This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/MNET.2024.3483570

Location-aware Smart Network Management in Advanced Networks: Design and Applied Proof of Concept

Antonio Tarrías[(1)], Imed Hadj-Kacem[(2)], Giacomo Bernini[(3)], Takai E. Kennouche[(4)], Carlos Álvarez[(1)], Hao Qiang Luo-Chen[(1)], Michael De Angelis[(3)], Aristotelis Margaris[(5)], Eduardo Baena[(6)], Emil J. Khatib[(1)], Sana Ben Jemaa[(2)], Stefania Bartoletti[(7)], Sergio Fortes[(1)]*, Raquel Barco[(1)]
[(1)]Telecommunication Research Institute (TELMA), Universidad de Málaga (UMA)
[(2)]Orange Labs, France
[(3)]Nextworks
[(4)]VIAVI Solutions
[(5)]Incelligent
[(6)]Institute for the Wireless Internet of Things, Northeastern University, Boston, MA, U.S.A.
[(7)]CNIT and University of Rome, Tor Vergata

***Abstract*—Smart network management is one of the key innovation areas for current and future generations of cellular networks. This field is especially meaningful for the use cases introduced in the Fifth Generation (5G) technology, with their varied scenarios and requirements, leading to a far more challenging management. Cellular networks have traditionally showed underperformance in specific conditions and scenarios, e.g. crowded places, high-speed scenarios, indoor environments or coverage holes. All the previous have one common point: they are related to the users' location. In this sense, users' localization has been proven as a key enabler to support smart analysis and decision over the networks. The present work proposes a complete location-based network management infrastructure, which is evaluated in a real network scenario. The proposed infrastructure presents a novel approach for the interconnection of several virtualized components and functionalities leveraging location information. The interconnected components are validated jointly using data from a real network.**

***Index Terms*—Localization, Context, Network Management**

I. Introduction

Network management has consistently played a pivotal role for Mobile Network Operators (MNOs) across several generations of cellular networks. Substantial efforts have been dedicated to achieving automated and seamless network management. In this context, Drive Tests (DTs) and network traces have been leveraged to optimize network performance in the past. Here, some of the most common network failures are related to users' localization aspects, such as crowded places during events, high-speed movement of users, indoor coverage problems, coverage holes, or capacity problems experienced users located at cell edges. Although these issues have been widely studied in the literature, they are still challenging to solve. Nevertheless, location information of users has demonstrated to play a key role in order to determine the network status [1–3].

The 5G technology aims to cater to diverse Use Cases (UCs) characterized by specific requirements. The main three UCs are: enhanced Mobile Broadband (eMBB), Ultra-Reliable and Low-Latency Communications (URLLC) and Massive Machine-Type Communications (mMTC). This means that scenarios are dynamic and heterogeneous, making network management especially challenging, since it has to be adapted to dynamic service requirements.

In addition, retrieving location information from users is not easy. Indeed, it is important to take into account regulations about users' privacy, as well as the availability of differing sources of location information. On the one hand, Global Positioning System (GPS) has traditionally been the main technology for outdoor positioning, while it does fulfill the expected requirements in indoor scenarios. On the other hand, 3GPP Rel-16 [4] introduces the aspects for 5G-based localization. 5G localization is still being enhanced in Rel-18 and Rel-19, where the use of novel features such as beamforming is under standardization to determine users' position in an efficient, seamless way. Therefore, the fusion of other technologies like Ultra-wideband (UWB) and Wi-Fi has been proposed in the literature and in 3GPP standardization, demonstrating an excellent performance in terms of accuracy [5, 6].

The key contribution of this work is the definition and realization in real-world of a novel approach for the deployment and application of location-aware network management. In particular, a location-aware network optimization is proposed, which consists of (i) identifying clusters of people or users whose coverage is poor, as well as (ii) detecting faulty cells which may cause coverage holes. Location information will enrich the Machine Learning (ML)-based techniques that use network information for network management. In particular, users' locations will be used by the Network Data Analytics Function (NWDAF), together with other network data, e.g., counters and Key Performance Indicators (KPIs) [7]. The proposed functionalities could also fit into the envisioned architecture for the Open RAN paradigm. To the best of authors' knowledge, this is the first time that a real-world location-aware network management infrastructure has been developed and evaluated under realistic conditions.

*Corresponding author

This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/MNET.2024.3483570

A virtualized infrastructure has been developed and deployed in a real-world scenario where different communication and localization technologies are available. Real-time data collection from different User Equipments (UEs) is performed while different functionalities are running and providing outputs related to the current network status.

The remainder of this paper is organized as follows: In Section II the proposed approach and the scenario that has been considered are described, including the physical and virtualized infrastructure as well as the technologies that have been used for its implementation. Section III reviews the functionalities that have been built on top of the infrastructure regarding the network management. Finally, the conclusions of this work are summarized in section IV.

II. System Overview

The system proposed in this paper implements a set of capabilities that involve real-time processing of network measurements and events, the identification of users' locations, and the exploitation of location information to deliver smart network coverage prediction and failure detection. The Proof of Concept (PoC) demonstrates the successful implementation of a set of containerized network functions (CNFs) that deliver location-based network management capabilities, and the integration with the developed LOCUS Platform capabilities, as shown in Figure 1.

This section will describe: 1) University of Malaga (UMA) Testbed, used to deploy a variety of wireless network technologies used for estimating user positions and monitoring network events; 2) LOCUS Platform and the common services that enable the development of smart network management functions, such as coverage optimization and failure detection.

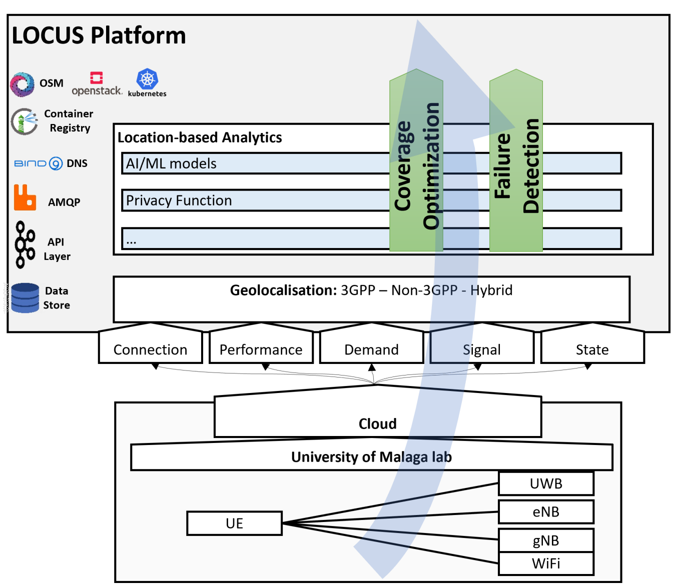

Fig. 1. PoC Architecture including physical and cloud-based elements, and software solutions in use.

UMA Testbed

The physical scenario is composed by teaching laboratories placed in the Faculty of Telecommunication Engineering of the UMA, Málaga, Spain. It is an indoor scenario for Research and development (R&D) which is covered with a large amount of different technologies, including LTE, Wi-Fi, UWB and 5G. These are private deployments composed by real commercial equipment from different vendors. The scenario is depicted in Fig. 2. The cellular networks are independent and composed by three 5G indoor cells and five LTE picocells, respectively. Both private networks cells are co-located on the ceiling to cover the whole scenario with good coverage. The 5G cells work in Standalone (SA) mode and transmit with a SS PBCH power of -17 dBm and are centered at 3774.990 MHz, using Time Division Duplex (TDD) mode. The LTE cell parameters are configured with a transmission power of -6.8 dBm, Downlink (DL) frequency at 2630MHz, and Uplink (UL) frequency at 2510 MHz. The UWB deployment is based on Qorvo DWM1000 devices while the Wi-Fi Fine Timing Measurement (FTM) APs are Google Wi-Fi mesh routers and they were placed on top of shelves (2 meters height) in order to cover the whole scenario with good visibility. Both UWB devices and Google Wi-Fi routers are set to their default configuration parameters, considering only the 5 GHz channel for Wi-Fi operation. The UWB devices transmit with a power of -14.3 dBm and they are centered in 6 GHz. The scenario is a teaching laboratory which presents several metallic elements such as computers, shelves, etc. Therefore, it is expected that the measurements are heavily affected by multipathing.

An Android application has been developed to capture all the ranging data from the network reference points: 5G and LTE base stations, UWB and Wi-Fi APs. The distance ranges with the 5G and LTE stations are estimated using the measured RSSI which is modeled by the indoor office propagation model [8]. To the best of our knowledge, there is no implementation yet to obtain more precise ranges in the cellular network, although localization based on Positioning Reference Signals (PRSs) are envisioned by 3GPP [4]. The WiFi-FTM ranges are directly obtained through the Android Application Programming Interface (API). For the UWB measurements, each UWB device is attached to an UE and connected via Bluetooth Low Energy (BLE) to read the UWB data. A limitation on the performance of the UWB devices is that the UWB tag can only receive the information from four anchors simultaneously due to the software provided with the DWM1000 family products. Thus, in order to reduce the impact of the reflections, the ranging information according to the Round-Trip Time (RTT) protocol is obtained. Timing ranging reduces the impact of multipathing in ranging estimations and the RTT neglects the need for clock synchronization as proposed for indoors technologies by [9].

LOCUS Platform

A unified and generalized platform has been designed and developed for the deployment of localization analytics functions and services, and their exposure towards Smart Network

This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/MNET.2024.3483570

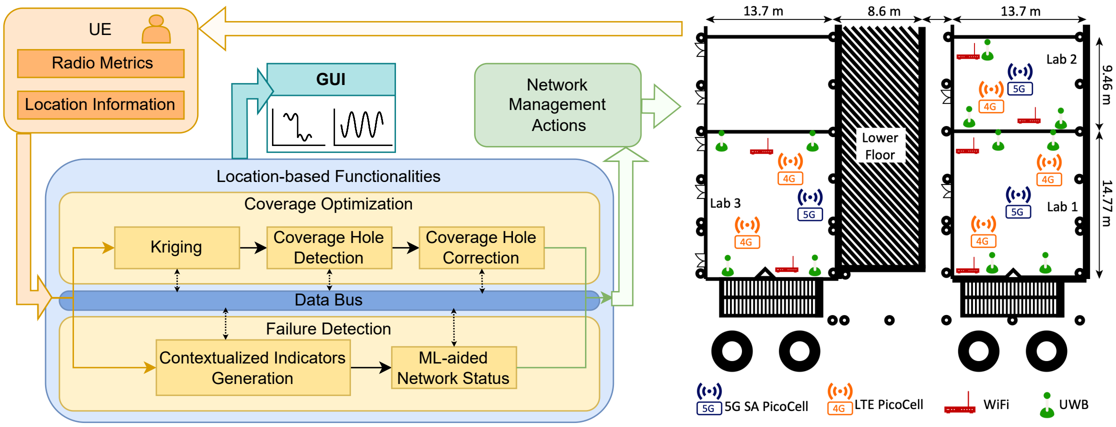

Fig. 2. Functionalities components diagram together with the physical scenario sited at UMA premises.

Management and 3rd party vertical applications that require (geo)location-awareness and analytics for their purposes [10]. More specifically, the platform in Fig. 1, named LOCUS Platform, implements localization analytics as a service solution on top of a flexible, scalable and virtualized infrastructure that allows to deploy and execute analytics services and functions (including ML pipelines) as virtualized elements across edge and core compute locations of the 5G network. This platform is physically sited in Athens, Greece. In particular, the goal is indeed to provide a common environment where the localization and data analytics can run as virtual functions, allowing cloud-native applications distributed across edge and core domains. Running such functions on top of a virtualized infrastructure enables a smooth integration of the location based services within 5G networks, being accessible for both network management and vertical customers. In addition, automation in deployment and operation of these virtualized localization analytics services can be achieved by adopting the ETSI Network Function Virtualization (NFV) Management and Orchestration (MANO) principles [11].

As depicted in Figure 3, the proposed platform prototype is composed of three main complementary components: the LOCUS API layer, the LOCUS platform control, and the LOCUS MANO, all integrated with the virtualized infrastructure. The API layer represents the northbound interface of the platform and is responsible for providing access to the virtualized analytics functions, ML pipeline services and ML model predictions when they run in the edge/core virtualized infrastructure. On the other hand, it exposes the data they generate as services that can be consumed by external applications (e.g., Smart Network Management). It is implemented leveraging on open-source tools for analytics and data consumption through advanced API gateway and service discovery features (based on Consul and Zuul).

The API gateway and service discovery features are linked with access control features (implemented through Keycloack), and are integrated with a custom catalog and a service subscription module that allows external applications and users to discover the available analytics services and activate them on-demand.

The LOCUS platform control (see Fig. 3) allows to decouple the API layer functionalities and the analytics services exposed towards external entities from the complexity of internal analytics functions management and execution, in terms of deployment as virtualized functions, data operations and constraints. It is implemented as a combination of software tools, which integrates custom applications for analytics service coordination, and relies on open-source tools for analytics service and ML pipeline management and virtualization (such as Apache AirFlow and Kubeflow).

The data exchange among the various localization and analytics functions, required to provide the specific end-to-end service logic, is facilitated by a dedicated data platform, which combines a solution based on RabbitMQ for real-time data streams exchange with a data persistence module based on Hadoop, Hive and Trino. These two solutions enable the analytics services and functions to communicate and exchange data following different paradigms, while supporting real-time and batch processing. For the purpose of the PoC presented in this paper, the RabbitMQ message queue module is used as a message broker, which receives messages from a producer (e.g. a localization or analytics functions), elaborates them in a so-called exchange, and route them to different queues, where one or multiple consumers process the message. Here, the exchange of type topic has been used, allowing the use of wildcard matching, where a routing key can define a pattern that matches multiple queues.

The third component of the platform is the MANO, which is implemented on top of the ETSI OSM open-source framework (i.e., the de-facto standard open source NFV orchestration platform), and provides NFV-oriented automation capabilities in the deployment and runtime operation of localization analytics functions and services as Virtual Network Functions (VNFs) and NFV Network Services. It supports fully cloud-native deployments and thus automated instantiation and configuration of localization analytics functions as containerized functions. Each localization analytics function and service part of the PoC presented in this paper has been therefore packaged following the ETSI OSM principles and standard NFV descriptors formats, and dockerized to be de-

This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/MNET.2024.3483570

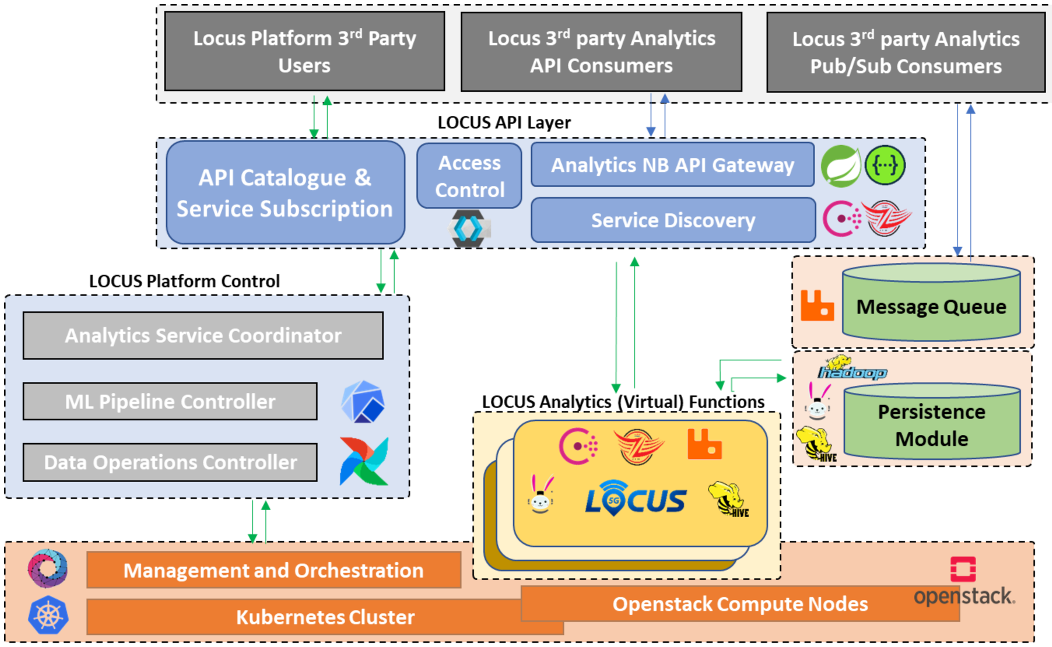

Fig. 3. LOCUS Platform Architecture Components

ployed as container. The LOCUS MANO is tightly integrated with the virtualization infrastructure, which realizes a realistic edge/core computing infrastructure where the localization analytics functions are deployed on demand. For the PoC, the virtualization infrastructure is implemented following a hybrid approach to leverage on de-facto virtualization technologies and support distributed edge/core cloud-native deployments. This allows to match the requirements imposed by the 5G network architecture, which is based on a high degree of network function virtualization that can be deployed at different computing locations. Specifically, it integrates a Kubernetes cluster with an Openstack infrastructure , with the aim of supporting both traditional virtual machine based services, as well as cloud-native applications more suitable to run at the edge using containerized services.

III. Network Management Functionalities

Two main location-aware network management functionalities are presented, focused on two main fields of the cellular Operations and Maintenance (OAM) activities: coverage optimization and failure detection.

Coverage Optimization

Continuous monitoring of radio coverage is an essential task for a MNO in order to guarantee the continuity of services to its customers. The primary objective is to reduce the number of locations where the signal level received by the user is low (i.e. below a threshold), also known as coverage holes. Other metrics to be monitored are the Signal-to-Interference-plus-Noise Ratio (SINR) which measures the quality of the useful signal coming from the serving cell divided by the interference of neighboring cells, the availability of resources, the reduction of congestion, etc.

This study focus on the supervision of radio coverage holes. An initial measurements collection is proposed on some positions for a preliminary learning phase, that enables the prediction on the other locations. Thus, the use case of coverage optimization consists in predicting a Radio Environment Map (REM). The modification of the transmission powers of some cell(s) is also proposed in order to correct potential coverage holes using Self-Organizing Networks (SON) techniques to automatically change the transmitted power of the cells and then proactively correct the problem.

The coverage optimization module is deployed as a service. Three Dockers are pipelined and exchange their outputs via a data bus (See Fig. 2). The main container, named “Kriging”, performs interpolation in order to predict the REM. From [12], the measured received signal power for a given UE from a given cell (either serving or interfering cell) in the logarithmic domain depends on several parameters. These quantities are the transmitted power of the cell, the distance between the considered UE and the cell and the path loss-exponent [13]. The measured received signal power also includes two zero-mean Gaussian random variables: the first one indicates the log-normal shadowing; the second one models any error in measurement. Both random variables are assumed to be independent.

In order to create the REM maps, the prediction of the received signal power is performed on the set of points for a well-defined area. The prediction is based on some measurements reported by several UEs located at different locations. Since the obstacles around the users located at close locations are almost the same, the corresponding shadowing signals are correlated. Thus received signal powers for both users are correlated, too. So, it is proposed to exploit this correlation to interpolate the received signal power at a new location. The Kriging interpolation technique is used since it

This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/MNET.2024.3483570

is the best linear unbiased predictor [14].

The module works in real time, i.e. real-time measurement collection and REM prediction are performed. Collected measurements include user location, Reference Signal Received Power (RSRP) and the cell identity. The Kriging block performs prediction of the RSRP and finds the corresponding serving cell for each test location. This results on a matrix containing, on each row, the coordinates of the test location, the predicted RSRP and the serving cell identity. This matrix is then transmitted to the next container by the RabbitMQ bus.

The "Coverage Hole Detection" container finds the locations where there exist anomalies in terms of coverage. It examines each row of the matrix received by the data bus. Each location where the predicted RSRP is below a predefined threshold is extracted. The set of locations where the RSRP is low are grouped into a second matrix. This matrix contains then the detected coverage holes. Each row of the matrix corresponds to the coordinates of the coverage hole, the predicted RSRP and its serving cell identity.

Lastly, the "Coverage Hole Correction" service receives the coverage hole matrix published on the bus. It calculates for each cell how to adjust the cell transmitted power in order to cover all locations where the coverage is not good enough.

Here, the modules are started, and the users are moving around the scenario randomly. Firstly, it is considered the positioning technology based on the combination of Wi-Fi and UWB as shown in Figure 4. It can be seen that the Kriging interpolator manages to predict the REM. Also, the module detects the coverage holes (in red points in Figure 4). It can be noticed that the coverage hole locations are close and grouped into two little areas. This validates the proposed approach since in reality, coverage problems are not randomly dispatched but quite close.

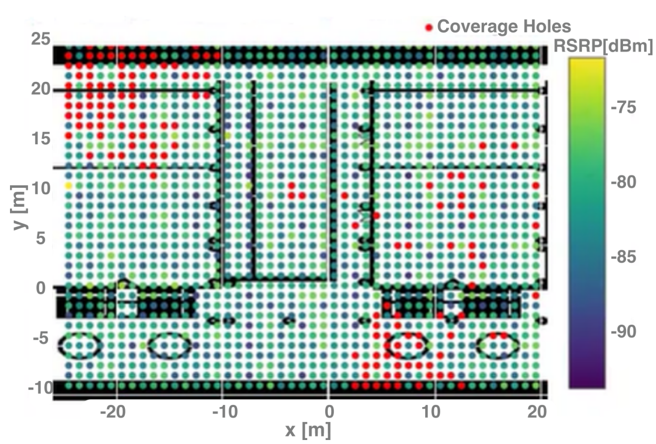

Fig. 4. Coverage holes prediction based on UWB and Wi-Fi positioning.

In Figure 5, a second positioning technology based on LTE is considered. Here, the REM prediction is compared with the one obtained with the baseline given in Figure 4 as it was demonstrated that the positioning technology based on Wi-Fi plus UWB is close to the ground truth [6]. By comparing Fig. 4 and 5, it can be observed that the accuracy of the geolocated measurements impacts the prediction precision.

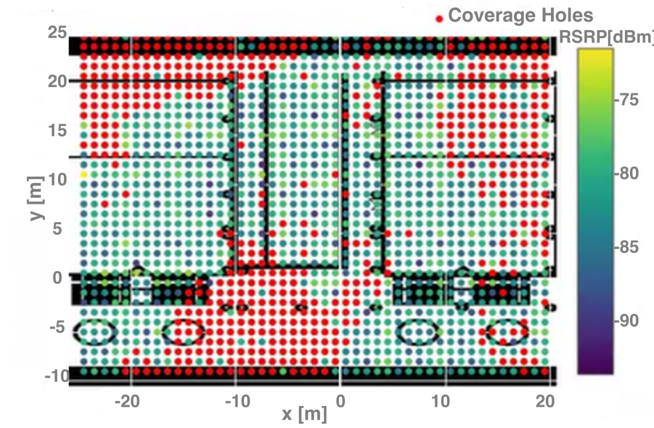

Fig. 5. Coverage holes prediction based on LTE positioning.

The work can be easily extended to the prediction of the SINR of a moving user. The prediction of the user's trajectory makes it possible to determine the future location of the user. The SINR maps are created from the RSRP maps already calculated in this study. The SINR is a metric used for resource allocation in cellular networks. Thus, the prediction of the future SINR value of a user equipment located at a new position can build an accurate resource reservation for it.

Location-aware failure detection

Context information is starting to be used for network management, i.e. information from different sources (weather, traffic, social events, etc.). Nevertheless, this kind of information is not always available. In contrast, new indicators were generated by taking into account the available cells covering the scenario and the areas where they may interfere each other. With these contextualized indicators [15], it is possible to have additional information about the scenario at low computational cost. To generate them, positioning information is obtained through the LOCUS platform, based on the radio technologies described in Section II. This positioning information is generated by opportunistic fusion of ranges from different source technologies [6].

In addition, the cell locations are mandatory to previously compute Voronoi areas. The Voronoi areas are also calculated for the assumption where one of the cells is missing, so overlapping areas refer to the coverage area of cells when their neighbor cells are not working. The cell centers and edges are also considered. Then, each received sample is related to one or more areas and indicators for each area are dynamically computed. If the samples are coming from static users, they will always update the same areas, which means the system will be able to detect, e.g. a cell outage, but it will not discover coverage holes. The system will have two perspectives of the scenario: on the one hand, a historical perspective based on all the samples that have been received and processed since the functionality was enabled; on the other hand, it also filters last received samples in order detect when a network failure has just occurred. A map is generated with the data that have been received, as illustrated in Fig. 6, and it is also updated when new samples are collected.

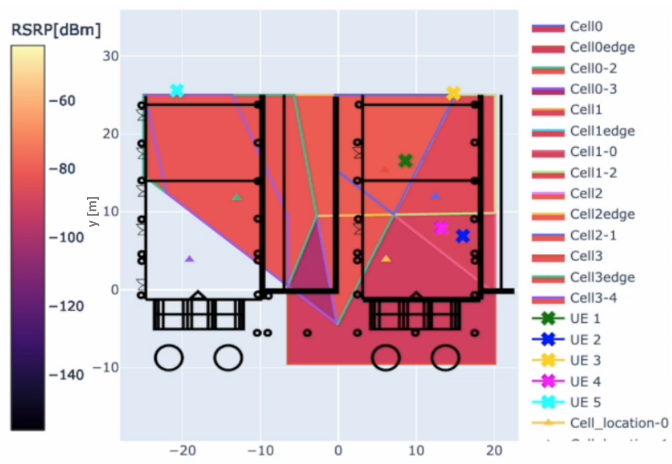

Fig. 6. Contextualized indicators computed over the scenario.

In the figure, the crosses represent the real-time positions for several UEs, and the triangles refer to the cell locations. Moreover, terminology CellX-Y means area where cell X is influenced by cell Y in case that cell X is not available. It can be observed that there are areas where the coverage is good, and other where it is worse. In addition, there are areas of the scenario where the contextualized area is not plotted, which means there are not recent samples involving that area.

Here, the functionality schema is also based on pipelined Docker containers, as depicted in Fig. 2. The first container is in charge of computing and updating the contextualized indicators for each area upon sample receptions. This information is then sent to the LOCUS platform where an ML-aided component returns whether there is any cell outage or every cell is working normally, being the contextualized indicators the input for this component. It is also possible to configure the number of historical samples, i.e., radio metrics provided by UEs together with their location, that are used to determine the current status of the network. This may improve the accuracy but reduce the reactivity of the system. The last container implements the Graphical User Interface (GUI), which shows the map and the time evolution graph, as well as the output of the ML-aided component indicating the network status.

The system achieved an accuracy of 90.7% when looking at last historical samples received, being able to detect when a cell is not working properly. However, a refined layer could be added to the system with an additional step consisting on analyzing the historical samples for each area, and then comparing to the last received samples. This would verify the ML model's output is correct (especially when it reports faulty cells), and thus reduce the number of false positives.

In this sense, a more powerful ML model could be trained with additional radio network quality metrics, such as SINR, or Reference Signal Received Quality (RSRQ), being able to provide more accurate results when determining the network status. On the other hand, Voronoi areas could be substituted by other areas, such as hexagons or even areas generated from the beam sets configuration and the cell sectors, both easily available for the MNO.

These functionalities enable new opportunities for the MNO to improve the network management. Their applicability is not restricted to radio quality metrics, but it could be extended to the Quality of Experience (QoE) metrics, which are crucial for the MNO to provide a good service to its customers. However, the regulatory framework should be considered, as the use of location information is subject to strict rules in some countries. In this sense, there are features that would implement localization techniques from the network, as the PRSs or the use of beamforming. The latter enables a beam-based localization with an accuracy high enough for the described functionalities and low enough to potentially comply with the regulations. In any case, the anonymity of the data must be guaranteed. On the other hand, these functionalities have been tested to receive data in real time, so that they could suggest actions in real time. However, there is a risk when taking actions in real time, so the system should be intelligent enough to properly decide whether a network configuration change should be applied or not in a specific moment.

IV. Conclusions

This work has presented the design and implementation of a real-world location-aware network management infrastructure, where network management functionalities leverage location information received in real-time. Location information has been demonstrated to be crucial for network management, even in an indoor scenario. The behavior of the different components working together over a virtualized infrastructure was analyzed, assessing the feasibility of the approach even when the management algorithms platform and the physical scenario were located in different countries. The tested functionalities have shown promising results with regard to exploiting location information in an indoor scenario. Moreover, the functionalities could be easily extended to be based on other metrics, including QoE, in order to be able to identify other issues related, e.g., to network capacity or congestion, in a particular situation or area. The proposed architecture supports this extension, as it is designed to be flexible and scalable, and to support the integration of new functionalities.

Acknowledgements

This work has been funded by the European Union through the project H2020 LOCUS (grant agreement n. 871249) . This work has been also funded by: Spanish Ministry of Universities - Ref. FPU20/02863.

References

[1] S. Bartoletti, L. Chiaraviglio, S. Fortes, T. E. Kennouche, G. Solmaz, G. Bernini, D. Giustiniano, J. Widmer, R. Barco, G. Siracusano, A. Conti, and N. B. Melazzi, "Location-Based Analytics in 5G and Beyond," *IEEE Communications Magazine*, vol. 59, no. 7, pp. 38–43, 2021.

[2] L. Chiaraviglio, S. Rossetti, S. Saida, S. Bartoletti, and N. Blefari-Melazzi, ""Pencil Beamforming Increases Human Exposure to ElectroMagnetic Fields": True or False?" *IEEE Access*, vol. 9, pp. 25 158–25 171, 2021.

This article has been accepted for publication in IEEE Network. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/MNET.2024.3483570

[3] S. Fortes, A. Aguilar-García, R. Barco, F. B. Barba, J. A. Fernández-luque, and A. Fernández-Durán, "Management architecture for location-aware self-organizing lte/lte-a small cell networks," *IEEE Communications Magazine*, vol. 53, no. 1, pp. 294–302, 2015.

[4] 3GPP, "Release 16 Description. Summary of Rel-16 Work Items," Technical Specification (TS) 21.916, 6 2022, version 16.2.0. [Online]. Available: http://www.3gpp.org/DynaReport/21916.htm

[5] F. Morselli, S. Bartoletti, M. Z. Win, and A. Conti, "Localization in 5G Ecosystem with Wi-Fi," in *2021 IEEE 22nd International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2021, pp. 441–445.

[6] C. S. Alvarez-Merino, H. Q. Luo-Chen, E. J. Khatib, and R. Barco, "Opportunistic Fusion of Ranges From Different Sources for Indoor Positioning," *IEEE Communications Letters*, vol. 25, no. 7, pp. 2260–2264, 2021.

[7] A. Tarrias, S. Fortes, and R. Barco, "Failure Management in 5G RAN: Challenges and Open Research Lines," *IEEE Network*, pp. 1–7, 2023.

[8] 3GPP, "Study on channel model for frequencies from 0.5 to 100 ghz," *Technical report (TR) 38.901, 3rd Generation Partnership Project (3GPP)*, 2017, publisher: 3GPP.

[9] J. A. del Peral-Rosado, R. Raulefs, J. A. López-Salcedo, and G. Seco-Granados, "Survey of cellular mobile radio localization methods: From 1g to 5g," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 2, pp. 1124–1148, 2017.

[10] S. Bartoletti and N. Blefari Melazzi, *Positioning and Location-based Analytics in 5G and Beyond*. Wiley, 2023.

[11] *GS NFV 002 v1.2.1; Network Functions Virtualisation (NFV); Architectural Framework*, ETSI NFV ETSI™NFV 002 V1.2.1 (2014-12), Dec. 2014.

[12] H. Braham, S. Ben Jemaa, and G. Fort, "Fixed rank kriging for cellular coverage analysis," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 5, pp. 4212–4222, 2017.

[13] V. S. Abhayawardhana, I. J. Wassell, D. Crosby, M. P. Sellars, and M. G. Brown, "Comparison of empirical propagation path loss models for fixed wireless access systems," in *IEEE Vehicular Technology Conference (VTC)*. IEEE, 2015, pp. 73–77.

[14] N. Cressie and G. Johannesson, "Fixed rank kriging for very large spatial data sets," *Journal of the Royal Statistical Society: Series B (StatisticalMethodology)*, vol. 70, no. 1, pp. 209–226, 2008.

[15] S. Fortes, C. Baena, J. Villegas, E. Baena, M. Z. Asghar, and R. Barco, "Location-awareness for failure management in cellular networks: An integrated approach," *Sensors*, vol. 21, no. 4, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/4/1501

BIOGRAPHIES

ANTONIO TARRIAS (atm@ic.uma.es) is pursuing a Ph.D. degree at the University of Malaga, in the field of cellular communications.

IMED HADJ-KACEM (imed.hadjkacem@orange.com) received the Ph.D. degree in information and communication technology in 2011. His research interests include artificial intelligence application to mobile network planning and optimization.

GIACOMO BERNINI (g.bernini@nextworks.it) is R&D Operations Leader with Nextworks, focused on 5G/6G network architectures and zero-touch AI-driven network management.

TAKAI E. KENNOUCHE (TakaiEddine.Kennouche@viavisolutions.com) is an AI/Data architect within the CTO Office at VIAVI Solutions, focusing on AI/ML applications for network testing and optimization, scalable data-driven solutions in the telecommunications domain.

CARLOS S. ÁLVAREZ-MERINO (cam@ic.uma.es) is received the Ph.D. degree in 2024, and is working as a Research Assistant with the Communications Engineering Department.

HAO QIANG LUO CHEN (hao@ic.uma.es) is currently pursuing the Ph.D. degree in the field of localization and Machine Learning (ML) application to cellular networks.

MICHAEL DE ANGELIS (m.deangelis@nextworks.it) is a R&D Software Coordinator at Nextworks Srl. He is working in 5G/6G research projects and consulting activities, focusing on SDN/NFV, edge/cloud and 5G technologies.

ARISTOTELIS MARGARIS (aristotelis.margaris@incelligent.net) holds a Ph.D. Thesis on "Machine learning applications for management of 3GPP networks". He works as a Big Data and AI Solutions architect at Incelligent involved in product development and H2020 research.

EDUARDO BAENA (e.baena@northeastern.edu) received a Ph.D. degree in telecommunication engineering, and his research interests include AI-based cellular network management, 5G/6G, cloud and edge computing and OpenRAN architecture.

EMIL J. KHATIB (emil@uma.es) received the Ph.D. degree in 2017. He is currently a Postdoctoral Researcher with the University of Málaga. His research interest includes security and localization in B5G/6G networks.

SANA BEN JEMAA (sana.benjemaa@orange.com) is a research engineer and project manager at Orange Labs. Her research interests include mobile/wireless communications, self-organising networks and artificial intelligence application for RAN management.

STEFANIA BARTOLETTI (stefania.bartoletti@uniroma2.it) received her Ph.D. degree in Electronics and Telecommunications Engineering from the University of Ferrara. She is currently an Assistant Professor at the Department of Electronic Engineering of the University of Rome, Tor Vergata.

SERGIO FORTES (sfr@ic.uma.es) ***(Corresponding author)*** holds a Ph.D. in Telecommunication Engineering from the University of Malaga. He is current Associate Professor at University of Malaga, being his research focused on Self-Organizing Networks for cellular communications.

RAQUEL BARCO (rbm@ic.uma.es) is Ph.D. in telecommunications from the University of Málaga, where she is currently Full Professor, specialized in mobile communication networks and smart-cities.