection. This may lead to extreme values reporting while the network conditions are not really degraded. It can also occur that the resources or tokens needed by the measurement collection application are in use or blocked by any other application, for example, an OS optimizer or cleaner application trying to free resources. In this case, almost all the data collected by a specific UE may be corrupted. These abnormal values are called outliers and they usually add noise to the analysis. Its detection and deletion become key, especially for automatic processing. However, they could also be the more apparent symptoms for detection algorithms, in which case deleting them would be detrimental for the system.

4) CLUSTERING

Furthermore, clustering techniques aim to find similarities between samples. Two types of clustering are envisioned: position-based and metric-based. In the first case, it is possible to find zones where people are usually very close to each other, e.g., a shopping mall or a crowded downtown street. However, the reported cluster metrics may actually be suitable when some users are being rejected by the network or the cell. The metric-based case aims to identify users that are reporting similar network conditions and, therefore, similar QoE. This allows to find users that may complain to their operator about their cellular services due to bad experience, and try to analyze the root cause of the problem, also by exploiting the localization information.

B. APPLICATIONS

The main aim of the proposed framework is to apply the information towards the enhancement of the network performance. Therefore, different applications have been identified and tested with real data. There is a wider range of possibilities when considering UE-side metrics for network management. A set of them are described below, together with the insights obtained from results.

1) MAP-LIKE QOE ANALYSIS

In addition, map graphing is helpful in representing the data. gCMs allow to know the location of samples, so their representation on a map may help to find areas with useful information from an operator perspective, e.g., poor coverage. Figure 4 illustrates a map containing the described techniques. It represents imputed KPIs (RSRQ), as well as the real and estimated KQI samples for the download time of a 2 Mb file experiment. The latter have been obtained by using ML-based techniques using the gCM low-layer metrics as input. Then, clusters can be represented over the map in order to geographically analyze their distribution and extract information of interest towards optimization.

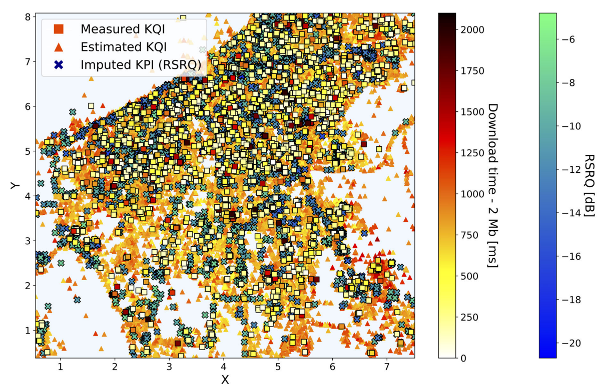

FIGURE 4. Map with original and estimated data for QoS and QoE.

Besides, the radio maps may assist a wide variety of applications, such as proactive interference management, resource provisioning and network planning, and spectrum security and surveillance [11].

2) REGRESSION

Besides, regression is a valuable application given the fact that it enables the QoE estimation, that is, KQIs based on QoS metrics. This has been widely addressed in the literature [19], together with service-oriented approaches (video transmission, cloud-gaming...) [20], [21], [22]. As commented before, users only care about the experience

(QoE), but not about the service (QoS). Thus, here is where operators need to make an effort. If ML-based models can properly estimate the QoE, metrics that operators do not usually have, they will really take advantage of them. This means a big step towards the efficiency, which is one of the objectives for future cellular generations.

QoE estimation enables the possibility of offering better performance to users as well as turning cells to sleep when the conditions are good enough for the number of connected users. This is envisioned by taking into account the localization information of users together with the location of points of interests. In addition, context information would enhance these procedures by providing, e.g., social events information or even cellular metrics predictions [23].

3) FAILURE DETECTION

Finally, the outputs of the described applications are beneficial regarding failure detection. From the regression of QoS/QoE indicators on areas where there are no available data for the coverage hole identification over a map, this gCM data becomes crucial. Therefore, the combination of map-like analyses and regression techniques serves as input for the failure detection. Failure detection is approached by first defining geographical areas, averaging the samples within each area, and then comparing the values of different parameters with respect to the normal case if known, or to the rest of the areas where a similar number of samples are available. In this approach, an area has fewer samples than others can lead to inconsistency on the failure detection mechanisms. To overcome this, data imputation is intended to be performed during the processing phase.

Moreover, dependency analysis between cell and gCMs is envisioned from the operator perspective. Operators are the only ones that can filter gCM samples to compare those connecting to their network. Thus, they can relate the historical cell metrics or statistics with the gCM data. This way, they are able to detect whether a problem detected on the gCMs is really a network problem or it was just related to a certain user(s), or location (e.g., inside a building).

IV. OPEN CHALLENGES

The previous results have shown how the described techniques can be applied, as well as the obtained results. However, there are still some challenges that to be overcome for the proper exploitation of the proposed framework.

- **Standardization:** Although these techniques could fit in the current 5G architecture, there is not a standardized solution for UE application or beacon software. Thus, solutions are currently being individually applied by third parties. While using this individualized approach, it will not be easy to integrate it with the Operations Support System (OSS). In contrast, if this was standardized, gCM could be enabled or disabled by operators and per specific area when needed. Or they could even be enabled on users sequentially to get rich information without affecting the overall performance. Similarly, the standardized solution must ensure the privacy of the users by avoiding sending identification information, thus preventing potential privacy leaks. The purpose of the gCM is to provide information overall, not about specific users, so no identification is required.
- **OpenRAN Compatibility:** When looking towards the OpenRAN paradigm, the exploitation of the UE-based metrics is envisioned as a rApp which is running on the Non-Real-Time (RT)-RAN Intelligent Controller (RIC). RIC is a software-defined component of the OpenRAN architecture that is responsible for controlling and optimizing Radio Access Network (RAN) functions. It is a critical element that enables disaggregation strategy as well as multivendor interoperability by enabling the onboarding of third-party applications. Here, OpenRAN integration would be feasible, but it is not yet mature enough on real deployments.
- **Data heterogeneity:** Regarding the UE application metrics, the most important challenge is to reduce the gap in terms of performance that exists between different devices. The current devices' heterogeneity introduces noise into the ML algorithms. This sometimes makes them impossible to work as expected. Besides, UE applications are not perfect, so bugs may derive into unreal samples. Here, requirements should be defined in order to distinguish whether a sample is considered or not. A possible solution regarding this issue is to consider different device categories, so that performance metrics can be compared to similar devices in a close location. The concept of similar devices ideally refer to the same model, but otherwise, the same chipset, device vendor, OS version, or other metrics previously identified as differentiating.
- **Real-time Filtering** There are also risks when using real-time collected data as input for the system. When certain user(s) enters a building, namely an indoor location, their UE reported data can be dropped significantly. These data should be filtered to avoid false positives in the failure detection mechanisms. Here, sensors available at UE can jointly be used for estimating whether users are indoor or outdoor. However, it could also happen due to a network problem. The latter case should require applying failure management actions on the network, but not the earlier. Then, it would require a really refined problem identification criteria, able to distinguish problems and normal operation.
- **Localization techniques:** Additionally, gCMs location is usually based on GPS, which is not suitable in indoor scenarios, and indoor positioning alternatives are generally not accessible for the users because they tend to be private deployment (e.g., UWB-based deployments). This means that it is difficult to determine whether users are indoors or outdoors, and consequently whether a massive drop on the QoS/QoE data should be labeled as a network problem occurrence. However,

5G-based positioning will overcome this problem in indoors by using specific signals, for example, Positioning Reference Signals (PRSs).

V. CONCLUSION

The aim of this work has been to review the use of gCMs towards future ZSM and to propose a novel approach to their processing and application to network management. Classic network management has been compared to the presented framework incorporating gCMs. For the analysis, real Mobile Next-Generation Crowdsourcing Metrics (gCM-Ms) and Stationary Next-Generation Crowdsourcing Metric (gCM-S) have been used. The different applications of this kind of data have been reviewed and evaluated, including their advantages and disadvantages.

The assessment has led to the identification of processing steps for gCMs as well as potential applications towards achieving ZSM. Finally, the key challenges have been identified, raising the need for standardized integration of the gCM into the OSS.

In subsequent research, the outcome of the present work has opened future research directions. Regarding data processing, a wide variety of ML techniques could enhance the achieved performance. Besides, additional metrics could be added both from UE and network sides. Also, this work presented a set of applications, but the proposed framework is open to novel applications that could be developed based on the gCMs. Moreover, although the joint utilization of network side metrics and gCMs is considered in the framework, the present work assessed the gCMs in isolation, as the availability of network side metrics is restricted to Mobile Network Operators (MNOs).

ACKNOWLEDGMENT

The authors would like to thank the partnership with Metricell Ltd., to provide an extensive dataset of anonymized metrics from real cellular network users.

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