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Towards Machine Learning and Data Driven Mobile Network Automation and Planning

CANER KILINC



Doctor of Philosophy

Institute of Computing Systems Architecture

School of Informatics

University of Edinburgh

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Abstract

Mobile networks are one of the largest and most ubiquitous deployed systems in the world with growing complexity and global demand. Mainly the mobile networks are primarily operated manually, which is a time-consuming process, and human involvement is error-prone. For instance, most investigations of service-related problems in operator networks are triggered by customers' complaints. This causes problems like customer service disappointment and churn. In addition, the manual annual network planning is inefficient to deal with the high uncertain growth and the manual daily network operations based on historical data escalate the OPEX. Recent technological advancements in computational capabilities and machine learning have given rise to a plethora of opportunities for data-driven solutions in various industries. In this thesis, we explore the opportunity for machine learning and data-driven mobile network automation and planning, considering four important problems. This work is enabled by real-world mobile network data, including those from a multi-national mobile network operator.

First, we consider wireless jamming problems which severely deteriorate and effectively shut down the network for users, and detection of jammer activation is a manually intensive and costly process. We present a novel scalable data-driven autonomous jammer detection framework termed JADE.

Second, we study mobile network demand characterization and forecasting from the perspective of enabling cost-effective mobile network planning. To this end, we conduct, for the first time, a demand characterization and forecasting study that is based on multi-year and nationwide region-level mobile network traffic data. Specifically, we analyze the demand characteristics of mobile and fixed wireless access (FWA) services at national and regional scales.

Lastly, using a data-driven approach, we solve the problem of hotspot (under-provisioning) problem at the cell level in operational mobile networks. We present a novel scalable data-driven hotspot cell detection framework termed CellDA (Data Driven Autonomous Under-provisioning Cell Detection) for operational mobile networks.

Lay Summary

Mobile networks are one of the largest and most ubiquitous deployed systems in the world with growing complexity and global demand. Mainly the mobile networks are primarily operated manually, which is a time-consuming process and human involvement is error-prone. For instance, most investigations of service-related problems in operator networks are triggered by customers' complaints. This causes problems like customer service disappointment and subscription termination. In addition, the manual annual network planning is inefficient to deal with the highly uncertain growth and the manual daily network performance operations based on historical data escalate the operation costs. Recent technological advancements in computational capabilities and machine learning have given rise to a plethora of opportunities for data-driven solutions in various industries. In this thesis, we explore the opportunity for data-driven and machine-learning mobile network automation and planning, considering four important problems. This work is enabled by real-world mobile network data, including those from a multi-national mobile network operator.

First, we consider wireless jamming problems which severely deteriorate and effectively shut down the network for users, and detection of jammer activation is a manually intensive and costly process. We present a novel scalable data-driven autonomous jammer detection framework termed JADE.

Second, we study mobile network demand characterization and forecasting from the perspective of enabling cost-effective mobile network planning. To this end, we conduct, for the first time, a demand characterization and forecasting study that is based on multi-year and nationwide region-level mobile network traffic data. Specifically, we analyze the demand characteristics of mobile and fixed wireless access (FWA) services at national and regional scales.

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified. Some of the material used in this thesis has been published/submitted in the conferences/journals listed below.

- **Caner Kilinc, Chuanhao Sun, Mahesh K Marina**, "5G Development: Automation and the Role of Artificial Intelligence" in *Wiley 5G Ref: The Essential 5G Reference Online Book*, October 2019.
- **Caner Kilinc, Mahesh K. Marina, Muhammad Usama, Salih Ergut, Jon Crowcroft, Tugrul Gundogdu, Ilhan Akinci**, "JADE: Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks," in *IEEE International Conference on Computer Communications (INFOCOM)*, May 2022.
- **Caner Kilinc, Mahesh K. Marina, Ilhan Akinci, Gokhan Kalem**, "Demand Characterization and Forecasting for Cost-Effective Mobile Network Planning," will be Submitted for publication.
- **Caner Kilinc, Mahesh K. Marina, Ilhan Akinci, Gokhan Kalem**, "CellDA: Data-Driven Autonomous Hotspot Cell Detection Framework for Operational Mobile Networks," will be Submitted for publication.

(*Caner Kilinc*)

... to my dearest wife, children, and parents.

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Chapter 1

Introduction

With the introduction of new wireless communication technologies every decade, mobile networks and management platforms have become highly fragmented. This condition led to inefficient capital expenditure (CAPEX) management and higher operating expenditure (OPEX).

In current practice, mobile networks are primarily manually operated. As a result, the quality of the delivered mobile services and customer experience is not well-known on the mobile operator side, and most of the investigations of service-related problems are triggered by customer complaints. This causes issues such as inefficient network planning and customer service disappointment, leading to customer churn [2, 3]. In addition, manual daily network planning accelerates the OPEX, leads to inefficient CAPEX management, and results in network under-provisioning and over-provisioning problems.

Without a dramatic increase in CAPEX and OPEX, meeting business and mobile service key performance indicators (KPIs) is only possible through data and machine-learning-driven solutions. Recent technological advancements in data storage and computation systems have given rise to many new automation use cases in industries. In this thesis, we primarily worked with a specific multi-national mobile network operator with approximately 40 million subscribers to identify four real operational network problems. Each problem mentioned below is based on actual operational mobile network datasets, which we employed to develop data-driven proactive machine learning (ML) solutions.

First, we survey data and ML-driven automation concepts in 5G (5th generation) and mobile networks. As a baseline for autonomous networks, we use an existing network's automation framework, i.e., long-term evolution, self-organizing networks

(LTE SON), part of The 3rd Generation Partnership Project (3GPP) LTE Release-8). However, LTE SON is still far from being well-developed, since the daily network operations require a high degree of manual intervention. Human involvement can lead to possible errors, cause inefficient CAPEX, and increase OPEX. Hence, automated network functions are essential to minimize operator effort and OPEX and enhance customer experience. Furthermore, to keep the OPEX at a reasonable level, network automation can be implemented by leveraging state-of-the-art artificial intelligence/ML (AI/ML) techniques. Furthermore, 5G launched in 2020 and took complexity to the extreme, leading to an even stronger need for a network automation framework. Finally, the 5G automation system will be powered by cutting-edge ML techniques. Accordingly, we also summarize and provide an overview of the literature on commonly used types of ML techniques, i.e., supervised, unsupervised, reinforced, semi-supervised, and distributed learning towards the automation of mobile networks.

Second, we consider wireless jamming problems, which severely deteriorate and can effectively shut down the network for users in operational mobile networks. The detection of the activation of jammers is unknown from the operator's side. Their detection is triggered by customer connectivity and quality-related complaints, and it is a manually intensive and costly process that can take days or even weeks to correct. To detect the jammers, we present novel scalable data-driven autonomous jammer detection (JADE) for operational mobile networks, a deep learning-based framework that leverages continually collected operator-side cell-level KPIs to automate the jammer activation detection process. We present real-world validation results and demonstrate the robustness of JADE in accurately detecting jammer activity across multiple frequency bands and in managing diverse types of jammers. We also show promising results for pinpointing jammer locations in a downstream-use case.

Third, we consider mobile network demand characterization and forecasting from the perspective of enabling cost-effective mobile network planning. To this end, we conduct the first demand-characterization and forecasting study, based on multi-year and nationwide regional-level mobile network traffic data. Specifically, we analyze the demand characteristics of mobile and fixed wireless access (FWA) services at national and regional levels. In addition, we introduce a clustering-driven methodology for national and regional mobile network regional demand-forecasting on a yearly timescale. Our results highlight significant diversity in regional-level traffic characteristics and differences between mobile and FWA services. Furthermore, unlike existing work on the effect of COVID-19 on mobile network traffic, we do not find any observable effect due

to COVID-19 on regional-scale traffic characteristics. Crucially, our clustering-driven methodology yields significant gains in accuracy, up to more than an order of magnitude relative to the baseline approach for mobile service demand forecasting in a scalable manner, while being effective for FWA service demand forecasting.

Finally, we also consider proactive cell-level resource overprovisioning problem forecasting from the perspective of cost-effective mobile network planning. The mobile operators plan the network resources and investment yearly or quarterly and determine overprovisioning cells, an activity that is an important input for the network planning process. Overprovisioning cells are presently identified manually by the operators, based on historical cell-level KPIs. However, cell overprovisioning degrades the quality of estimate (QoE) and quality of service (QoS) for mobile subscribers. Therefore, cell overprovisioning must be managed proactively and frequently, e.g., daily. In this use case, we conduct the first cell-level overprovisioning forecasting study, based on a nationwide one-year cell-level mobile network KPIs. Specifically, we analyze the cell-level KPIs and evaluate the performance results of cell-level overprovisioning detection and forecasting models.

1.1 Thesis Contributions

This thesis aims to address the various manual use cases and challenges that cause inefficient CAPEX, escalate the OPEX, and lead to QoS and QoE degradations in mobile networks. To do so, we survey data and ML-driven automation concepts in 5G and mobile networks. We then examine all four use cases outlined above and propose data-and ML-driven solutions for the problems they present.

1.1.1 Automation and the Role of AI in 5G

In this work, we provide an overview of 5G (§2.3) and survey the automation concept in existing and future operational mobile networks as well as data/AI/ML driven automation use-cases and challenges (§2.4). In summary, we make the following key contributions:

- We provide an overview of LTE SON and present 5G automation concepts and frameworks.
- We compare the prominent 5G automation frameworks, namely Open Network Automation Platform (ONAP) and Open Source MANO, where the ONAP frame-

work has enriched network automation functions and stands out as the choice of the majority of the telecommunications industry.

- Finally, we summarize the front-line AI models and provide a literature review on AI applications in the scope of mobile network automation.

This work has been published as Wiley 5G Ref book chapter:

- **Caner Kilinc, Chuanhao Sun, Mahesh K Marina**, "5G Development: Automation and the Role of Artificial Intelligence" *Wiley 5G Ref: The Essential 5G Reference Online Book*, October 2019.

1.1.2 JADE: Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks

In this work, we tackle the wireless jammer activation detection problem. We propose JADE, a novel data-driven jammer activity detection framework for operational mobile networks (§4.5) which addresses this problem for the first time. It incorporates two custom-tailored semi-supervised deep learning-based anomaly detection methods for the jammer detection task along with an adaptive thresholding mechanism. JADE also leverages transfer learning towards efficient modeling and ease of deployability. We also extensively evaluate the JADE framework using a 4G radio access network (RAN) dataset from a multinational mobile network operator (§4.6).

This work makes the following contributions:

- Our results show that the anomaly detection methods developed for JADE outperform a wide range of commonly used anomaly detection methods when applied to the jammer detection task, and also confirm the effectiveness of JADE's adaptive thresholding mechanism.
- We demonstrate the robustness of the JADE framework powered by transfer learning in accurately detecting jammer activity across multiple frequency bands and diverse types of jammers.
- We also present real-world validation results by applying our methods in the operator's network for online jammer detection.
- As a downstream use case of JADE, we consider jammer localization. Specifically, we demonstrate the potential for pinpointing jammer locations based on jammer

activity detections in the mobile network using JADE and combining them with cell site location data.

This work was reported in the following publication:

1. **Caner Kilinc, Mahesh K. Marina, Muhammad Usama, Salih Ergut, Jon Crowcroft, Tugrul Gundogdu, Ilhan Akinci**, "JADE: Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks," *IEEE International Conference on Computer Communications (INFOCOM)*, May 2022.

1.1.3 Demand Characterization and Forecasting for Cost-Effective Operational Mobile Network Planning

In this work, we focus on mobile traffic demand characterization and forecasting with network planning in mind. We present a novel mobile traffic demand characterization and forecasting study with network planning in mind. Our study is unique in that it is conducted in collaboration with a prominent national-scale mobile network operator and uses multi-year and nationwide region-level mobile traffic volume data collected from the operator's network (§5.2). On the demand characterization front, we analyze the traffic demand characteristics at both national and regional scales and also study how COVID-19 affected these characteristics (§5.3). We then introduce a clustering-driven approach for yearly forecasts of mobile traffic demand at regional and national scales and evaluate it with respect to the baseline approach (§5.4). Finally, we investigate the demand characteristics of fixed wireless access (FWA) traffic that is growing in importance [4, 5] vis-à-vis mobile traffic and the effectiveness of our clustering-driven approach for FWA traffic demand forecasting (§5.5).

In summary, in this work we make the following contributions:

- Nationwide mobile service demand exhibits a generally upward trend consistent with industry mobile data traffic forecasts but there is significant diversity at the regional level owing to the contextual differences (population and land use composition) between the regions.
- With respect to Covid, we notice a change in pattern in mobile traffic volume at the national level in some months during Covid affected years (2020 and 2021) but for the most part we do not find any observable effect of Covid on the region scale traffic characteristics.

- Our clustering-driven methodology yields at least an order of magnitude improvement in accuracy compared to the baseline approach for mobile service demand forecasting while being scalable and practical.
- We observe that FWA service demand characteristics are markedly different from that of the mobile service, especially at the national level. Yet our clustering-driven demand forecasting methodology is still effective, halving the forecasting error relative to the baseline approach.

This work is put together as a paper and is currently under submission.

1. **Caner Kilinc, Mahesh K. Marina, Gokhan Kalem, Ilhan Akinci**, "Demand Characterization and Forecasting for Cost-Effective Operational Mobile Network Planning," Submitted for publication.

1.1.4 CellDA: Data-Driven Autonomous Hotspot Cell Detection Framework for Operational Mobile Networks

In this study, we focus on the hotspot cell detection problem, and for the first time, we consider hotspot cells as a network performance problem of operational mobile networks rather than as an annual network planning issue, and in particular focus on the problem of automatically detecting hotspot cells. To this end, we present CellDA, which to the best of our knowledge is the first automated hotspot cell detection framework for operational mobile networks. By treating hotspots as ‘abnormal’ or ‘anomalous’ from the mobile RAN infrastructure side, CellDA approaches hotspot detection as an anomaly detection problem. CellDA is envisioned for operator-side deployment and considers cells at each tower site as measurement vantage points. It continually monitors the time series of various cell-level KPIs to detect anomalous behavior over time. For the evaluation, we use large-scale real mobile network data with daily time resolutions over a period of one year, comprising 4000 cells collected across 4 cities with different characteristics by a market-leading mobile operator with more than 40 million subscribers (§6.2). Using this dataset, we provide evidence on the feasibility of automated and proactive hotspot cell detection. We also extensively and visually elaborate the hotspot cell KPIs to improve and addresses hotspot predictability in mobile networks (§6.4.2). To the best of our knowledge, this is the first study that approaches hotspot cell detection as a performance issue and proposes an autonomous hotspot cell detection framework.

The contributions of his work are summarized as follows:

- We illustrate the relationship between physical resource block (PRB) utilization and 4G downlink traffic volume via a heatmap and demonstrate the trade-off between over-provisioning and under-provisioning of the cells.
- We develop a set of deep neural network models for hotspot cell detection and compare their performance.
- For the best-performing model, we also assess the time horizon over which a hotspot cell can be detected.

This work is put together as a paper and is currently under submission.

1. **Caner Kilinc, Mahesh K. Marina, Gokhan Kalem, Ilhan Akinci**, "CellDA: Data-Driven Autonomous Hotspot Cell Detection Framework for Operational Mobile Networks," Submitted for publication.

1.1.5 The Research Methodology

In this Ph.D. thesis, the obtained research approach follows the quantitative experimental method within the context of empirical data-driven research. We employ open-source data processing and machine learning tools, such as scikit-learn [6] and TensorFlow [7], to extract insights from the data and design machine learning models for the operational mobile network automation frameworks.

The empirical data-driven methodology is structured around the following milestones:

1. **Use-cases and Data Collection:** In the preliminary phase, extensive interviews with experienced mobile network engineers are conducted to explore the complex challenges faced by mobile network engineers. The identified high-priority problems helped us to shape the aforementioned research problems as use cases. The relevant datasets are collected for each use case across the real operational commercial mobile networks.
2. **Data Preprocessing:** This stage involves cleaning and preparing raw data for exploratory data analysis and statistical examination. During this phase, we address real-world wild data problems such as missing data, outliers, and other data quality issues through implemented data pipelines [8].

3. **Feature Extraction and Selection:** This is a critical step for our empirical data-driven machine learning model development approach. The feature extraction methods enable to transform the data into a more suitable representation by generating new features in order to capture meaningful patterns with statistical relationships. Furthermore, the feature selection focuses on choosing a subset of the most relevant features, aiming to improve model performance, reduce dimensionality, and enhance interpretability [9].
4. **Model Selection and Development:** In this fundamental phase, we consider a range of machine learning algorithms, starting with baseline models e.g. linear regression or basic classifiers to establish benchmarks. We then progressively increase model complexity and evaluate performance using appropriate metrics. The best-performing machine learning models are selected and the selected models' performances are iterative until optimized.
5. **Model Training and Testing:** In this stage, the data splitting, validation, and testing strategy is defined to ensure the robustness of the models as well as to prevent overfitting or underfitting problems [10].
6. **Results Analysis and Presentation:** Experimental results are carried out, and key findings are highlighted through tables, charts, and visualizations, allowing for comparisons between different models. We summarize the experimental outputs along with domain-related interpretations.

By following this structured empirical research methodology, we ensured that a scientific empirical data-driven machine learning model development research is conducted carefully, and our findings are well-supported and meaningful in the context of our research objectives.

1.2 Thesis Organization

The rest of the thesis is organized as follows.

In **Chapter 3**, we present the 5G automation concept and data-driven network automation use cases. This work has been published in Wiley 5G Ref: The Essential 5G Reference Online Book, October 2019. [11].

In **Chapter 4**, we present a novel data-driven jammer activity detection framework for operational mobile networks, JADE. We extensively evaluate and demonstrate the

robustness of the JADE framework using a real 4G radio access network (RAN) dataset. This work has been published in the IEEE International Conference on Computer Communications (INFOCOM 2022) [12].

In **Chapter 5** we present a novel mobile traffic demand characterization and forecasting study with network planning in mind. Our study is unique in that it is conducted in collaboration with a prominent national-scale mobile network operator and uses a multi-year and nationwide region-level mobile traffic volume data collected from the operator's network.

In **Chapter 6**, we present a novel data-driven hotspot cell detection framework for operational mobile networks, CellDA. We extensively evaluate the CellDA framework using a real 4G radio access network (RAN) dataset.

Last but not least, **Chapter 7**, we summarize our works and conclude the thesis. Here we also discuss some limitations of the presented work and provide future research directions.

Chapter 2

Background

As a baseline provides an overview of LTE SON before moving on to 5G automation and associated frameworks. Furthermore, ONAP and OSM are compared, and evidently, the ONAP framework has enriched network automation functions and currently stands out as a choice of the telecommunication industry. Finally, this chapter also summarizes the cutting-edge ML (including deep learning) techniques and discusses their use in the context of mobile network automation. *This chapter provides a comprehensive background with a detailed description of the current and future state of mobile network automation and data-driven intelligent use cases in operational mobile networks.*

2.1 Mobile Networks

5G is going to affect every industry and every individual on the earth by leveraging the renaissance of technology. However, by introducing a new wireless communication technology every decade, the heterogeneity and complexity of mobile networks increased significantly. The existing mobile networks are massively deployed, and the management systems are in silos, henceforth, not optimal to configure the necessary level of automation for the daily network operations. Meanwhile, mobile networks and management platforms also became highly fragmented. Henceforth, the network management tasks itself became costly for mobile operators.

5G has indeed very challenging KPIs, such as 1 ms latency and 99.999% reliability, which are acknowledged by [13]. Meeting these requirements for 5G is unlikely by existing manual network monitoring, management, and optimization techniques. Thus a new automation framework is needed for 5G. Also, all the manual network operations lead to a serious escalation in the case of OPEX. Without a dramatic increase in OPEX,

dealing with the estimated data growth, and providing the mobile services while meeting the KPIs for each challenging use-case [14] is only possible by realization of the cutting-edge AI/ML functions in 5G.

5G is the first mobile communication technology that is going to be deployed as distributed cloud systems and thoroughly leans on novel networking technologies such as distributed clouds, software-defined networking (SDN), and network function virtualization (NFV). All these technologies, together with state-of-the-art ML and AI models, constitute an intelligent monitoring and automation framework for 5G.

Furthermore, cutting-edge AI models are used in automation systems and provide pro-activeness to anticipate each requirement and specific needs. In wireless systems, AI/ML models can be used to handle complex network problems such as resource and service optimization, network management, and decision-making. Indeed, beyond providing better mobile services and tailored resources for each mobile subscriber without impacting the other subscribers is only possible by getting insights of data to automate mobile networks fully.

Besides, each mobile operator has different business characteristics and operational needs. By considering mobile operators' needs, ONAP and OSM 5G automation frameworks are proposed. These frameworks provide APIs. By using these APIs, the operators can broaden their operational network capabilities and developed their network automation systems and functions based on business and operational needs. It is also essential to identify AI application use-cases for network performance improvements. Thus, this document provides a comprehensive overview of 5G automation frameworks and state-of-the-art AI models as well as applications of AI models in mobile networks.

2.2 Overview of Automation in 4G LTE Networks

LTE is designed to provide mobile multimedia internet services such as video streaming, and interactive video. Furthermore, LTE network deployment and operations are extremely complicated. There are many milestones to take into account during the network deployment and operation life-cycle, for instance, planning, performance monitoring, failure mitigation, and failure correction, and so on.

All these milestones are computation-consuming, costly, and error-prone, and perhaps the most important is that any slight oversight may result in customers' dissatisfaction with a significant loss of revenue. Also, to achieve a certain quality of experience for the user, operators must identify and diagnose performance problems as quickly as

possible.

Besides, the existing mobile networks are managed by centralized remote network management applications and systems, with almost all functions of network planning, configuration, and optimization supported by computer-aided tools such as ManageEngine [15] and PAESSLER[16].

2.2.1 SON for Automation of Management and Control in LTE

As a big step towards network automation, SON has been introduced first time in 3GPP LTE Release-8 in order to minimize human intervention and maximize efficiency in planning, deployment, and maintenance activities. The 3GPP LTE SON [17] aims to realize network automation mainly in three categories:

- *Self-configuration* is a process where newly deployed network components are configured during the automatic network installation phase to set-up parameters, for instance a unique Physical Cell Identity (PCIs) and a list of neighboring cells, and download the necessary software for the network operation. Furthermore, during the self-configuration phase, an IP address is assigned to the new cell and linked to a gateway plus LTE core network.
- *Self-optimization* mainly includes optimization of coverage, capacity, handover, and interference. In 3GPP SON, the self-optimization is reflected in lots of use-cases: Automated Configuration of Physical Cell Identity, Mobility Load balancing optimization, Inter-cell Interference Coordination, and the others.
- *Self-healing* means automatic problem detection and diagnosis. These features mainly specified in 3GPP LTE Release 10. For example, capacity problems depending on slowly changing environment, e.g., seasonal variations of the human population in a certain geographical location.

2.2.2 Realizations of LTE SON in Practice

A considerable number of SON automation functionalities are described by the 3GPP standards, which are now indispensable for operating the mobile networks to improve the network performance and reduce the OPEX. Different network product vendors provide various types of SON solutions for mobile network operators. For instance, Ericsson provides a SON Optimization Manager tool which runs together with Ericsson Network

Manager and Network IQ software and supports different use-cases such as multi-vendor and multi-RAT technology modules to mediate the tool as a centralized network monitoring and automation platform. The tool continuously analysis the complex network data and exploits smart automation algorithms to assure that the mobile network is always running at its best. Moreover, the tool addresses the critical SON use-cases such as network monitoring in order to collect performance and configuration related data and also analyzing and processing the collection in order to adjust network configuration parameters automatically. The automation functions can be performed either as a closed- or open-loop manner and continuously runs during the network operations.

Some examples of use-cases implemented in Ericsson SON Optimization Manager tool are listed below:

- Automated cell outage handler compensates a cell outage from surrounding cells to provide lost coverage, which is a beneficial feature, especially during extreme situations like natural disasters.
- Automated VoLTE optimization creates the perfect balance between mobile broadband and VoLTE support.
- to improve the radio link performance Remote Electrical Tilt antenna(RET)are controlled.
- 3G and 4G mobile network neighbor relations optimized via Centralized Automatic Neighbor Relations (C-ANR), which prevents up to 20% the unnecessary call drops, for instance, due to missing neighbors.
- To continuously monitor and optimize the relationship between the neighboring cells to calibrate the best possible balance of coverage, and capacity, there are two new complementary features introduced for 3G and 4G Coverage and Capacity Optimization and Centralized Mobility Load Balance (CCLB).

There are other LTE SON management solution platforms developed by other network equipment vendors as well. For instance, Huawei proposed SingleSON [18] which optimizes real-time network operations across the protocol stack layers and networks components. It aims to improve the OPEX efficiency and enable the operators to increase throughput as a long-term solution. Huawei also has a emerging product aka Next Generation SON (NG SON)[19].

Besides Ericsson and Huawei, other main vendors also proposed their solutions for SON. For example, Nokia proposed EdenNet [20]. EdenNet is a centralized SON platform that automates operations, eliminating complexities from multi-vendor, multi-RAT, and across the protocol stack layers. The multi-vendor capability is supported by the Operations Support Systems interoperability initiative (OSSii). Different from most SON platform in the LTE era, EdenNet can support AI-based functions such as AI-driven closed-loop automation and Machine Learning-based decision. Other SON products in the LTE system include the Crosswork SON Suite by Cisco [21], TEOCO SON [22], and more.

In the LTE system, some SON functions, such as Automatic Neighbour Relation (ANR) and Plug and Play (PnP), have been deployed by the operators and brought gains. However, the standardization effort on SON so far has been mainly focused on a limited set of use-cases and on defining the interfaces. Furthermore, the adoption of SON in practice has been slow since it was always seen as an optional complementary solution to the existing RAN rather than its integral part. With this backdrop, key targets for the NG SON are to improve the O&M efficiency significantly and help operators keep pace with the complexity of fast-evolving wireless networks. Additionally, the NG SON should significantly enhance network performance through self-organizing intelligence.

2.3 5G Overview

2.3.1 5G Use Cases

5G designed to operate multiple challenging services efficiently and meet challenging service requirements and corresponding KPIs [13]. Targeting such KPIs triggers innovation of new 5G use-cases and new mobile applications as well as services that are difficult to anticipate from today. Nevertheless, as illustrated in Fig. 2.1 [23], 5G use-cases can be mainly categorized as follows:

- Enhanced Mobile Broadband (eMBB) is existing mobile broadband services to increase the user experience. The eMBB use-cases require very high data rates and large bandwidths.
- Massive Machine Type Communications (mMTC) is a massive number of IoT (Internet Of Things) devices. For instance, devices, which are cheap and requires

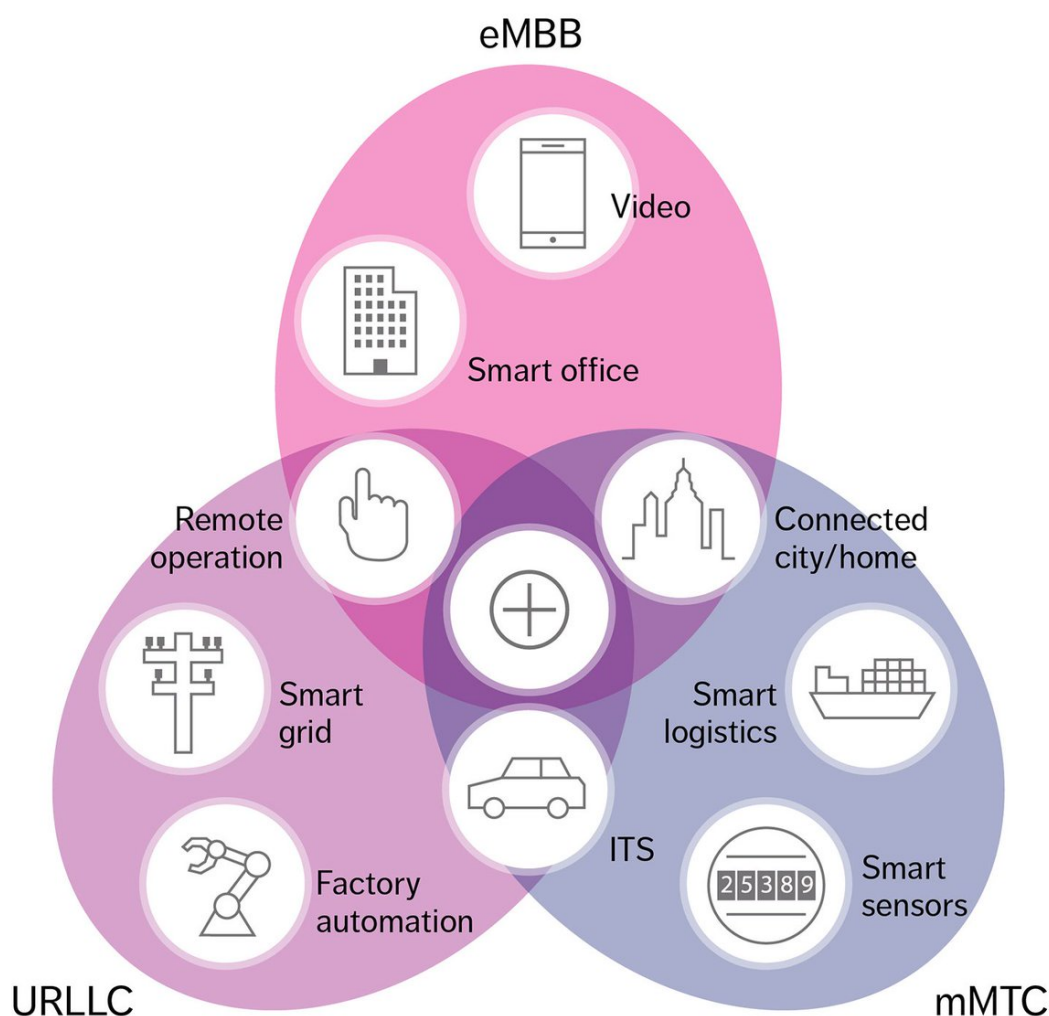


Figure 2.1: Types and examples of currently envisioned 5G use case.

very low energy and bandwidth, high connection density, and also enhanced coverage.

- Ultra-Reliable Low Latency Communications (URLLC) such as traffic safety and factory automation scenarios, require very low latency and very high reliability.

2.3.2 5G Architecture

5G network architecture standardized by 3GPP, as illustrated in Fig.2.2 the access method is not necessary to be wireless in 5G, which means wired methods such as optical fiber is also included in 5G AN. Meanwhile, WiFi and Satellite are all integrated with 5G AN. Unlike the LTE network, 5G UEs might have their interface to the core

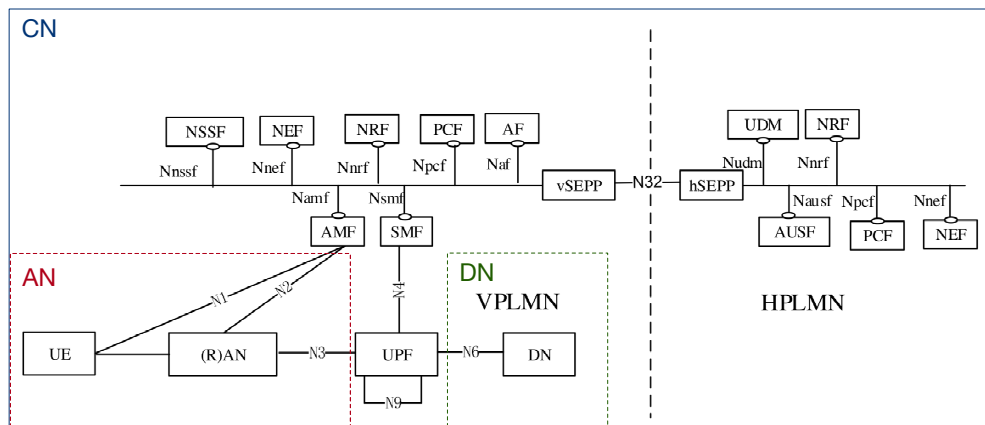


Figure 2.2: 3GPP 5G Architecture

network, and this is mainly designed for services with strict latency requirements, e.g., remote-controlled vehicles, telesurgery, and factory automation.

Furthermore, some of the main functions of 5G core network are listed namely; Authentication Server Function (AUSF), Access and Mobility Management Function (AMF), Unstructured Data Storage Function (UDSF), Network Exposure Function (NEF), Network Repository Function (NRF), Network Slice Selection Function (NSSF), Policy Control Function (PCF), Session Management Function (SMF), Unified Data Management (UDM), Unified Data Repository (UDR), User Plane Function (UPF), Application Function (AF). Moreover, Network slicing will be supported as well. When roaming is considered, functions like AUSF will be activated to carry out authentication.

2.3.3 Network Slicing

5G network is surely much more complex than ever with stricter requirements in many aspects. Thus, a more flexible and efficient autonomous network system is necessary for 5G. In order to provide tailored services and allocate adequate resources dynamically based on each subscribers' needs, network slicing is proposed as a key solution in the autonomous networks, which is included in the architecture of 5G.

Enabled by SDN and NFV, Network Slicing is an end-to-end logical network provisioned with a set of isolated virtual resources on the shared physical infrastructure [24]. It refers to the partitioning of one physical network components into multiple virtual networks, and each component is optimized for a specific application as well as service. The general architecture of an end-to-end network slicing system is illustrated in Fig. 2.3 [25]. The benefits of network slicing are mainly reflected as follows:

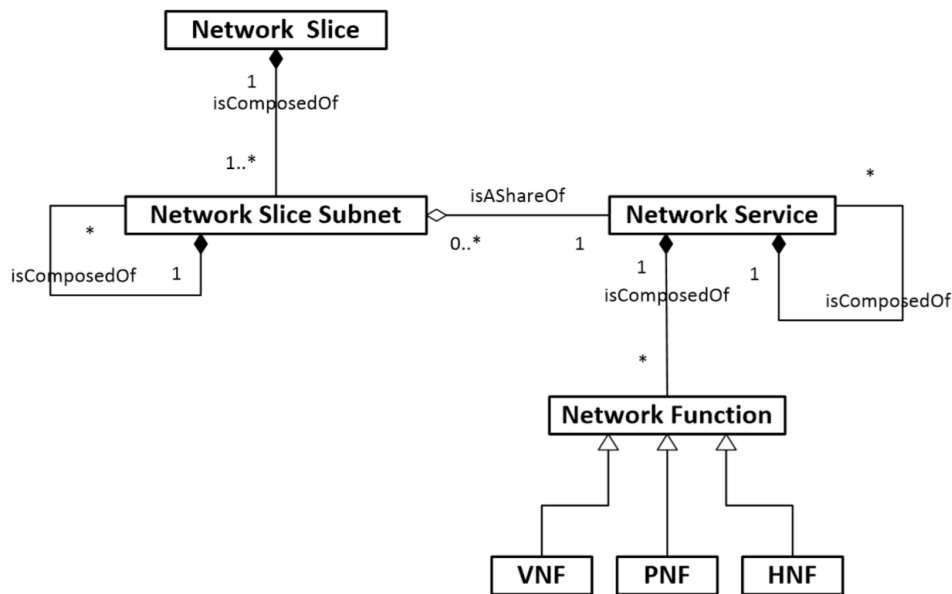


Figure 2.3: 3GPP Network Slicing Architecture

1. provides logical networks with better performance one-size-fits-all networks
2. scales up or down as based on the needs of the service and also the number of users changes (different services and environment/context).
3. isolates the network resources of one service from the others; the configurations among various slices do not affect each other. Therefore, the reliability and security of each slice can be enhanced.
4. the slices can be customized according to service requirements; it can optimize the allocation and use of physical network resources.

2.4 Automation in 5G

Due to the increased computation power, e.g. data centers, the training time of the ML/AI algorithms reduced significantly. Thus the AI/ML models became applicable for many industries. However, the cutting edge AI/ML models are not yet exploited by the telecommunication industry, not yet standardized by 3GPP, nor implemented yet in the existing LTE products. Therefore, when the recent achievements of AI models taken into account, one can claim that LTE SON has a lack of intelligence. The lack of intelligence hinders the LTE SON paradigm from meeting the ambitious 5G

KPIs requirements. Henceforth, without improved intelligent SON in daily network operations, i.e., managing and serving daily services and service optimizations are going to be cumbersome and costing significantly.

The 5G automation framework also orchestrates all the heterogeneous network components, radio resources, and services in a multi-operator environment. Multi-operator management and orchestration refers to the automated management of services and unified network resources in multi-technology environments which includes distributed cloud and network components across the multi-operator infrastructure.

In 5G, the dynamic network monitoring will enable the operators to perform real-time resource monitoring, management, and network configuration of relevant radio networks as well as the core networks. The mobile services and the network infrastructure will be tailored via well-known technologies such as SDN and NFV. Also, with the help of NFV and SDN, the embedded network monitoring and cloud computation resources 5G aims to provide services, e.g., innovative media services, aiming to improve the end user's QoE and creating new business opportunities for service providers. Besides, a mobile operator has business characteristics and challenges, which need to be tackled on a daily basis.

2.4.1 5G Automation Frameworks

Since the traditional networks' management landscape is high fragmented, henceforth, to monitor and guarantee to achieve the required KPIs is quite challenging for future networks. Instead of the fragmented management system, a long-term open-source network management and orchestration platform with automation capabilities on a massive scale, including multi-site and Multi-Virtual Infrastructure Manager (VIM) for both physical and virtual network elements is necessary. Moreover, mobile operators must scale and need to implement new service offerings to be able to deliver various services simultaneously. This leads to additional costs in the case of CapEx which includes installing new data center equipment to upgrade the existing equipment and software. In order to avoid such kind of cost, the operators are eager to use Software Defined Network (SDN) and Network Function Virtualization (NFV) to minimize the investment cost and increase the return.

The end-to-end network management vision is transforming from managing resources to autonomous managing services. A network management system is considered to be automated with AI models if it performed management operations in a manner

that satisfied self-configurable, self-healing, self-optimization, and self-protection [26]. The functions are also required to detect the dynamic changes in any of the network components and also in the surrounding environment, which might have a violation of the management objectives, such as trigger appropriate configuration or, more precisely, adaptation mechanisms, without disturbing the network performance. Data-driven AI-based automation systems are key enablers to monitor and plan network resource management based on predicting the needs of each individual and the use-case. The AI-based automation systems also enable the system to orchestrate all the network resources and realize an optimal QoE while avoiding additional OPEX. For instance, emerging resources and parameters across communication layers from the physical layer to the application layer provides much reliable and intelligent resource management. Thus, automation is leveraging the operations strategy from the quality of the connectivity to QoE and QoS. The ultimate target is to automate the management functions, and there is an urgent need for a common automation platform for the telecommunication industry.

The network automation is not just helpful but necessary in 5G. Without a network automation framework, the network will not be scalable and operable due to the anticipated scale and the desired functional complexity. For instance, in 3GPP Rel 15, one of the most critical potential challenges for network slicing is autonomic management. Technologies like SDN and NFV are moving networks toward software-based automation and higher network flexibility by exploiting software virtualization and programmability. Thus, network providers will be able to partition network infrastructures into virtual networks (i.e., slices) with characteristics tailored to meet the specific needs of applications and services built on top of it. In this scenario, the adoption of some degree of automation and orchestration is vital for convergent resource management and service delivery operations, as addressed by the Management and Orchestration (MANO) component within the ETSI NFV Architectural framework [27].

Moreover, the 5G SON conception is far from well-developed because of state-of-the-art automation technologies such as deep learning that are not yet applied to real network products, which are still under development progress. There is also a strong need for intelligence and automation in data analysis, as well. Current methods today lack the adaptability and flexibility required to become feasible solutions to 5G networks. Although mobile operators collect a massive amount of data from the network in the form of network measurements, control and management interactions, and even data from their subscribers, current methods applied to configure and optimize the network are very rudimentary. Such methods consist of manual configuration of thousands of

base-station parameters, periodic drive tests, and analysis of measurement reports by operators to continuously optimize the network [28]. Furthermore, operators also require skilled personnel always to observe alarms and use monitoring software at the Operation and Management Center (OMC) to perform self-healing. Henceforth, the autonomic MANO in 5G is necessary. In the context of 5G networks, automation might be applied in several domains, such as: 5G Radio Access Split [29], Mobile Edge Computing [30], Cloud RAN [31], Software Enabled Networks [32], Network Access Control [33], 5G Core Networks [34], Network Slicing Life-Cycle Management [35] and so on.

Many autonomic MANO platforms were proposed to this end such as the Open Source MANO (OSM) [36] and ONAP [37]. ETSI's OSM is developed for ETSI NFV management, while ONAP is another independent organization focus on the similar things. There are also many relating projects based on or powering these platforms such as the ETSI "Experiential Networked Intelligence (ENI)" project [38] which exploits the state of the art AI techniques and context-aware policies to define a cognitive network management architecture. ETSI also is running the Zero-touch project [39], which focuses on end-to-end network automation and service management. Most of these platforms are open-source and accelerate the 5G network automation process. Telecommunication working groups also consider these challenges and problems mentioned above in ETSI, ITU, and others. Currently, ONAP and OSM are the most widely used open-source platform in both the research and industrial, which will be described in the next subsections on a high level.

Chapter 3

Related Work

For each use case, we present the most characteristic works and show how the research evolved throughout the years. We also discuss shortcomings that drive the need for the novel solutions presented in the following chapters. *In this chapter, we present an overview of the literature related to the data-driven use cases discussed in the context of this thesis.*

3.1 JADE: Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks

In the last decade, wireless jamming has received considerable attention in the research literature. The earlier work, surveyed in [40, 41], mainly focused on jamming in the context of ad hoc and sensor networks; and 802.11 based wireless LANs and multihop networks. A significant early work [42] considers jamming in sensor networks.

Considering 802.11 networks, [43] examines local and collaborative detection methods while [44] focus on distinguishing different types of jamming attacks. More recent works in this line of research focus on machine learning-based jammer detection [45, 46, 47, 48, 49] with most of them taking a supervised classification approach and concluding that the random forest method performs the best.

More closer to our target setting, jamming in mobile networks (specifically 4G/LTE) is considered in [50, 51, 52]. In contrast to our focus on jammer detection in operational mobile networks, these works concentrate on highlighting vulnerabilities of the LTE system to jamming attacks and proposing mitigation methods. [52] also presents a threat assessment of the LTE system that identifies the weakest points in its physical (PHY)

layer while [50, 51] observe that jamming the uplink is more effective for an attacker than the downlink due to the relatively lower transmission power limit for LTE UEs in the former. Moreover, there are more recent works such as [53] that reviewed broadly vulnerabilities 5G and jamming attack models. [54] presents a jamming detection method for 5G downlink by utilizing the user radio link quality, while [55] focused on an anonymous jamming detection and classification scheme in 5G non-standalone where cross-layer statistical parameters in an anomaly detection combined with a causality analysis approach. [54] presents a statistical method detection algorithm for O-RAN.

We are unaware of any previous work that leverages KPI data to detect jammers in mobile networks (by treating them as anomalies or otherwise). But there exist works in mobile networks and beyond that use KPI data for anomaly detection [56, 57, 58]. While [56, 58] are focused on mobile networks augmented with self-organising network features, OPPRENTICE [57] targets anomaly detection in the context of Internet-based service delivery. [56, 57] advocate the use of supervised classification for anomaly detection based on ensemble methods (specifically random forest in OPPRENTICE [57]), and manual labeling to address the ground-truth issue. On the other hand, [58] uses a simple Z-Score [59] like statistical method to detect anomalies at the KPI level and then uses correlation among KPI anomalies to determine cell-level anomalies. ABSENCE [60] is another broadly related work that detects service disruptions in mobile networks using anonymized call detail record (CDR) data. The essential idea here is to monitor spatio-temporal customer usage based on anonymized CDRs and identifying deviations from historical usage as anomalies.

Also broadly related is the recent work on deep learning based RF/spectrum anomaly detection from the spectrum monitoring perspective [61, 62, 63, 64, 65] to detect unauthorized transmissions, misconfigured transmitters, etc. In contrast to these works, the anomaly detection methods we develop rely on cell-level KPI data and are tailored for automated and scalable jammer detection in operational mobile networks. Our work is also unique due to the use of an operator provided 4G network dataset for evaluations and real-world validations.

3.2 Demand Characterization and Forecasting for Cost-Effective Operational Mobile Network Planning

Prior work on mobile network demand forecasting falls into two distinct categories, as discussed below.

In the first category, the focus is on forecasting market dynamics, where diffusion modeling based forecasting of increase in number of mobile subscribers has received most attention [66]. Recent work in this thread investigated multi-country analyses of diffusion models [67] and on forecasting the timing of the introduction of a new technology (e.g., 5G, 6G) [68]. Popular industry global mobile data traffic forecast reports from Cisco [69] and Ericsson [4] also broadly fall in this category; as outlined in these reports, the methodology behind their forecasts relies on using historical data, market trends and industry analyst data and reports. In other work in this category, Oughton et al. [70] examined the demand for 5G in the UK under different data demand growth assumptions and looked at different alternatives on the supply side to serve that demand.

The works in the second category aim at forecasting future mobile network traffic demand based on modeling the observed traffic data characteristics [71, 72, 73] survey papers pointed out for future research such as 5G network slicing and dynamic resource allocation use cases [74, 75, 76]. Most work in this category is however aimed at optimizing mobile network operations or informing radio resource allocation (e.g., [77, 78, 79]). Data and predictions in these works are spatially and temporally fine-grained at the cell/city level and in the order of milliseconds to minutes. Characteristics of such fine-grained traffic data are very different from the same data at large geographical scales and time frames relevant for mobile network planning. The works in [80] and [81] are closer to our focus in that they are motivated by network planning but limited in geographical scope (to a city) and to short time horizons (up to a month). In summary, in contrast to the above-discussed mobile network demand characterization and forecasting works, our study is aimed at supporting the annual nationwide planning process of mobile operators to determine the CAPEX and OPEX budget. Spatial granularity at the region level and yearly time horizon we consider is in tune with the mobile network operator planning process in practice. Moreover, none of the above works consider the traffic characteristics and predictability of FWA service that is growing in prominence.

3.3 CellDA: Data-Driven Autonomous Hotspot Cell Detection Framework For Operational Mobile Networks

Over the past decade, hotspot detection has attracted a fair amount of attention from both the telecommunications industry and academia. However, the majority of research has considered hotspot detection based on geographical data as part of network performance optimization to deploy additional radio resources such as small and picocells. These early studies were based on the number of mobile users and their distributions to determine the best possible deployment locations and regions where the network traffic load is excessively high [82, 83, 84, 85, 86]. For instance, [83] proposes the use of Gaussian Mixture Model (GMM) model on mobile user data to identify hotspots and user densities while [85] recommends predicting potential hotspots from the presence of virtual small cells that form only when traffic volume and user density are extremely high. In contrast, we focus on automated, data-driven hotspot detection based on cell-level KPI time series at daily granularity.

In general, most of the early data-driven studies in mobile networks have used statistical methods (e.g., Exponential Smoothing, Moving Average, Auto Regressive (AR) and Auto-Regressive Integrated Moving Average (ARIMA)) that have been widely adopted to pursue the short-range dependence of network traffic [87, 88, 89]. However, network KPIs are time series, possessing non-linear and complex characteristics that led to the design of methods [90, 72, 88] to guide mobile network investments and optimization, both at the network and radio cell levels, that focus on trends, seasonality and anomaly prediction.

With the diversity of mobile service applications, network traffic characteristics are much more complex with some non-linear time-series features, and statistical models are not suitable for the network-KPI prediction problem [87, 91, 92]. So recent studies have examined proactive network resource allocation optimization utilizing ML based approaches. For instance, [93] forecasts hotspots based on spatial traffic analysis using Gaussian random field (GRF) while [94] implemented the K-means clustering algorithm to identify the mobility patterns of users where each cluster centre corresponded to a hotspot center. On the other hand, [84] compared geotagged Tweets and hotspots distributions along with the use of a Generative Adversarial Networks (GAN) model trained to generate data on the distribution of intra-cell hotspots. Meanwhile, [85] adopted a deep learning approach to predict the appearance of hotspots in hybrid beamforming scenarios and compared several long short-term memory (LSTM) based methods with

ConvLSTM to anticipate user distribution. [95] focused on predicting the network-level user density in temporal and spatial domain by using LSTM neural network is adopted to predict the number of UEs in every small zone.

The research carried out in [92, 96, 95, 97, 98] is more closely aligned with our study aim in that they were also motivated by hotspot detection. Particularly, [92, 96] are two early works that propose using tree-based machine learning models such as random forest. However, tree-based models are not robust as demonstrated in [99]. The other closely related works [95, 97, 98] have the following limitations: (1) only one single LSTM-based model has been taken into account in these works as standalone components; 2) evaluated on small data that is collected in limited in geographical scope (i.e. to a city); and (3) limited historical data i.e. a maximum of three days. In addition, one of the most recent works, more aligned with our work, focuses on-demand UAV-assisted wireless networks (OWN) deployment such as [100, 54] where in general has three sequential steps: dynamic demand prediction, proactive deployment, and resource allocation fine-tuning.

In our work, differently from the other previous works, for the first time, we validate and compare the performance of various promising deep neural networks extensively including the LSTM models proposed in [95, 99]. Also for the first time in the scope of hotspot detection, we propose an automated hotspot cell detection framework and present performance results. Finally, we examine the accuracy of hotspot cell detection performance over different time horizons.

Chapter 4

JADE: Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks

Jamming is the intentional interference aimed at disrupting wireless communications services and as such can be seen as a denial of service (DoS) attack [42, 40]. The use and sale of jamming devices (commonly referred to as *jammers*) is therefore illegal in many countries (e.g., [101, 102]) and any violations may result in imprisonment or fines (e.g., [103, 104]). Nevertheless, jammers targeting all wireless communications technologies continue to be widely available and in fact quite affordable (see [105, 106, 107], for example). The threat posed by jammers to robust wireless communications including on mobile networks is expected to become worse in the future with low-cost and open-source software-defined radio (SDR) platforms becoming easily available to arm malicious actors [108, 52, 109].

The activation of jammers can severely deteriorate the service quality in a mobile network. Fig. 4.1 shows the impact on selected cell-level key performance indicators (KPIs) due to the presence of a jammer, using data from an operational 4G network. We observe that the jammer activation effectively shuts down the network for users, forcing uplink (UL) and downlink (DL) traffic volumes and throughputs down to near-zero. The levels of received signal strength indicator (RSSI) can also be elevated by over 20dB (100x increase) with a jammer. These results highlight the potential risk posed by jammers to the robustness of mobile networks. This applies not just to currently deployed 3G and 4G networks that the society heavily relies on for personal mobile communications, emergency response systems and public safety networks but also for

future 5G networks that aspire to support diverse use cases including ultra-reliable and low-latency communications services (e.g., connected vehicles, remote surgery). *In this chapter, we consider jamming in operational mobile networks and in particular focus on the problem of detecting jammer activity in this context.*

4.1 Problem Statement

The jammer detection in current practice, however, is a highly manual process that is costly and slow, resulting in degradation in user QoE while the jammer induced interference is detected and resolved. When significant service quality deterioration or network outage is noticed, which may be prompted by user reporting, radio network engineers manually examine large volumes of multi-dimensional network KPI data to diagnose the problem, which may also require field testing. Moreover, when jammer activity is intermittent it can be perceived as a radio network problem and result in misguided network reconfigurations/optimizations. Thus, in current operational mobile networks, according to the operators themselves, it may take days or weeks after the jammer activation for it to be detected. This suggests that jammer detection is a perfect use case for automation in mobile networks that can not only lead to savings in OPEX costs for operators but also enhance user QoE. Jammer detection is also the first step that can enable further troubleshooting to identify and pinpoint the interference source.

In view of the above, we aim at automated jammer detection for operational mobile networks that can automatically and quickly detect jammer (de-)activations, then trigger alarms to kick-start downstream resolution processes. While this clearly involves reliable detection of all kinds of malicious jammers, we also aim to detect the operation of other unintentional interference sources (e.g., malfunctioning devices, DECT phones) that can cause jammer-like impact on the network. Achieving this goal, however, is hard as it requires addressing the following challenges:

1. Any available ground-truth label information on jammer activations to build an automated detection system may be limited to small parts of the network and/or short periods of time due to the scale of the task and manual nature of the process. So practical jammer detection methods need to generalize well to be applied to bulk of the data that is “unlabeled”.
2. Jammers can have very diverse behaviors. Some jammers once activated may stay continuously active while others exhibit complex discontinuous activation

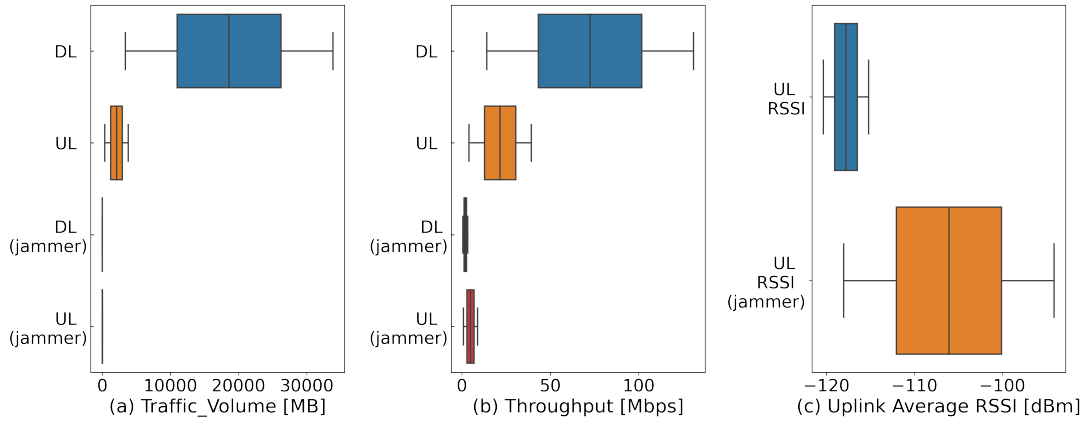


Figure 4.1: Impact of jammer presence on three cell-level KPIs: (a) UL/DL traffic volumes; (b) UL/DL throughputs; and (c) uplink RSSI.

patterns. They also differ from each other in their type (e.g., military, drone specific jammer, DECT phone), the networks (e.g., 3G, 4G) and frequency bands they target. In our real-world dataset we have encountered jammers that can affect as many as ten different frequency bands. Moreover, newer types of jammers with a prior unknown characteristics can emerge over time.

3. Jammer related activity needs to be disambiguated from network KPI dynamics induced from normal and expected behavior (e.g., due to user mobility, network overload). But this can be challenging, for example, with active but distant jammers.

To this end, we present *JADE*, which to the best of our knowledge is the first automated jammer detection framework for operational mobile networks. By treating jammer activity as ‘abnormal’ or ‘anomalous’ from the mobile radio access network (RAN) infrastructure side, *JADE* approaches jammer detection as an anomaly detection problem [110, 111, 112]. *JADE* is envisioned for operator side deployment and considers cells at each tower site as measurement vantage points. It continually monitors the time series of various KPIs at each of these cells to detect anomalous behavior over time. At the core of *JADE* are two deep learning based time-series anomaly detection methods that we developed; they work with multivariate KPI data at each cell. In the first method, a multi-variate long short term memory (LSTM) neural network model tracks the variation of uplink RSSI observed at each cell to predict its future value and detects an anomaly (jammer activation) when the difference between the predicted and the actual value is more than a *threshold*. The second method models multivariate KPI time series using a LSTM autoencoder model and the associated reconstruction error

over time is compared against a threshold to detect jammer activation.

To address the several challenges outlined above (i.e., limited labeled data, ability to detect new and a priori unknown jammer activity, discrimination of jammer activity from normal KPI dynamics), JADE operates in a *semi-supervised anomaly detection mode* [110] in that it relies only on ‘normal’ data for training the above outlined models. This jammer agnostic nature of JADE also makes it robust for detecting jammers that may exhibit adversarial behaviors. JADE also embeds a mechanism to adaptively set thresholds to detect anomalies, thereby adjust the boundary between normal and abnormal events. To efficiently support the detection of jammers at scale in real-world mobile networks across multiple cells and operating frequency bands, we employ transfer learning [113] to develop one frequency and cell agnostic model instead of a different model for each cell and frequency band.

The key contributions of our JADE work are summarized in (§1.1). Nevertheless, for the convenience of the reader, the key contributions of this study are listed below.

- We propose JADE, a novel data-driven jammer activity detection framework for operational mobile networks (§4.5) which addresses this problem for the first time. It incorporates two custom-tailored semi-supervised deep learning based anomaly detection methods for the jammer detection task along with an adaptive thresholding mechanism. JADE also leverages transfer learning towards efficient modeling and ease of deployability.
- We extensively evaluate the JADE framework using a 4G radio access network (RAN) dataset from a multinational mobile network operator (§??).
 - Our results show that the anomaly detection methods developed for JADE outperform a wide range of commonly used anomaly detection methods when applied to the jammer detection task, and also confirm the effectiveness of JADE’s adaptive thresholding mechanism.
 - We demonstrate the robustness of the JADE framework powered by transfer learning in accurately detecting jammer activity across multiple frequency bands and diverse types of jammers.
 - We also present real-world validation results by applying our methods in the operator’s network for online jammer detection.
 - As a downstream use case of JADE, we consider jammer localization. Specifically, we demonstrate the potential for pinpointing jammer locations based

on jammer activity detections in the mobile network using JADE and combining them with cell site location data.

4.2 Datasets

A unique and noteworthy aspect of our work is the use of real 4G RAN datasets from a multinational mobile network operator for our evaluations. Overall, these datasets outlined below consist of about a million samples of radio network KPIs measured at an hourly time resolution over several months.

Training dataset. This dataset contains ‘normal’ data collected during periods with no jammer activation which is verified by the radio engineers from the operator’s network. It is used for training the two semi-supervised anomaly detection methods we developed as part of the proposed JADE framework. This dataset consists of around 700,000 measurement samples in total that were collected over a period of three months from 266 different cell tower sites, hosting 339 distinct cells operating over five LTE) uplink frequency bands: 852-862 MHz, 1745-1765 MHz, 1765-1775 MHz, 1970-1980 MHz, and 2500-2520 MHz. Each sample is a time-stamped (at hourly granularity) tuple of 9 different radio network KPIs measured at a cell: Uplink and Downlink Traffic Volumes (MB), Average Uplink and Downlink User Throughputs at PDCP Layer (Mbps), Average Uplink RSSI (dBm), E-UTRAN Radio Access Bearer (ERAB) Setup Success (%), Evolved Radio Access Bearer (ERAB) Drop (%), LTE Random Access Channel (RACH) Success (%), and Voice over LTE (VoLTE) drop (%).

Testing dataset. In contrast to the training dataset, this dataset corresponds to periods with jammer activation events. Specifically, it is made up of three sub-datasets, each corresponding to a different jammer’s activity over a 3 week period. These three jammers are arbitrarily named by the operator as J16, J17 and J22. Among these, J16 affects three frequency bands (1745-1765 MHz, 1765-1775 MHz, 2500-2520 MHz) and has a discontinuous (on/off) activation pattern. On the other hand, J17 and J22 have continuous activation patterns, which means once activated they stay active until they are switched off. J17 and J22 operate on 2500-2520 MHz and 1765-1775 MHz bands, respectively. All these three sub-datasets are manually labeled by radio network engineers from the operator with ground-truth on jammer active/absent for each sample. These ground-truth labels are key to our study in that they enable evaluation of different jammer detection methods considered in this work. Overall the testing dataset consists of 255600 samples with ground-truth annotated KPI data. KPIs captured in each sample are same as in the

training dataset. Each of the three sub-datasets contain data for at least 50 cells.

For the above datasets, we have conducted preprocessing steps to impute missing values with the average of neighboring values and normalized each KPI value via min-max normalization. We did further feature extraction based on the time-series of the above listed KPIs, following a similar methodology to the one in [114], which led to 82 features in all. Besides the datasets described above, the proposed JADE framework and constituent jammer detection methods are validated through trials on the operator side. In §4.6.3, we present results for two additional different jammers (labeled J23 and J19) encountered during the field trial period. In the case study on jammer localization based on jammer detection events (§4.6.4), we also use the ground-truth location data for J16, J17 and J22 jammers along with the location data of surrounding cell tower sites from the operator to assess jammer localization accuracy.

4.3 Evaluation Metrics

Here we describe our metrics to evaluate the various jammer detection methods developed/considered in this paper. These metrics are defined in terms of four possible outcomes that can result from applying a jammer detection method, which are:

- True-Positive (TP): Jammer activity detected when such activity is actually present, as per the ground-truth.
- False-Positive (FP): Jammer activity detected when in fact there is no jammer activity.
- True-Negative (TN): Jammer activity not detected when jammer activity is absent as per the ground-truth.
- False-Negative (FN): Jammer activity not detected even though jammer is actually active.

An effective jammer detection method minimizes both FPs and FNs. Two commonly used measures to assess the extent to which a given method achieves these goals are *Precision* and *Recall*¹, as defined below:

$$Precision = \frac{TP}{TP + FP} \quad (4.1)$$

$$Recall = \frac{TP}{TP + FN} \quad (4.2)$$

Higher values for both these metrics are desired. A lower value of precision (equivalently, a higher number of FPs) leads to an increase in OPEX to diagnose, confirm and

¹Recall is sometimes also referred to as Sensitivity or True Positive Rate.

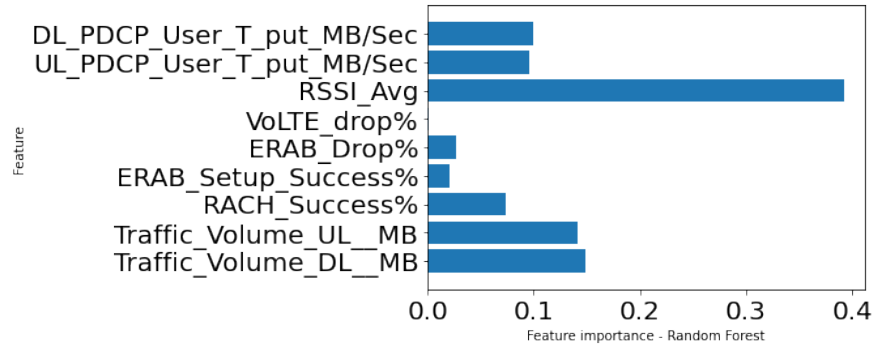


Figure 4.2: Relative importance of different features (KPIs) for the random forests based classifier.

localize jammer activity (e.g., by field visits and testing), when in reality, there is none. On the other hand, a lower value of recall (equivalently, a high number of FNs) shows that the method in question fails to detect all jammer activation events and thus risks prolonged degradation of user QoE until the jammer activity is eventually detected and stopped. Given the above, having high precision and high recall are equally important. As such, we consider a composite metric called *F1-Score* that weighs precision and recall equally by taking a harmonic mean of the two, as defined below:

$$F1-Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \quad (4.3)$$

4.4 Limitations of Supervised Binary Classification Approach

A straightforward approach to jammer detection is to treat it as a supervised binary classification problem. In fact, most recent works on jammer detection [45, 47, 48, 115, 49], though aimed at 802.11 networks, take this approach, and show Random Forests (RF) [116] to be the most effective classifier. Here we assess the effectiveness of supervised binary classification approach towards jammer detection in operational mobile networks, considering RF as the classifier.

Since we need a labeled dataset for training and testing with supervised classification, we use one of our ‘testing’ sub-datasets for the J16 jammer (outlined in section 4.2) for this study. Each sample in this dataset is a 9-tuple KPI data labeled as jammer active/absent. The dataset overall spans over 60 cells across three different frequency bands: 35 cells in 1745-1765MHz; 17 cells in 1765-1775MHz; and 9 cells in 2500-

2520MHz. It is a fairly balanced dataset with 60% (40%) jammer active (inactive) samples. We do a 70/30 split of this dataset to create training and test data for the RF based binary classifier, which leads to a test set with 11 cells in 1745-1765MHz; 5 in 1765-1775MHz; 3 in 2500-2520MHz.

We first use the RF feature importance [6] test to examine the relative importance of the different features from the classifier’s perspective with the results shown in Fig. 4.2. We find that the average uplink RSSI is the most important feature, followed by UL/DL traffic volumes and throughputs. Interestingly, the percentage of VoLTE drops has the least predictive effect on the classifier, perhaps because call drops could happen due to a myriad of factors beyond the jammer presence e.g., due to network overload or coverage issues.

Fig. 4.3 shows the box plot results for precision, recall, and F1-score metrics, separately for each frequency band where the J16 jammer operates, with each box plot capturing the distribution for the metric across different cells. We observe that precision and recall values are less than ideal, and range between 0.7-0.8 and 0.55-0.75, respectively. The relatively lower recall results indicate that this supervised classifier method errs more towards missing some jammer activation events than causing false alarms. The combined effect, measured by F1-score, is worse with a median value between 0.5 and 0.7.

Crucially, this poor classification performance is noticed for cases with fewer cells and less data in the training dataset. This highlights a key issue with supervised classification based approach to jammer detection – more and diverse “labeled” data is needed. Compared to getting “normal” class data, it is difficult and very costly to produce a large and diverse labeled dataset with “jammer activation” events. More data can be available for “normal” periods as reflected by our datasets (where 700,000 samples or at least 70% of the total data is for the “normal” category), but supervised classifiers fail to take advantage of such data.

4.5 The JADE Framework

In this section, we describe our proposed JADE framework for data-driven automated jammer detection in operational mobile networks in detail. By way of motivation, we start by examining the limitations of commonly used jammer detection approach based on supervised classification, thereby highlight a challenge that an effective jammer detection method design needs to address.

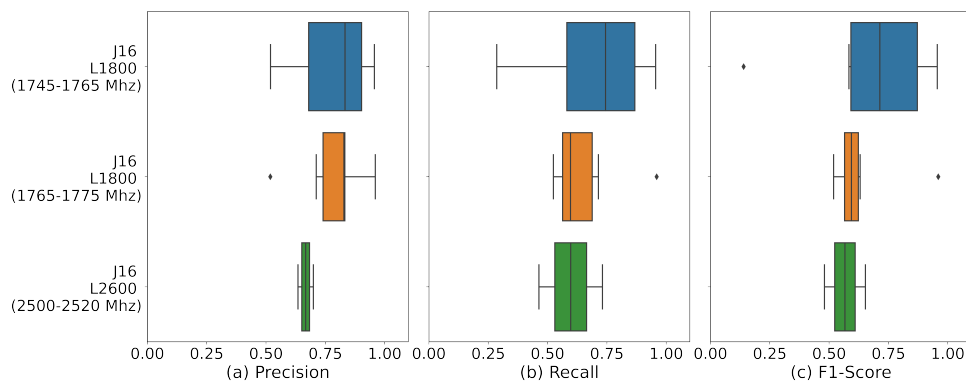


Figure 4.3: Precision, recall and F1-score performance of random forests based supervised binary classifier.

4.5.1 JADE Overview

The foregoing discussion not only highlights limitations with the supervised classification based approach but a key challenge to be addressed in jammer detection method design, i.e., limited or no data labeled with jammer effect. Another challenge is that there exist numerous types of jammers and each has its own different characteristics and impact on mobile network performance (e.g., due to affecting different sets of frequency bands). Gathering training data that represents all jammer types is simply impractical. Moreover, identifying the decision boundary between normal network behavior and that affected by jammer activity through the radio network KPIs is challenging due to the inherent KPI dynamics.

Our proposed JADE framework (illustrated in Fig. 4.4) addresses the above challenges. JADE is envisioned for operator-side deployment and considers cells at each tower site as measurement vantage points to aid in online jammer detection. It relies on continual monitoring of time series of various KPIs at each of these cells and collecting this data at the operator RAN data lake facility. This data is then preprocessed to address issues such as missing values by imputing with neighboring ones before putting it through the jammer detection pipeline in JADE.

JADE approaches jammer detection in an operational mobile network as a time-series anomaly detection problem [110, 111, 112] by considering that jammer activity manifests as ‘abnormal’ or ‘anomalous’ in the time series of radio network KPIs. To address the aforementioned challenges, JADE adopts the *semi-supervised* form of anomaly detection [110] by solely relying on and leveraging potentially abundant ‘normal’ data for model training. This also makes JADE independent of the type and behavior of a jammer, thereby enabling robust detection across diverse types of jammers. At the

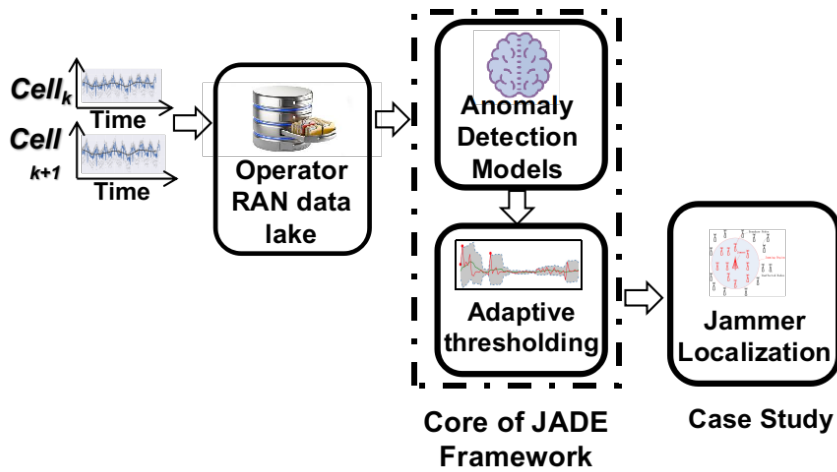


Figure 4.4: Illustration of the JADE Framework.

core of JADE are two alternative deep learning based anomaly detection models. Besides, JADE incorporates an adaptive mechanism for these models to set thresholds that represent the boundary between normal and anomalous samples. Also, rather than have a separate anomaly (jammer) detection model per cell or frequency band, JADE employs transfer learning [113] towards *one* cell and frequency band agnostic model. We elaborate on the above components of JADE in the following subsections.

4.5.2 Deep Learning Models for Cell-Level Anomaly Detection

Here we describe the two anomaly detection based models we develop as part of JADE for jammer activity detection: (1) Autoencoder [117] based model; (2) RSSI prediction based model. Both these models operate at the cell level and take multivariate time series data for radio network KPIs as input but aim to detect anomalous samples in the time series through different approaches, as elaborated below. Since we are dealing with time-series data, we use LSTM [118] cells in the architecture of both models.

Autoencoder based Anomaly Detection Model

Fig. 4.5(a) illustrates the proposed LSTM autoencoder based model that takes multivariate time series as input. The core idea is to encode each input sample using an LSTM network and decode it using another LSTM network. Anomaly detection relies on the (in)ability to faithfully decode the input sample. With a sufficient amount of training data (i.e., normal samples), the AE model learns to reconstruct the normal samples. The reconstruction error for normal samples will therefore be lower compared to the reconstruction error of samples in the presence of a jammer.

As mentioned above, the AE model has two components: an encoder and a decoder. The encoder represents the input sample in the latent space, whereas the decoder aims to reconstructs the latent domain back to the input sample. The encoder in our model consists of four layers. The number of LSTM cells in the first layer is equal to the number of features in the input sample while the following three layers have 512, 64, and 4 LSTM cells, respectively. Then the decoder reconstructs the input sample from the 4-dimensional latent space. The decoder also consists of four layers where the number of LSTM cells in its first three layers are 4, 64, and 512, respectively. The number of LSTM cells in the last layer of the decoder equals the input sample size (in terms of features) to the AE model.

We use Mean Squared Error (MSE) as a loss function and trained the model for 20 epochs for every cell in the training dataset. We empirically optimize the hyper-parameters with grid search [6]. We use RMSprop as an optimizer and RELU as an activation function with a batch size of 64. Since the network KPIs have inherent noise and variations, we did not introduce any additional noise in the input of the AE towards better generalization.

RSSI Prediction based Anomaly Detection Model

We now present an alternative anomaly detection model for jammer activity detection that focuses on predicting the uplink RSSI over time, considering that this KPI is seen to be the most important feature in our earlier study on supervised binary classification based jammer detection (Fig. 4.2). The essential idea here is to train a time-series prediction model that takes as input multivariate time series of KPIs and predicts the RSSI for each following time step. The prediction error is expected to be low for ‘normal’ samples as the model is trained with data consisting of such samples. But the presence of jammer activity can yield higher prediction errors, which can then be identified as anomalies (jammer activation events).

4.5.3 Adaptive Thresholding

The two anomaly detection models described in the previous subsection produce a reconstruction/prediction error for each new sample in a cell KPI time series. But to detect whether that sample is an anomaly (due to jammer activity or other such interference), we need a threshold (error level) representing the boundary between normal and anomalous samples. Correctly setting this threshold is equally key to

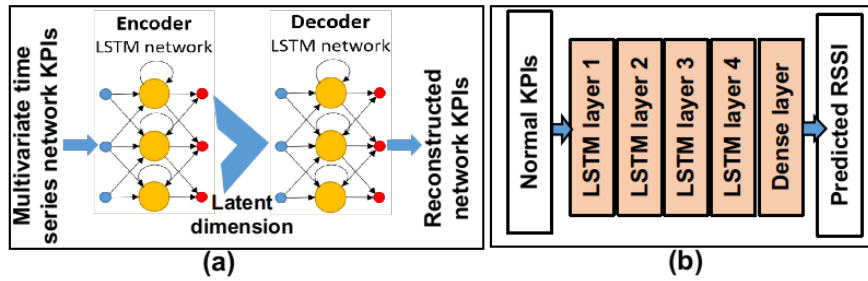


Figure 4.5: (a) Autoencoder based anomaly detection model; (b) RSSI prediction based anomaly detection model.

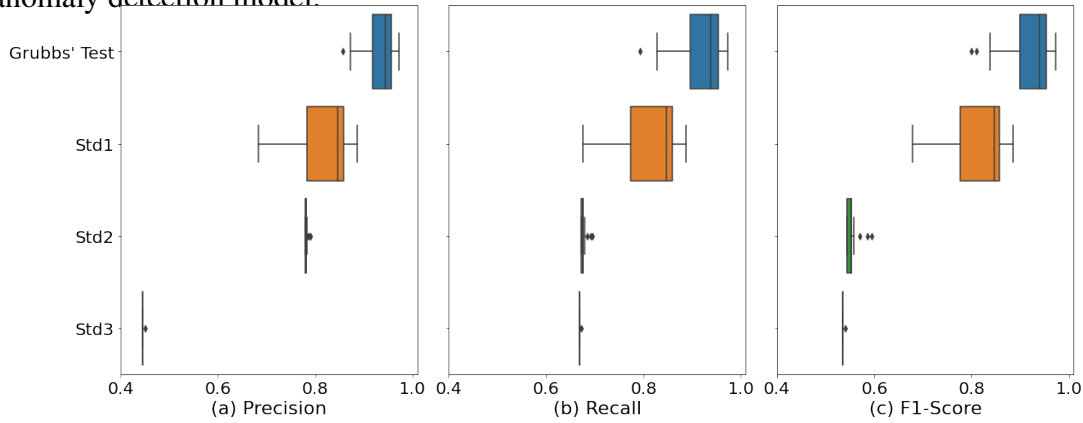


Figure 4.6: Representative result showing the performance gain with our Grubbs' test based adaptive thresholding approach compared to the state-of-the-art $n\sigma$ approach.

effective jammer detection. It can be seen as deciding the tradeoff between FP and FN probabilities.

Different approaches are taken for this thresholding in the literature. Some works do this manually, relying on human expert feedback to set/adapt thresholds (e.g., [56, 57, 119]) but this is unviable in our setting. Feng et al [63] simply use the median reconstruction error as the threshold, which is again not robust. Most recent wireless anomaly detection works, however, approach this thresholding by assuming that errors are generated from a Gaussian distribution. Some of these works [61, 62, 65] set the threshold based on a desired FP probability, which is not appropriate in our setting as we also would like to have equally good precision and recall performance.

Other works [60, 58, 64] adopt a $n\sigma$ thresholding approach for some small value of n where σ is the standard deviation of the error distribution. This essentially means that a sample is considered an anomaly if its error (reconstruction/prediction error in our case) is more than $n\sigma$ away from the mean of the error distribution, obtained using (normal) training data. While the reconstruction/prediction errors across all samples in the training data also follow a Gaussian distribution in our case (results not shown due

to space limit), we find the $n\sigma$ thresholding approach is not robust in our setting, as we show shortly. We observe that this is because of the diversity among cells and so the impact of a jammer on those cells is also different. There also exist other works (e.g., [120]) that empirically obtain a fixed threshold.

We instead take a tailored adaptive thresholding approach on a per cell basis by examining the time series of (reconstruction/prediction) errors in each cell to detect anomalies. Our proposed approach to this issue can be seen as an adaptation of Grubb's Test [121] for single outlier detection in univariate data. Note that the data for thresholding purposes refers to either reconstruction or prediction errors, depending on the anomaly detection model used, and it is therefore univariate. In the following, we describe our proposed thresholding method.

We start by defining two hypotheses: H_0 : There are no outliers in the data; and H_1 : There is exactly one outlier in the data. We also define Grubb's test statistic to be calculated for each new data (error) sample Y_i :

$$G_{calc} = \frac{\max|Y_i - \bar{Y}|}{s} \quad (4.4)$$

where \bar{Y} and s , respectively, represent the mean and standard deviation of the error data samples considered for outlier detection. Based on the above, we detect an outlier (Y_i) or equivalently, reject the null hypothesis (H_0 hypothesis of no outliers) if the calculated test statistic is greater than a critical value (as defined on the right hand side of the equation below):

$$G_{calc} > \frac{(N-1)}{\sqrt{N}} \sqrt{\frac{(t_{\alpha/(2N), N-2})^2}{N-2 + (t_{\alpha/(2N), N-2})^2}} \quad (4.5)$$

where N is the number of training error samples considered initially, t refers to the t-distribution and α is the significance level (related to the desired confidence interval). If, on the other hand, G_{calc} is less than or equal to the critical value then we conclude there is no outlier in the set of N samples.

We bootstrap the above statistic calculation with a series of N error samples (ϵ) from the training data and view it as a window. Then when we apply an anomaly detection model (one of the two from the previous subsection) to each new sample in the radio network KPI time series for a cell, we slide the window and include the new error sample ϵ_{new} to recalculate the statistic. If it is greater than the critical value, the new error sample corresponds to an outlier (anomaly) and so we undo the window sliding to ignore ϵ_{new} . Otherwise, ϵ_{new} is now part of the set of error samples considered for

outlier detection. In this work, we set α to 0.05 (equivalent to 95% confidence interval) and empirically set N to 25.

Fig. 4.6 demonstrates the effectiveness of our above described Grubb's test based thresholding approach with the $n\sigma$ approach for different typical values of n (1, 2 and 3) for the J16 UL-1800 (1745-1765 MHz) test dataset and using the multi-KPI RSSI prediction based anomaly detection model. Box plots reflect the distribution of each metric across all cells in this dataset. These results clearly any single static threshold is not effective generally, while our adaptive approach always yields the best performance. We have observed similar performance improvement with our approach with the other test datasets (omitted due to space limitations).

Fig. 4.5(b) illustrates our RSSI prediction based anomaly detection model, which leverages the state-of-the-art LSTM based time series prediction model architecture. Our model consists of four LSTM layers (the input layer, three hidden LSTM layers) and one fully connected output layer. The LSTM cells in the input layer are equal to the number of features in each input sample. The following three hidden layers have 32, 16, and 8 LSTM cells, respectively. The output layer is a fully connected dense layer with a single neuron that outputs RSSI predictions. Specifically, our model predicts the RSSI for the following 10 time steps based on multivariate KPI time series for the past 10 time steps, along a moving window. Like in the AE model, the hyper-parameters are experimentally optimized with grid search, RELU is used as an activation function, and the batch size is 64.

Single and Multi-KPI models

We consider two variants of the above-described models:

- *Single KPI model* that considers only one KPI, specifically RSSI. In essence, AE and RSSI prediction versions of this model deal with RSSI KPI time series. Note that each sample in the input time series to these models is multivariate with 74 different features, due to feature extraction during data preprocessing.
- *Multi-KPI model* that considers all 9 KPIs in our dataset, including other KPIs like uplink/downlink throughput and RACH success rate. This is naturally a multivariate time series with 82 features in each sample of the input time series, again due to the feature extraction step.

These single and multi-KPI models allow us to understand the added benefit of considering the various different KPIs beyond just the uplink RSSI.

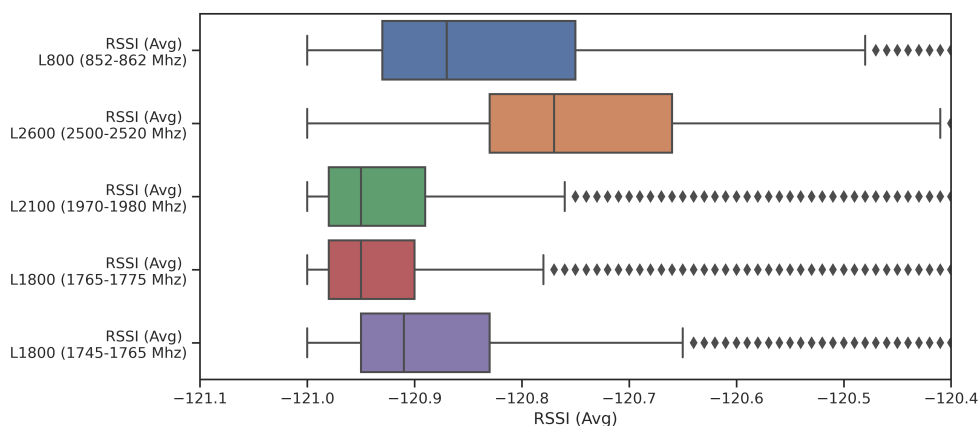


Figure 4.7: Average RSSI distribution across cells using different uplink frequency bands.

4.5.4 Transfer Learning

Our proposed solution for detecting jammer activity via anomaly detection model with adaptive thresholding approach thus far implicitly considered a single cell scenario. In practice, however, each cell tower site hosts multiple cells, possibly configured on different frequency bands. Moreover, an operator’s network deployment may have thousands of such cell sites. But training and maintaining a per cell or even per frequency band anomaly detection models is not scalable from a deployment perspective.

We therefore aim at a single cell and frequency agnostic anomaly detection model, one per each alternative discussed in §4.5.2. We cannot, however, base such a model by training it on single cell or even single frequency band as different cells and frequency bands have diverse behavior in terms of radio network KPIs and jammer effect. For example, the RSSI distributions across cells on different uplink frequency bands shown in Fig. 4.7 clearly highlight such diversity. So we train our target cell and frequency agnostic model using ‘normal’ data from different cells and frequency bands. To make this training efficient, we leverage transfer learning (TL) [113].

Specifically, we train the cell and frequency agnostic model as follows. We start with a frequency band and a cell within that band. Once the model is trained with data for that cell, we treat that as the start point for training on a different cell from the same frequency band, reusing the already trained model’s weights as opposed to starting from scratch. Once the model is trained across all cells of a frequency band, then it is used as the base model for training on cells for another frequency band. We repeat this process until we cover all frequency bands and cells in the training data, which ultimately results in the frequency and cell agnostic model.

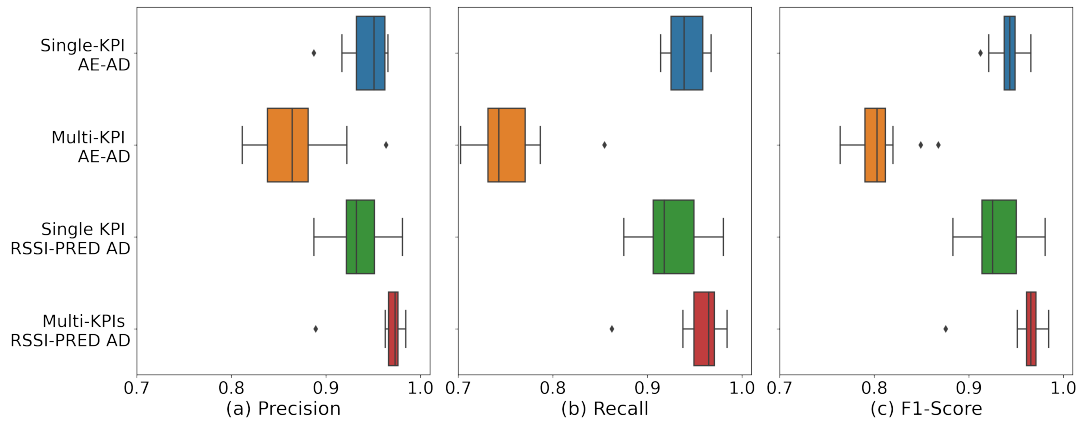


Figure 4.8: Relative performance of AD models in JADE on the J16 UL1800 (1745-1765 MHz) test dataset.

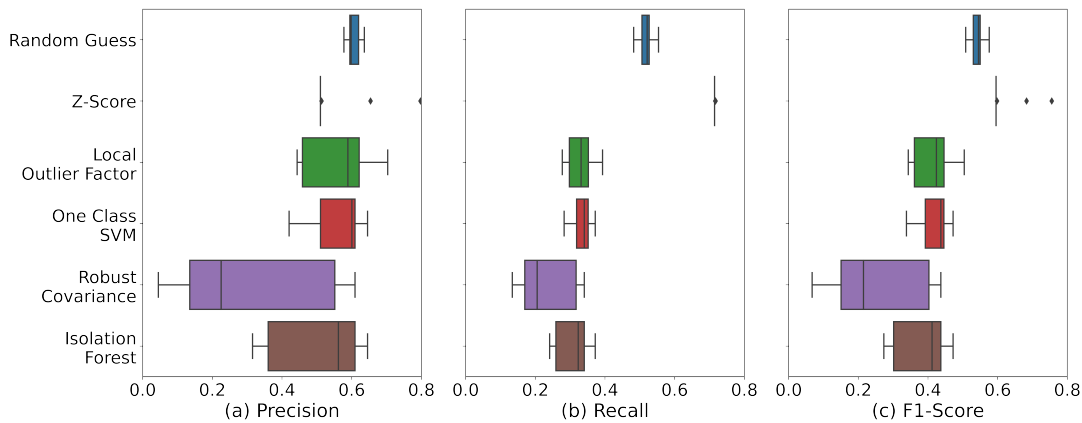


Figure 4.9: Performance of baseline AD methods on the J16 UL-1800 (1745-1765 MHz) test dataset.

4.6 Evaluation of JADE

In this section, we evaluate the performance of the proposed JADE framework using the operator provided 4G RAN datasets described in §4.2 in terms of the precision, recall and F1-score metrics defined in §4.3.

4.6.1 Comparative Evaluation of Anomaly Detection Methods

In the previous section, we have already presented evaluation results that show the effectiveness of the adaptive thresholding mechanism in JADE. Here we evaluate the different anomaly detection model alternatives in JADE relative to commonly used AD methods [110, 122].

Recall from §4.5.2 that the JADE framework offers four different AD models: AE and RSSI prediction based models, each with single and multi-KPI versions. We train

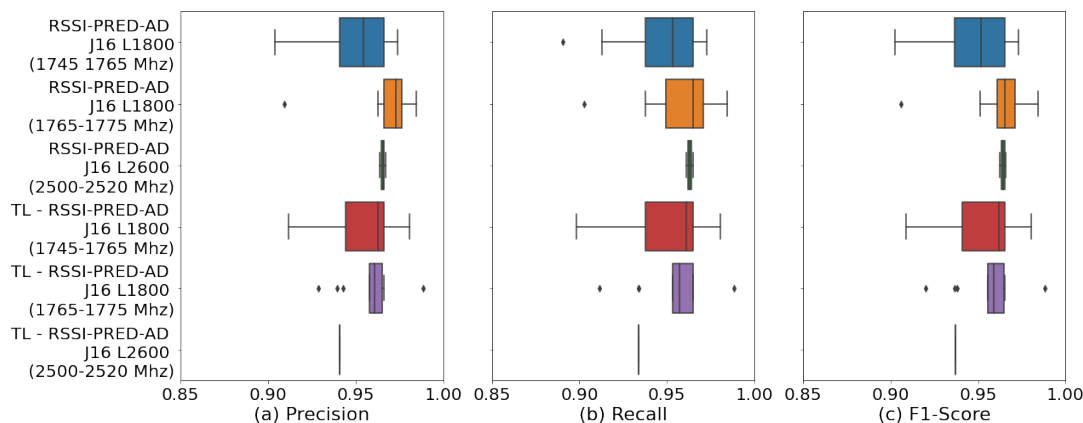


Figure 4.10: The performance of multi-KPI version of RSSI prediction based AD model in JADE on different J16 frequency bands, comparing TL based frequency-agnostic model with frequency-specific models.

these models using the training dataset (§4.2). We evaluate using the J16 UL-1800 (1745-1765 MHz) part of the testing dataset. For comparison, we consider five diverse and commonly used AD methods: Z-Score, Local Outlier Factor, One-Class SVM, Robust Covariance and Isolation Forest. To make these baseline methods work with our multi-dimensional KPI data, we use Principal Component Analysis (PCA) [123] based dimensionality reduction to represent the dataset in two-dimensional space.

Fig. 4.8 shows the performance comparison between the four JADE AD models. We observe that the multi-KPI version of AE based AD model performs worse than the other three models, especially in terms of recall. However the single KPI version (specifically RSSI) of the AE model relatively performs much better. We attribute this to the characteristics of KPIs other than RSSI that allow reconstruction even in jammer presence, resulting in some jammer activations going undetected. RSSI prediction based AD models both perform well with higher than 0.9 values in all three metrics. The multi-KPI version of RSSI prediction based model offers the best performance overall, which suggests that considering all KPIs is beneficial although marginally. Relatively, the baseline methods perform quite poorly with values for all metrics less than 0.6, which is no better than the random guess based on the known probability of jammer activation events in the test dataset as prior (Fig. 4.9). These results provide a convincing justification for developing tailored AD methods for KPI based jammer detection as we do in JADE.

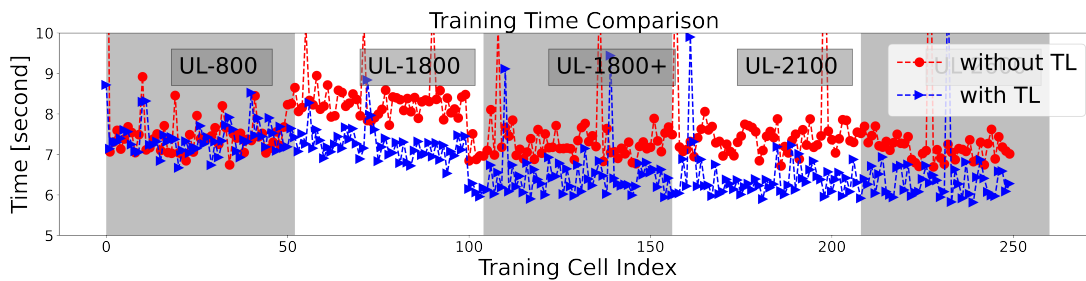


Figure 4.11: Training time gain from using TL to train the frequency-agnostic multi-KPI RSSI prediction based AD model.

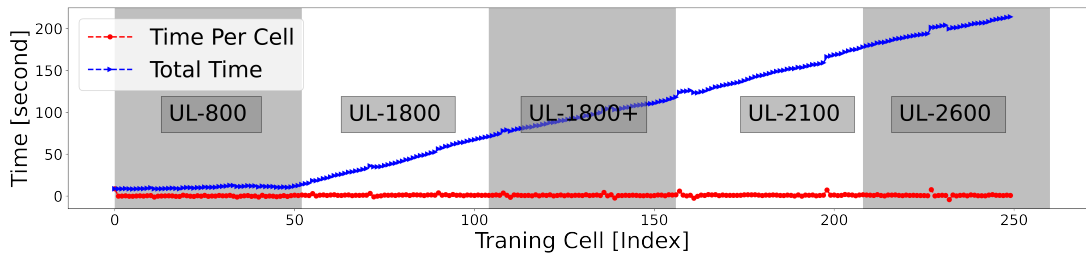


Figure 4.12: Training time improvement from using TL to train the frequency-agnostic multi-KPI RSSI prediction based AD model.

4.6.2 Robustness across Diverse Frequencies & Jammer Types

So far we have considered the JADE performance on one uplink frequency band (J16 UL-1800) and with jammer type (J16). Here we evaluate across different frequency bands and jammer types to assess its robustness. For this study, we consider the best performing model from the previous experiment as the JADE AD model – the multi-KPI version of RSSI prediction based AD model.

We first compare the jammer detection performance between frequency-specific and frequency-agnostic versions of the chosen JADE AD model on different frequencies that J16 jammer operates on. The frequency-agnostic version is obtained with TL based training as described in §4.5.4. Results shown in Fig. 4.10 indicate that the frequency-agnostic model, though marginally worse than its frequency-specific counterparts, yields greater than 0.9 value for all metrics in more than 90% of the cells. The training time from using TL relative to not using it is shown in Fig. 4.11, which clearly demonstrates the training efficiency gain that TL provides.

To study robustness of JADE jammer detection performance, we apply the TL based frequency-agnostic model as in the previous experiment on J17 and J22 parts of the testing dataset. Results shown in Fig. 4.13 clearly confirm the effectiveness of JADE for these

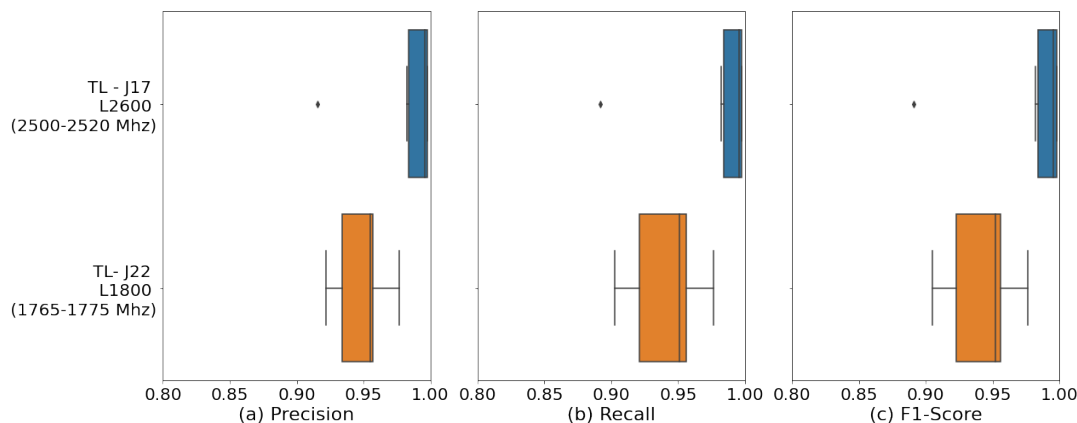


Figure 4.13: The performance of TL based frequency-agnostic JADE AD model on J17 and J22 part of the testing dataset.

other jammer types. The root of the robustness property of JADE lies in its design choice to rely on semi-supervised form of anomaly detection, training only on ‘normal’ data.

Despite the significant improvement in the performance of the jammer activity detection provided by the JADE framework, its lack of generalization to multiple cells under a diverse set of frequencies is still not sorted. Since the training data is limited to one uplink frequency, the JADE framework does not perform well when directly applied to cells with different uplink frequencies. Thus, there is still a large gap between the proposed JADE framework and an operational jammer detection framework. This problem of a frequency-specific model for each cell also leads to a significant training overhead and run-time complexity and renders the system impractical.

To resolve this generalizability issue in the JADE framework, we propose a TL-based frequency-agnostic model (section 4.5.4) that can adapt various cell conditions of different uplink frequencies. We evaluate the performance of the TL-based anomaly detection model on the J16 test data across all frequencies. The results of the proposed TL-based method are reported in figure 4.10. It is evident from the figure 4.10 that for all frequencies of the J16 test data, the proposed frequency agnostic model has achieved more than 90% performance for all evaluation parameters for nearly 90% of cells. This performance is quite similar to the results of frequency-specific models, which indicates that the TL-based frequency agnostic model has mitigated the lack of generalizability of the JADE framework.

The TL-enabled frequency-agnostic model has ensured that the JADE framework can detect the jammer activity across multiple frequencies in the cellular network, thus solving the generalizability issues. Figure 4.11 depicting the benefit of utilizing TL in

terms of the training time saved per cell while transferring the insights from teacher to the student model and training the JADE framework across different frequencies in different cells. Another way to look at this benefit is presented in Figure 4.12, where it is evident that if the JADE framework is trained separately for each cell without using the TL, the training time increases linearly, and once we shift to the TL-enabled frequency agnostic JADE framework, a clear reduction in the training time per cell across all frequencies is noticed. The inherent property of the TL method of transferring the insights from the teacher model (i.e. weight initialization) to the student model ensures that the student model requires less time to get the acceptable level of performance.

Another property of the JADE framework is its ability to detect various jammer types in different frequency bands. Figure 4.13 depicts the performance of the TL-enabled JADE framework on J17 and J22 jammer data. We observe that for both jammer cases, the JADE framework performs almost identical to the J16 case. The values of the evaluation parameters are nearly 90% for 90% of the cells.

4.6.3 Field Validation

So far our evaluation of JADE performance was based on operator provided data labeled with ground-truth on jammer activity (i.e., the testing dataset in §4.2). We now present results validating JADE performance in the field at the operator side. For this purpose, we provided the radio network engineers at the operator with the implementation of JADE's TL based frequency-agnostic AD model, as in the last experiment. It was used to reliably detect a different type of jammer (J23) with discontinuous activation pattern as shown in Fig. 4.14.

JADE was also used at the operator side to detect a military grade jammer (J19) targeting different uplink frequencies. Due to the complex nature of this jammer activity, it was not practical, like with J23, to manually label the ground-truth by the operator's radio engineers. Nevertheless, we visually demonstrate in Fig. 4.15 how JADE is able to detect jammer activity on a sample cell affected by this jammer. During the field trial period, JADE was also used to detect jammer-like activity that was eventually diagnosed to be due to a hardware related problem (see Fig. 4.16), which shows the versatility of our JADE approach to detect both intentional and unintentional interference behavior affecting mobile network operations.

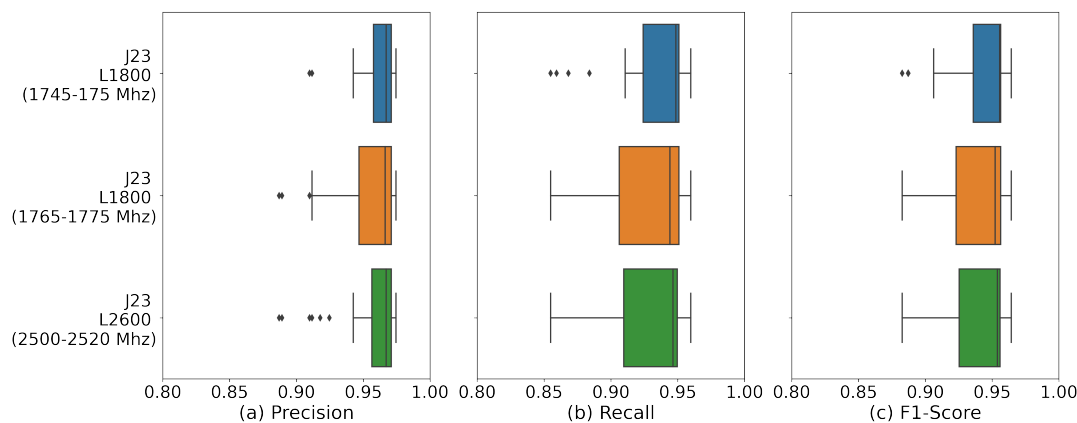


Figure 4.14: Operator-side field validation with J23 jammer.

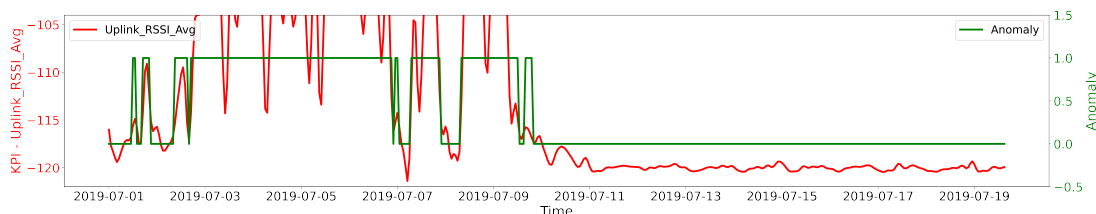


Figure 4.15: Detection of J19 military jammer activity on a sample cell with JADE.

4.6.4 Jammer Localization Case Study

Here we briefly discuss a case study for JADE on jammer localization. The idea is to use the jammer detection results with JADE in conjunction with cell site location data to estimate a jammer's location. Jammer localization is a kind of transmitter localization problem as cell sites surrounding a jammer detect its activity (with JADE) as receivers and it can be localized based on sensed signals at those sites.

As our purpose here is not on jammer localization algorithm design per se but rather on showing the usefulness of JADE for such downstream task, we consider three most commonly used transmitter localization algorithms [124]: max RSSI, centroid and weighted centroid. With max RSSI, the location of the cell site where jammer is detected with max RSSI is taken as jammer's location estimate. With (weighted) centroid, (RSSI weighted) geometric center of cell site locations that detect the jammer is estimated as the jammer location. We use the ground-truth jammer locations provided by the operator to calculate location estimation errors as Euclidean distance (between ground-truth and estimated locations).

Fig. 4.17a) shows the obtained results for J16, J17 and J22 jammers in our testing dataset while Fig. 4.17b) zooms in on the results for J17 case. Even with these commonly used localization algorithms, we find that jammers can be localized within a few hundred

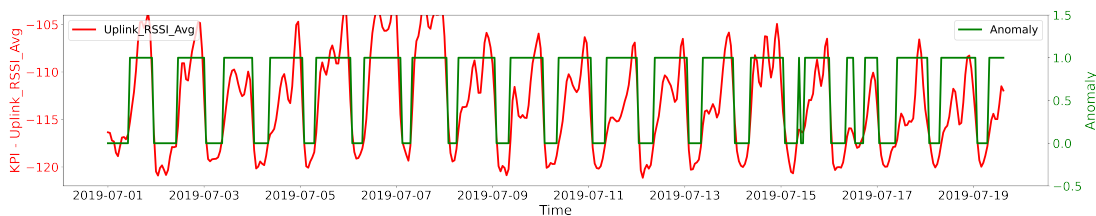


Figure 4.16: Detection of hardware induced interference with JADE during the field trial period.

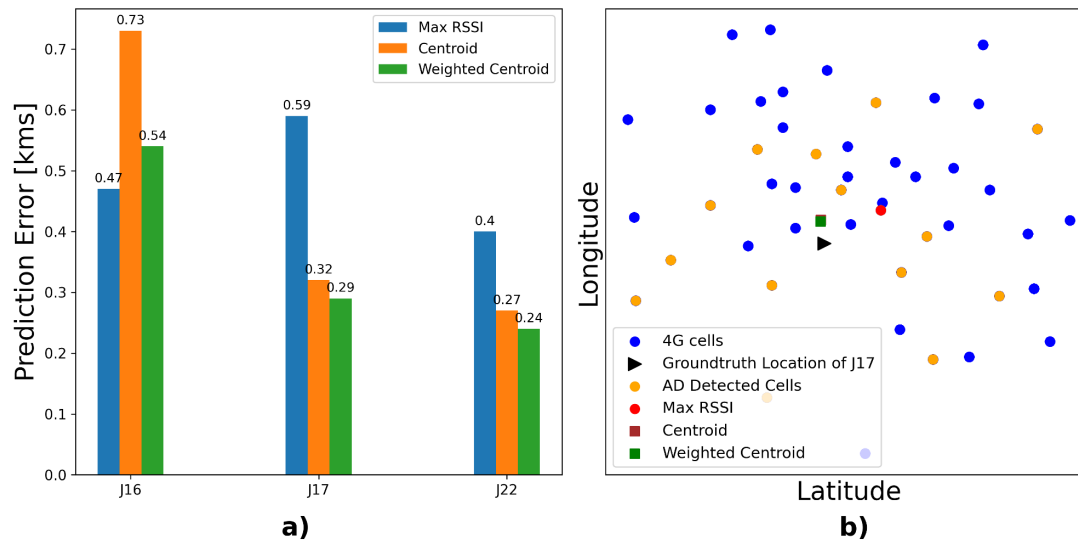


Figure 4.17: a) Jammer localization errors with different algorithms; b) Location estimates for J17 jammer.

meters of the ground-truth, which is sufficient in practice for radio engineers to pinpoint the source of jamming activity. Between the three jammers considered, J16 is located in the country side with sparser mobile network infrastructure, explaining the relatively higher localization errors.

4.7 Summary

In this chapter, we have presented deep learning-based data-driven, to our best knowledge first online framework JADE for jammer activity detection in operational mobile networks. We also provide promising experimental and field validation results on the use of jammer detections from JADE in tandem with the localization of jammers along with cell site location data.

Chapter 5

Demand Characterization and Forecasting for Cost-Effective Operational Mobile Network Planning

Network planning is arguably among the most important aspects of deploying and running a mobile network [125]. The outcome of the planning process determines the operator's capital expenditure (CAPEX), operating expenditure (OPEX) as well as the efficiency and service quality of the network [126]. The planning problem in its essence is aimed at obtaining a cost-effective solution for determining the number of base stations to be deployed, their locations, and configuration parameters to optimize coverage and capacity. Mobile network planning research has been going on for decades, tracking the evolution of different generations (2G–5G). Most work in this area has focused on developing approximation algorithms and heuristics for planning problems (that tend to be computationally hard), considering unique characteristics and constraints posed by each new generation (e.g., 2G [127], 3G [128], 4G [129], 4G HetNet architecture [130], 5G [126]). There is also work accounting for user mobility [131], accommodating load balancing across cells [132], and examining the interaction between network planning and operations [133]. *In this chapter, we present a novel mobile traffic demand characterization and forecasting study with network planning in mind.*

5.1 Problem Statement

Across all these aforementioned works, cost-effectiveness stands out as a common target and for a good reason. On one hand, over-provisioning can ensure optimum network

coverage and capacity but can be very costly in terms of the infrastructure investments that the operator would find it hard to recoup from the subscription revenues. Under-provisioning, on the other hand, can cause degradation of service quality for the users and in turn risk customer churn [2, 3]. *The key to cost-effective mobile network planning lies in understanding and reliably estimating future demand as then the planning expenditure can be tuned to match the demand so as to strike a right balance in between over- and under-provisioning.* In other words, having dependable demand forecast enables good estimation of overall annual capital and operational expenditure budget for the operator along with its allocation down to a regional level. As such, demand is a key input to the planning process [126, 134].

However, mobile network traffic demand over time evolves in uncertain ways and so is hard to estimate. This has been recognized as a big challenge for network planning in general [135, 136]. For example, Yang and Kuipers [135] note that *“In network planning one designs the network ... based on a “guesstimate” of the amount of traffic ... through the network in the future. Clearly, not being able to foretell the future means that one of the biggest challenges in network planning is how to deal with traffic uncertainty. If not solved appropriately, the network operator has to resort to overprovisioning, which is costly.”* Mobile networks are no different. There are several reasons why it is difficult to forecast mobile network traffic demand, especially across a nation and typical planning time horizons of a year:

- Potential number of subscribers and the operator’s market share in the country of interest may vary over time.
- Both user level and network level demand can vary due to several factors: introduction of new devices and device capabilities, technology driven infrastructure evolution (e.g., rollout of 5G), emergence of new applications and services including those with data rich content.
- There can be discrepancy between potential (maximum) and actual demand due to the changes and diversity in network usage patterns within and across regions.
- Special or unforeseen events can alter the mobile network demand characteristics. COVID-19 pandemic is a perfect example that has shown to have a significant impact on network traffic [137, 138, 139].

Early work on mobile network planning has considered worst-case demand at each location by estimating it from geographic and demographic data (and discretizing it through the demand node concept) [140]; this clearly results in over-provisioning. Recent

work on mobile demand forecasting for network planning purposes, on the other hand, is limited in geographical scope (e.g., a city) and also to short time horizons (up to a month) [80, 81]. §1.1.3 discusses related work in detail.

The key contributions of this work are summarized in (§1.1). Nevertheless, for the convenience of the reader, the key contributions of this study are listed below.

- Nationwide mobile service demand exhibits a generally upward trend consistent with industry mobile data traffic forecasts but there is significant diversity at the region level owing to the contextual differences (population and land use composition) between the regions.
- With respect to Covid, we notice a change in pattern in mobile traffic volume at the national level in some months during Covid affected years (2020 and 2021) but for the most part we do not find any observable effect of Covid on the region scale traffic characteristics.
- Our clustering driven methodology yields at least an order of magnitude improvement in accuracy compared to the baseline approach for mobile service demand forecasting while being scalable and practical.
- We observe that FWA service demand characteristics are markedly different from that of the mobile service especially at the national level. Yet our clustering driven demand forecasting methodology is still effective, halving the forecasting error relative to the baseline approach.

5.2 Dataset

A unique aspect of our work lies in the use of a real-world mobile network traffic dataset that is well suited for demand forecasting to inform the operator’s annual planning process. Our dataset consists of multi-year nationwide traffic volume data as a time series at a weekly granularity. It is collected from a prominent national scale mobile telecom operator’s network with around 40 million customers and represents over 40% of the nation’s subscribers. Spatially, the traffic volume is at the level of smaller regions (966 different regions in total) that map to the granularity of areas to which the operator’s overall annual planning budget is allocated. Nationwide weekly network traffic volume is essentially the sum of traffic volumes seen across all these individual regions. As 5G presence of the operator is currently quite limited and majority of the network traffic is carried over 4G, we only focus on 4G traffic volume data in this paper.

Our dataset for mobile network traffic spans two different services provided by the operator: mobile and FWA. For the mobile service, the data is over a continuous 4 year (200+ weeks) period between 1st Jan 2018 and 31st Dec 2021. The data for the FWA service spans a two year period from 1st Jan 2020 to 31st Dec 2021. In our analysis, we also consider demographic and land use related context information for each region obtained from public sources. Specifically, the context for each region consists of 6 attributes – population of the region (from the most recent census) and the fraction of the region’s land use falling into 5 different land use types (dense urban, urban, suburban, rural and seasonal). Note that the fractions for each of the 5 land use types in each region add up to 1.

5.3 Mobile Service Demand Characterization

In this section, we study the characteristics of mobile service demand (traffic volume) at national and regional scales, which have implications for its forecasting studied in §5.4. In the process, given the time span of our data, we also conduct a unique analysis of the effect of COVID-19.

5.3.1 National and Regional Demand Characteristics

Fig. 5.1 left plot shows the changes in mobile service traffic volume at the national scale within and across years. We observe a generally upward trend within each year. The upward trend also continues across years – this can be seen by imagining the time-series for different years strung together in sequence as one long time series. The above observation is consistent with industry mobile data traffic forecasts (e.g., [4]). Interestingly, the generally increasing trend in mobile service demand is seen even through the Covid affected period in years 2020 and 2021. The probability densities of traffic demand in different years obtained with kernel density estimation (KDE) also confirm this observation, as shown in Fig. 5.1 right plot.

The demand patterns at the individual regions, however, have a high degree of diversity. To illustrate this point, Fig. 5.2 shows the evolution of mobile service demand over the 4 year period (2018–21) for four example regions. Of these, the region 719 is dominated by seasonal areas and so exhibits traffic peaks for some months of each year (during the summer) and otherwise has low traffic. The region 72 is the opposite where the traffic is higher and keeps growing over time except during seasonal months when

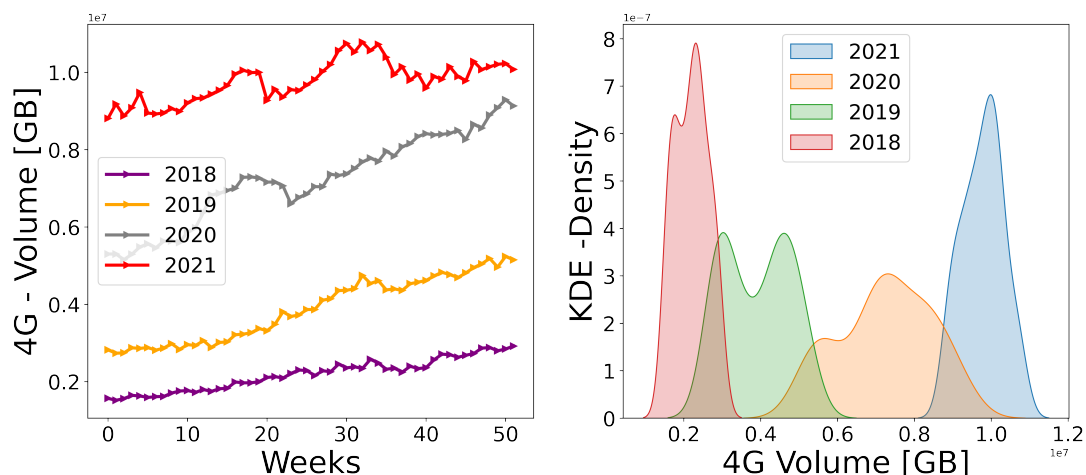


Figure 5.1: Nationwide mobile service demand over time (weeks) across different years (left) and corresponding probability densities (right).

there is a dip (i.e., reverse-seasonal behavior). The region 470 is similar to region 72 except that demand increase over time and reverse-seasonality are milder. The region 1 shows vastly different patterns from the above regions as it is largely rural with relatively low traffic volume and unnoticeable demand increase or seasonality.

We now demonstrate that the above observation about the diverse nature of different regions and its impact on their mobile service demands holds in general. For this, we compute the correlation (using the Pearson correlation coefficient) between mobile traffic volume in a region and its corresponding contextual attributes (population and land use composition). Fig. 5.3 shows these correlations. Here ‘Overall’ represents the overall traffic volume in each region over the 4-year period of our dataset. Focusing on this overall demand (first row or column in Fig. 5.3) and overlooking ‘Pre-Covid’, ‘Covid’, and ‘Diff’ cases, we observe that regions with higher population and urban-ness are likely to have higher demands, which is intuitive. We also observe that regions with bigger seasonal components would have higher demand relative to rural-heavy regions, consistent with what we have seen in Fig. 5.2. Demand and the extent of seasonality in a region are, however, still negatively correlated, which is expected given that high demand occurs only during seasonal months in such regions.

5.3.2 COVID-19 Effect

We now look at the effect of COVID-19 more closely. To this end, referring to Fig. 5.1 left plot, we observe that indeed the time-series pattern in some months of the year has

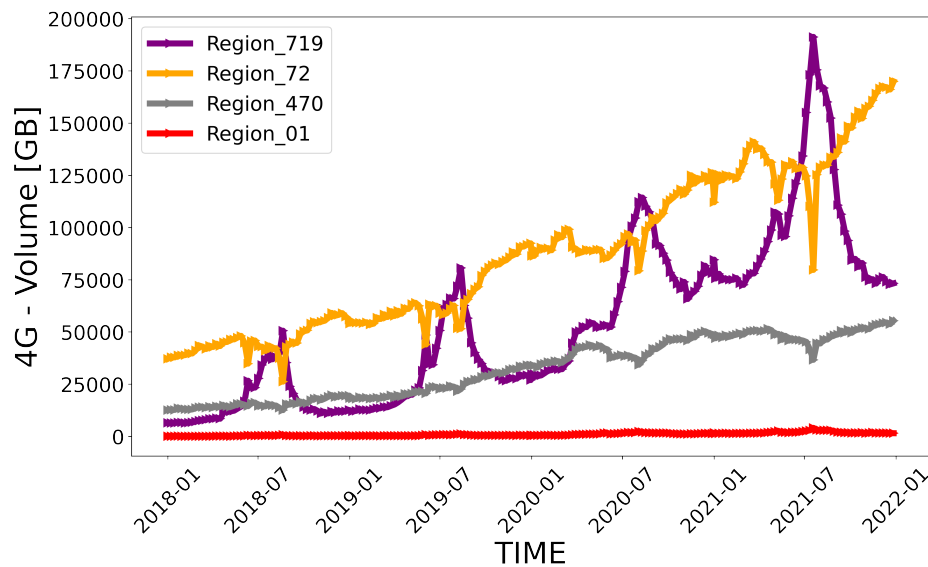


Figure 5.2: Mobile service demand over the years for selected regions.

altered in Covid affected years (2020 and 2021), somewhat correlated with lockdown periods. To get a region level view, Fig. 5.4 compares the per-region mobile traffic volume of Pre-Covid (2018+2019) and Covid (2020+2021) periods. This shows a very different picture in contrast with what is reported in the literature on the effect of Covid on mobile network traffic [137, 138]. Here we in fact see an increase in traffic across all regions during the Covid affected years.

To get a detailed insight from the result in Fig. 5.4, we split it into three successive pairs of years (2018–19, 2019–20, 2020–21) and compute the Euclidean distance between traffic volume time series for each pair and region, as shown in Fig. 5.5. We observe that the pattern of changes across years is largely similar between Pre-Covid (2018–19) and at the time of Covid (2019–20 and 2020–21). This shows that Covid effect is not apparent at the region scale. This is also confirmed by the correlation results in Fig. 5.3, where ‘Pre-Covid’, ‘Covid’ and ‘Diff’ respectively represent per-region traffic volumes in 2018+19, 2020+21 and the difference between the previous two. We observe that there is little difference in correlations between Pre-Covid, Covid and Overall cases. The ‘Diff’ also exhibits similar correlations as the others.

Overall, our analysis suggests that the Covid effect is not apparent for the region scale data we consider for operator planning purposes as each region is typically a composition of different types of land uses and any shifts in traffic patterns between them may not be apparent at the region level. It may also be the case that the effect of Covid on network traffic is country dependant. Prior studies on Covid impact are mainly

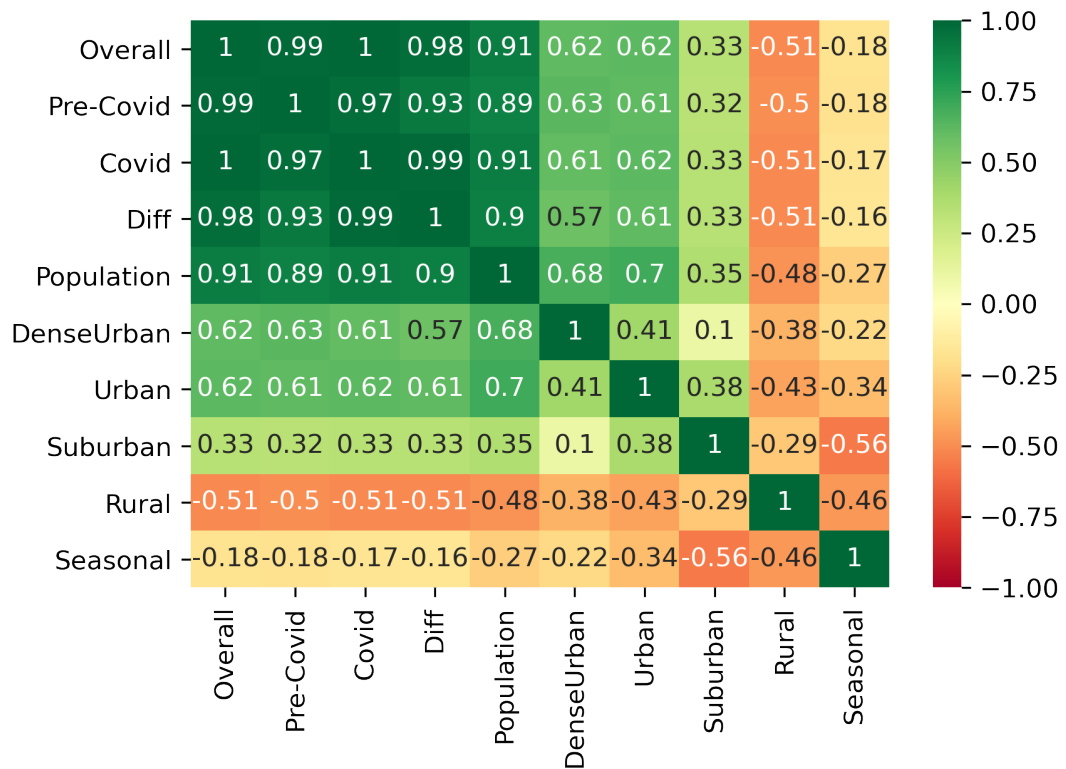


Figure 5.3: Correlation between different cases of mobile service demand in each region and its corresponding contextual attributes (demographic and land use information).

based on data from European countries [137, 138, 139].

5.4 Mobile Service Demand Forecasting

In this section, we focus on the forecasting of mobile service demand at national and regional scales. We start by considering a simple minded approach to motivate our proposed clustering based approach that is presented later in this section. To evaluate the forecasting accuracy, throughout we use root mean squared error (RMSE) as the metric.

5.4.1 Our Clustering-Driven Approach: Motivation & Overview

As our goal here is to forecast mobile service demand at national and regional scales, two possible routes to this end can be conceived. One is to take a ‘top-down’ route where historical national level demand data (by accumulating region level demands) and forecast the national level demand for the coming year first. While this route works

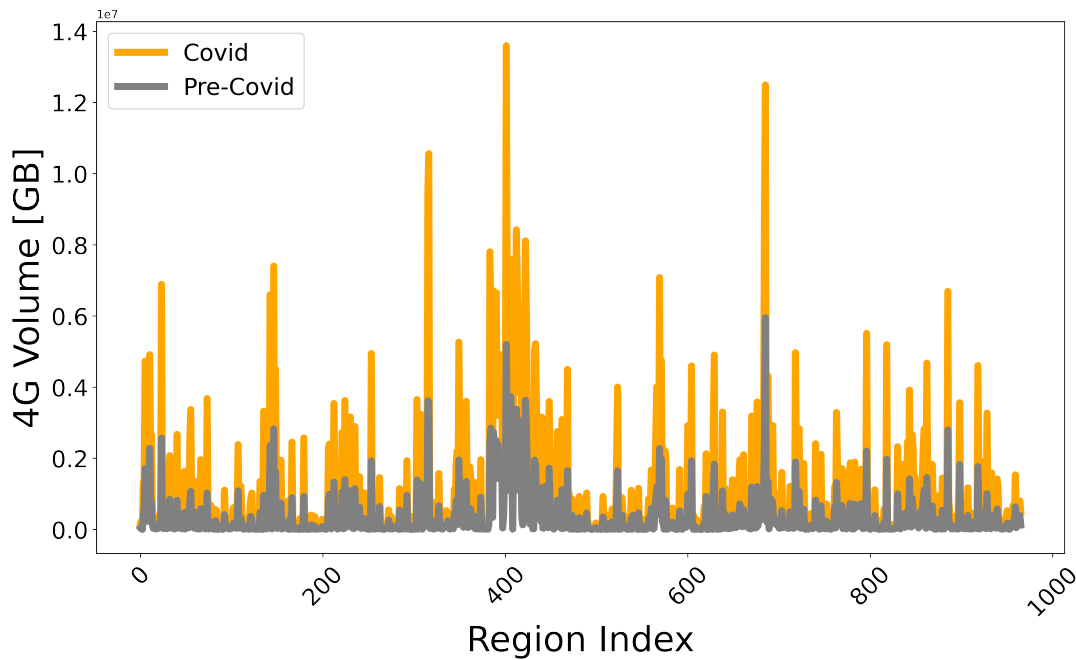


Figure 5.4: Comparison of mobile service traffic volume in each region between Pre-Covid (2018+2019) and Covid (2020+2021) periods.

so far, obtaining a region level forecast from the national level forecast is not possible. So we have to take the alternative ‘bottom-up’ route where region level forecasts are first obtained from historical regional level demand data then accumulate these forecasts to get the national level forecast.

Now that we know we ought to make the forecasts in a bottom-up manner, a straightforward approach is to pick a state-of-the-art forecasting method to perform region level forecasts and accumulate them to obtain national level forecast. Given the significant diversity across regions (§5.3), this would mean training and tuning a separate forecasting model per region, which is not scalable when there are many regions. On the other hand, using the same model for each region compromises forecasting accuracy as we demonstrate here considering Prophet [1], a cutting-edge statistical method that is found to be effective for many time-series forecasting problems.

Fig. 5.6 compares three alternatives. The ‘red’ bar represents the directly doing national level forecast with Prophet using its default parameters. The middle ‘green’ bar shows Prophet national level forecast with optimized hyper-parameters using grid-search [141]. Finally, the ‘blue’ bar represents the same model as in the ‘green’ bar but applied for each individual region and results accumulated to get the national level demand forecast estimate. This experiment highlights two points: (1) hyper-parameter

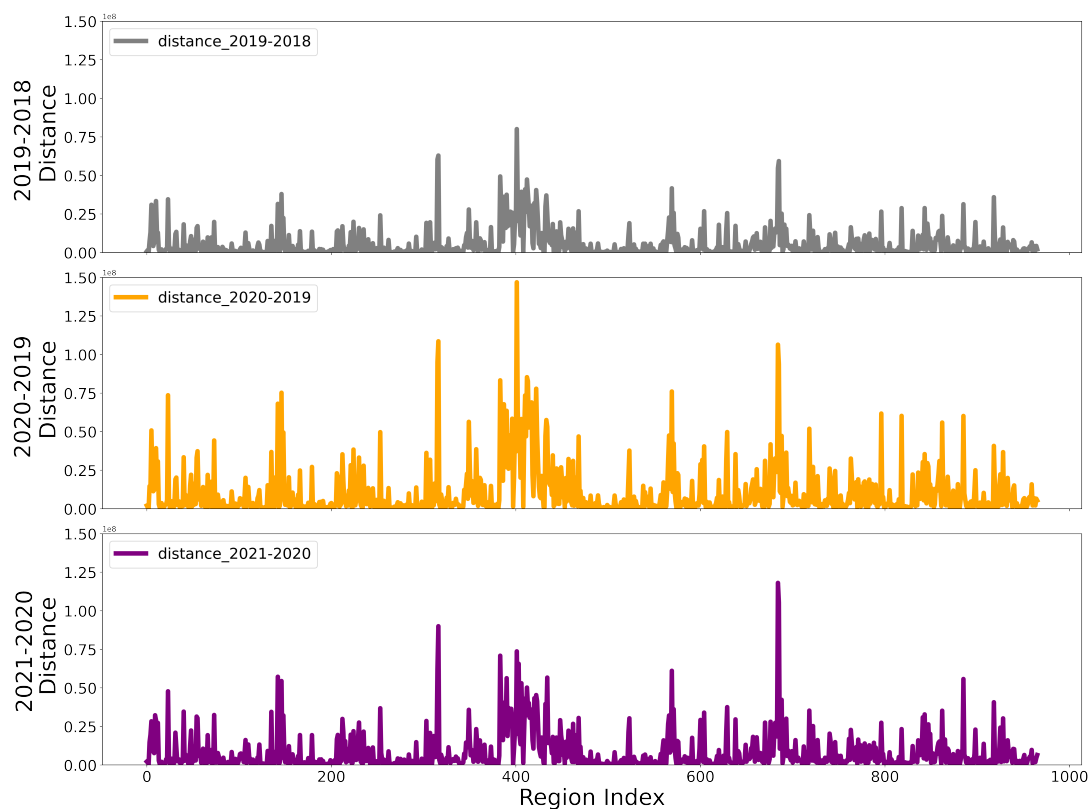


Figure 5.5: Per-region traffic volume time-series differences between successive years (2019–2018, 2020–2019 and 2021–2020) calculated using Euclidean distance.

tuning is key to getting more accurate forecasts – error reduces by half from red to green bar; (2) using a model that does not use customized hyper-parameters for each region comes at the cost of accuracy – blue bar is over 60% worse than the green bar.

Motivated by the above, we take a clustering-driven approach for scalable and reliable forecasts of mobile service demand at regional and national scales. As noted above, we perform forecasting in a bottom-up manner at regions first then add them to obtain a national level forecast. The essential idea behind our approach is to group different regions based on the similarity of their traffic demand time-series into a small number of clusters. For each such cluster, we then pick a time-series forecasting method that is effective for that cluster. These two clustering and forecasting steps are elaborated and evaluated in the following two subsections.

Fig. 5.7 illustrates our approach. Our approach enables a data driven way to inform future investment and operational planning for operators in their Annual Operations Review (AOR). Data here is region level time series of mobile service traffic volume that is continually collected at the operator’s data lake facility. This data undergoes standard pre-processing (handling missing values through imputation, normalization, etc.) before

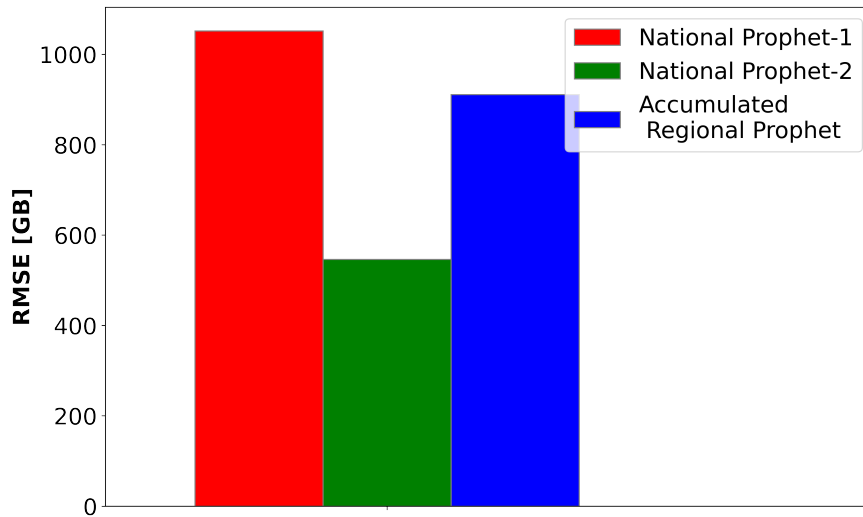


Figure 5.6: Comparison of three alternative national level demand forecasts based on the Prophet [1] method.

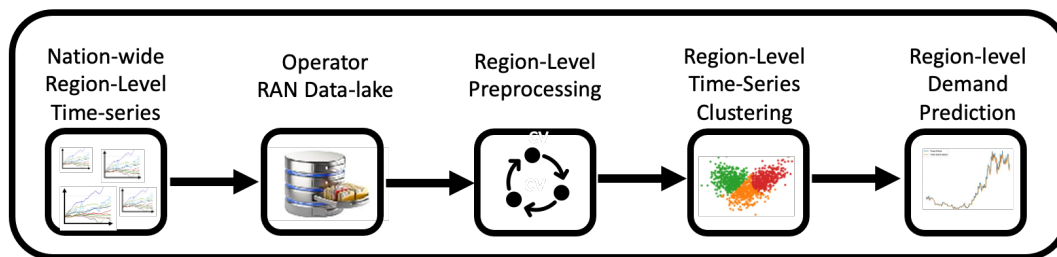


Figure 5.7: Our clustering-driven demand forecasting approach illustrated.

being put through the sequence of region clustering and region-level demand prediction applied separately within each cluster.

5.4.2 Clustering Regions

Methods and Metrics

To group regions into a small number of clusters, we cluster regions based on the similarity between their respective historical demand time series. From the large number of existing time-series clustering methods [142, 143], we consider a diverse and representative set of methods that are listed in Table 5.1. When performing clustering using any of these methods, a key underlying question is to quantify the similarity between a given pair of time series. We use the Euclidean distance between the two time series in question, which is not only the most commonly used measure [143] but also justified in our case given that time series being compared are of equal length.

Table 5.1: Time-Series Clustering Methods Considered

Clustering Method	Category
K-means	partition-based
Hierarchical	hierarchical-based
BIRCH	hierarchical-based
Gaussian Mixture	density-based
DBSCAN	density-based
Spectral	graph-based

Metrics for assessing the quality of clustering can be external or internal [142]. External measures such as Rand Index and Adjusted Mutual Information are only applicable when the class labels (ground-truth clusters) are available. Since that does not hold in our case, we have to rely on internal measures. We consider three commonly used internal measures, as outlined below:

- *Silhouette Score*, ranging between -1 and 1, is calculated based on the difference between inter and intra cluster distances. The score value near zero indicates overlapping clusters and negative values indicate poor clustering quality.
- *Calinski–Harabasz Index* is calculated as the ratio of the sum of inter-cluster dispersion and the sum of intra-cluster dispersion for all clusters (where the dispersion is the sum of squared distances). Higher values indicate better clustering.
- *Davies–Bouldin Index* is calculated based on the mutual separation between clusters. Minimum value for this index is zero and lower values indicate better clustering.

To determine the optimal number of clusters, we rely on the elbow method [144]. Specifically, we empirically examine the relationship between a cluster quality metric (which in our case is one of the three metrics above) and the number of clusters. The ‘elbow’ point of this curve indicates the optimal number of clusters.

Evaluation

Here we evaluate different clustering methods listed in Table 5.1 with respect to above outlined quality metrics using our per-region mobile service demand time series data. We consider two cases for clustering: (i) univariate time series data for each region where only the historical demand data is used; (ii) multivariate time series data, which additionally uses the 6 contextual attribute values for each region (§5.2). Fig. 5.8 and

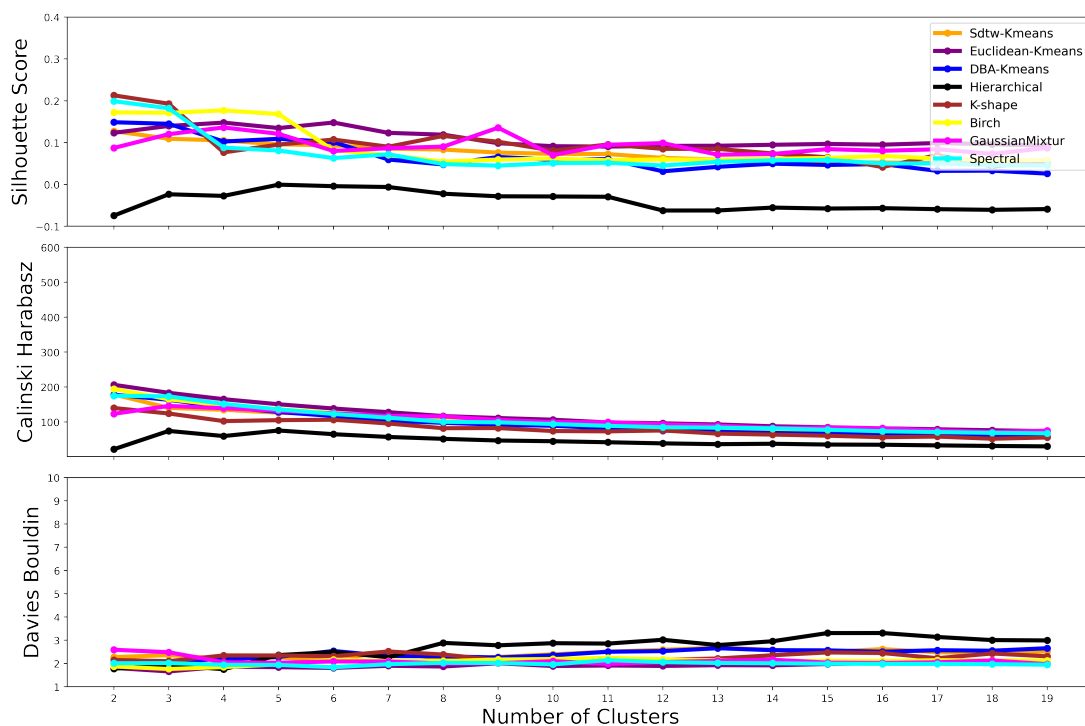


Figure 5.8: Univariate time series region clustering results.

Fig. 5.9, respectively, show the clustering results for these two cases with demand time series data for 2018 and 2019 (104 weeks). Compared to the univariate clustering, we observe that Silhouette and Calinski–Harabasz scores (where higher is better) are approximately doubled with multivariate clustering while there is no significant change in Davies–Bouldin scores (where lower is better).

Across all three cluster quality metrics, multivariate clustering with Euclidean K-means is seen to be the best method with $K = 7$ optimal number of clusters as per the elbow method. When we further visually inspected analyzed each of these 7 clusters, we found that Cluster-6 only has a few regions whereas Cluster-7 contained just one region. So we treated the region in Cluster-7 as an outlier and merged it to Cluster-6. As a result, we end up with six clusters for this data. Moreover, to understand if data from the Covid period affects clustering, we compared clustering results with data from two periods: 2018+2019 and 2019+2020. We found that the optimal number of clusters and the cluster membership did not change between these two periods, indicating that there is no Covid effect on clustering.

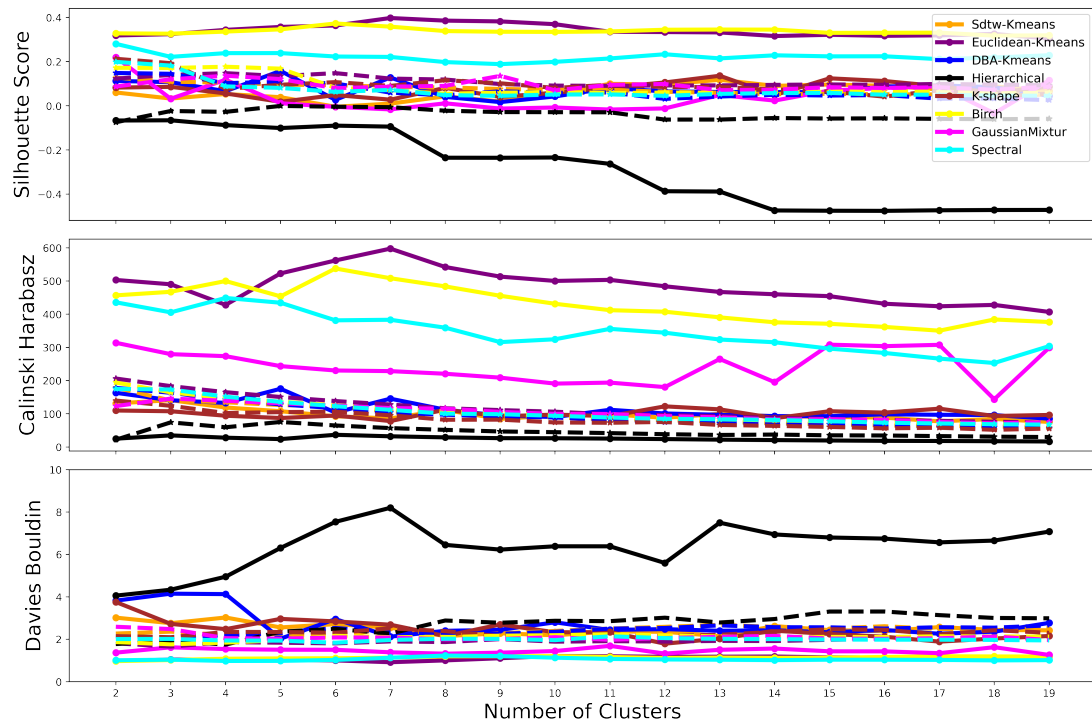


Figure 5.9: Multivariate time series region clustering results.

5.4.3 Intra-Cluster Time-Series Demand Forecasting

Here we consider the step of mobile service demand forecasting for regions falling within a cluster. This is a time-series forecasting problem.

Methods

There exist a large variety of time-series forecasting methods [145, 146], which broadly fall into three categories: statistical, shallow machine learning (ML) and neural network (NN) models. As in the clustering case, we consider a diverse and representative set of forecasting methods as outlined below and listed in Table 5.2.

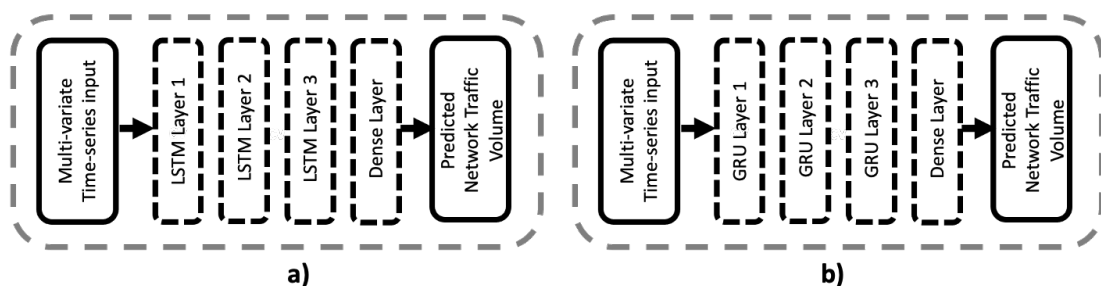


Figure 5.10: a) LSTM and b) GRU based demand forecasting models.

Table 5.2: Time-Series Forecasting Methods Considered

Forecasting Method	Category
ARIMA	Statistical
SARIMA	Statistical
Prophet	Statistical
GPR	ML
Isotonic	ML
RBFnet	NN
GRU	NN
LSTM	NN

- Statistical Models: *ARIMA* is a traditional univariate statistical time-series forecasting model that has originated from Autoregressive (AR), Moving Average (MA) and ARMA models and tailored to deal with non-stationary data. *Seasonal ARIMA (SARIMA)* is ARIMA extended with a seasonality parameter. *Prophet* [1] is a newer and popular univariate statistical time-series forecasting model. It works well on outliers, instantly changing time-series data, is able to fit seasonal data with holiday effects.
- ML Models: *Gaussian Process Regression (GPR)* is a Bayesian ML time-series forecasting method that uses Gaussian Process (GP) priors to provide a posterior outcome and is fully specified by its mean function and covariance function [145]. *Isotonic Regression* fits a non-decreasing real function to 1-dimensional data with the nice property it is not constrained by any functional form so long as the function is monotonically increasing.
- NN Models offer robustness and capability to deal with non-linear time-series data. Most popular NN models for forecasting are *Radial Basis Function Neural Networks (RBFNet)* and Recurrent Neural Network (RNN) based models, including *Long and Short Term Memory (LSTM)* and *Gated Recurrent Unit (GRU)* models. RBFnet has a feed-forward structure consisting of a single hidden layer for a given number of locally tuned units which are fully interconnected to an output layer of linear units. LSTM is a state-of-the-art NN based time-series forecasting model. Fig. 5.10a) shows the structure of our LSTM model, which consists of three LSTM layers (the input layer, two hidden LSTM layers) and one fully connected output layer. The LSTM cells in the input layer are equal to the number of features in each input sample. The following three hidden

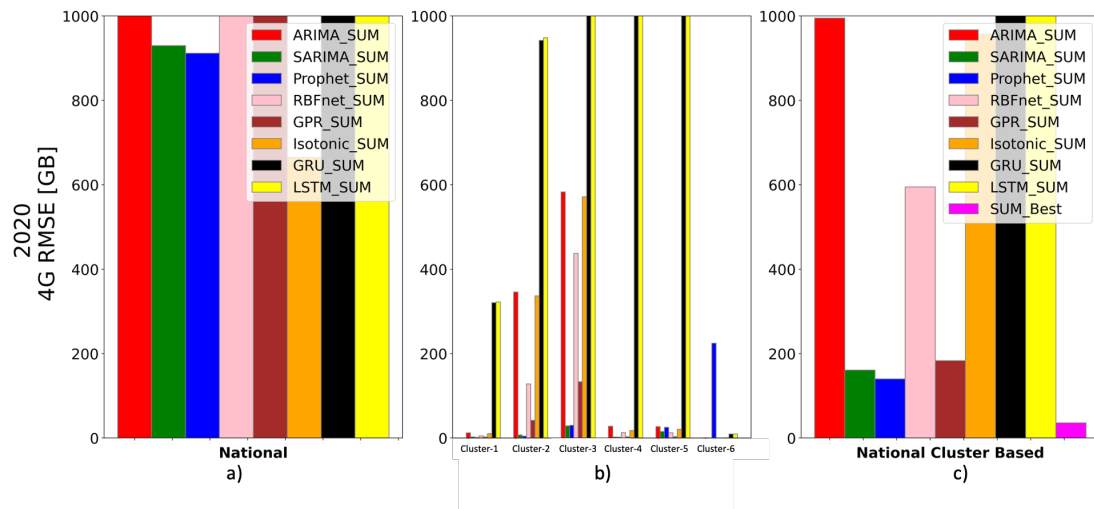


Figure 5.11: Results comparing our clustering driven approach c) with baseline approach a) when forecasting national level mobile service demand for 2020.

layers have 32, 16, and 8 LSTM cells respectively. The output layer is a fully connected dense layer with a single neuron that outputs the demand predictions. RELU is used as an activation function, and the batch size is 64. The GRU model we use is shown in Fig. 5.10b); it is identical to our LSTM model except that LSTM cells are replaced with GRU cells.

Evaluation

Here we evaluate the forecasting step of our clustering driven methodology, building on the clustering results from §5.4.2. As stated earlier, we use RMSE as the forecasting accuracy metric. Instead of looking at the accuracy of forecasting demand for each individual region, we focus on the accuracy of forecasting cumulative demand at the national level for a year (at a weekly granularity), which is dependant on such region level forecasts. We compare our clustering driven approach with the baseline approach of forecasting region level demand using any of the methods from Table 5.2 and adding up those forecasts.

First, we consider the case using the data from 2018 and 2019 for training and forecasting demand for 2020. Fig. 5.11a) shows the results with the baseline approach, including with Prophet as in the earlier Fig. 5.6. We observe that Isotonic Regression based forecasting performs the best among the different methods. Prophet and SARIMA yield accuracies in the middle, whereas NN based models particularly GRU and LSTM perform poorly. This can be attributed to the fact that we are forecasting in a low data

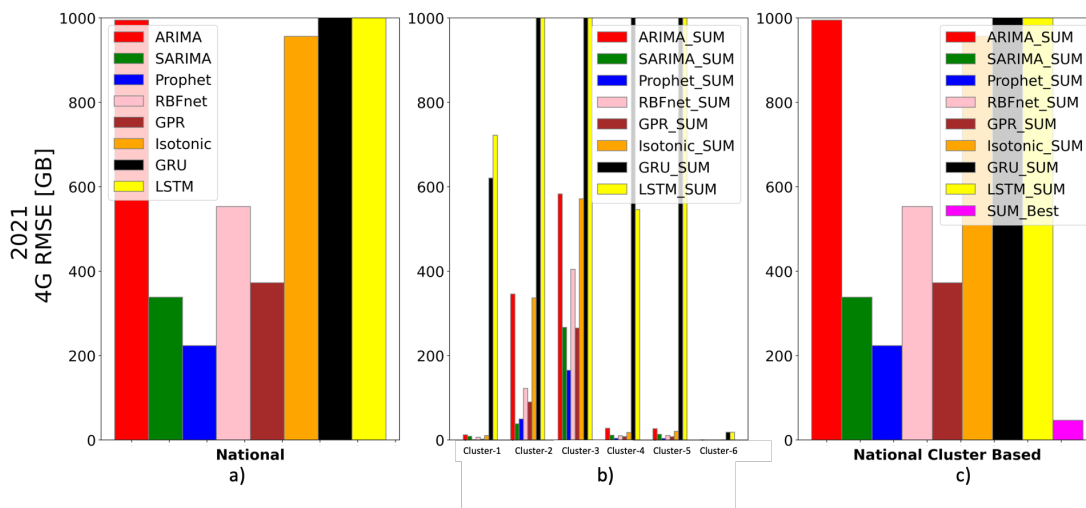


Figure 5.12: Results comparing our clustering driven approach c) with baseline approach a) when forecasting national level mobile service demand for 2021.

regime with just 104 samples used for training; prior work (e.g., [147]) also observed that NN models can perform worse in such scenarios. In general though, these baseline results allow us to assess the benefit with our clustering based approach, as discussed next.

Fig. 5.11b) shows results with our approach for forecasting accuracy with different methods within each cluster. Note that the hyper-parameters for each forecasting method in a cluster are determined by applying grid search on the cluster’s centroid (the most representative point within the group). We observe that Prophet is the best performing model in *Cluster – 1*, *Cluster – 2* and *Cluster – 4*, while SARIMA, GPR and RBFnet respectively perform best in *Cluster – 3*, *Cluster – 5* and *Cluster – 6*. These results highlight an important advantage with our approach allowing us to pick a different forecasting method for different clusters (subsets of regions).

Fig. 5.11c) shows the results with our approach when one of the eight forecasting methods in Table 5.2 is used for regions within each cluster and results accumulated to obtain national level demand forecast. We observe that if limited to using the same forecasting method across all clusters, then Prophet, SARIMA and GPR provide the most accurate forecasts, still significantly better than the baseline results in Fig. 5.11a). However, when best forecasting method is chosen within each cluster, accuracy of national level forecasts shows a further dramatic improvement (represented by ‘SUM_best’ in Fig. 5.11c)). Compared to the best case baseline result with Isotonic model, best case with our approach yields a nearly 20x reduction in RMSE.

We have carried out a similar analysis forecasting demand for 2021 while using the data from the preceding three years for model training. This case is different from the above case in that there is training data for one more year but that is a Covid affected year. Results in Fig. 5.12 again show an order of magnitude gain in forecasting accuracy with our clustering driven approach relative to the best baseline result. These results overall show that our two step clustering driven approach helps tailor the forecasting models to the regional characteristics to optimize forecasting accuracy while being scalable.

5.5 Mobile versus Fixed Wireless Access

So far, we focused on demand characterization and forecasting for the traditional mobile service. But increasingly fixed wireless access (FWA) is emerging as a significant alternative service for mobile network operators with more and more operators providing this service [5, 4]. According to the most recent Ericsson Mobility Report [4], FWA data traffic already accounts for 20 percent of the global mobile network traffic and is expected to grow five times by 2027. Similarly, there are currently 100 million FWA connections globally and they are expected to double in the next five years.

In light of the above, in this section we analyze the characteristics of FWA traffic and assess if our clustering driven methodology is still effective to provide high accuracy demand forecasts. To this end, we use FWA service demand data from the same operator whose mobile service traffic we studied earlier in the paper. However, in sharp contrast to the mobile service, this FWA service is relatively new and so the data only spans two years – 2020 and 2021.

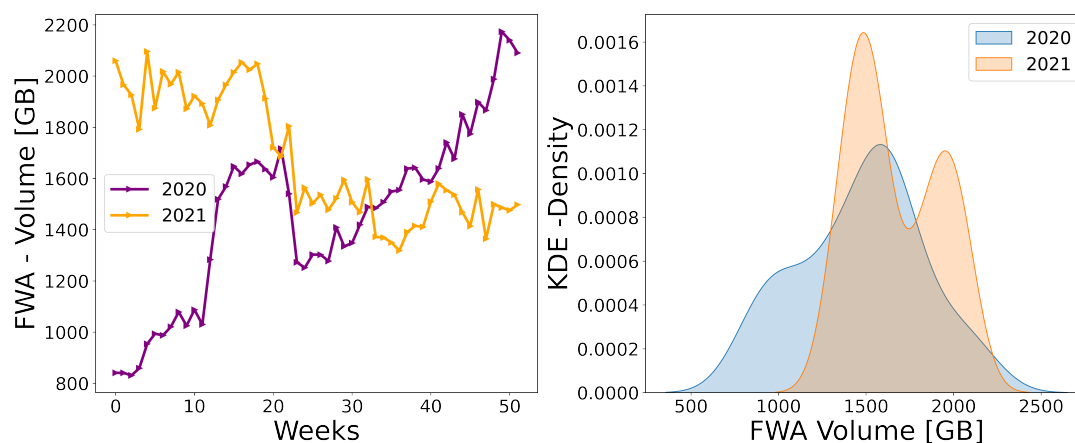


Figure 5.13: Nationwide FWA service demand over time (weeks) across different years (left) and corresponding probability densities (right).

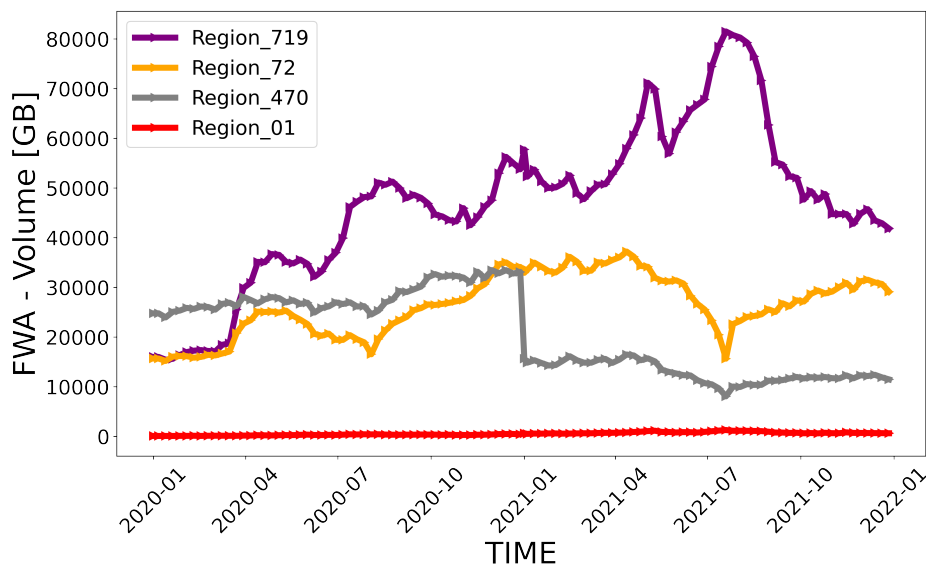


Figure 5.14: FWA service demand over a two year period for selected regions.

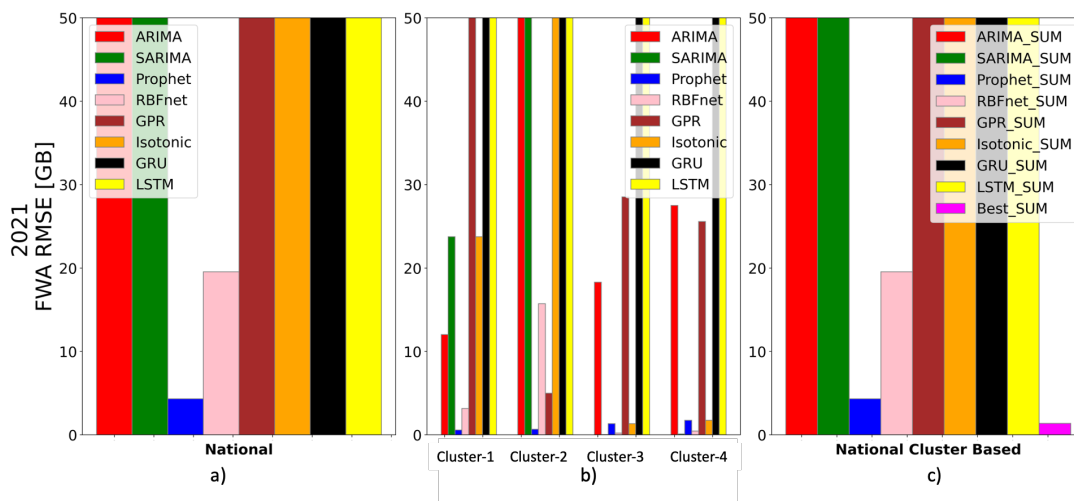


Figure 5.15: Results comparing our clustering driven approach c) with baseline approach a) when forecasting national level FWA service demand for 2021.

Fig. 5.13 shows the national level FWA demand characteristics across a two year period of 2020 and 2021. We observe that FWA service demand pattern is somewhat similar to the mobile service in its first year of the service introduction, showing an upward trend and also differently exhibits a significant surge during the first wave of COVID-19 pandemic as observed for ISP network traffic in prior studies [137]. However, national FWA service traffic showed a downward trend in 2021 due to pricing related customer churn (according to the operator). These national level FWA demand characteristics overall are markedly different from that of the mobile service seen previously

(compare Fig. 5.13 with Fig. 5.1). Region level characteristics, however, are broadly similar to what we saw previously for the mobile service in that there is a significant diversity among different regions (compare Fig. 5.14 with Fig. 5.2).

We have applied our clustering driven methodology from §5.4 for the case of FWA service demand forecasting, using data from 2020 for clustering and forecasting model training and forecasting regional and national FWA service demand for 2021. Differently from the mobile service case, we observe fewer clusters (4) with FWA (see Fig. 5.15b)). In terms of forecasting accuracy, however, the best case with our clustering based approach still yields half the RMSE error compared to the baseline (compare Fig. 5.15c) with Fig. 5.15c)). These results are remarkable considering that FWA is a service in its early years of adoption and so has limited historical data. They demonstrate the versatility of our clustering based forecasting methodology for use across different mobile network services.

5.6 Summary

In this chapter, we have conducted a unique mobile network demand characterization and forecasting study with the aim of enabling cost-effective network planning for the operator. We also provided several novel insights based on a multi-year and nationwide region-level mobile network traffic data. Last but not least, we introduced a clustering-driven mobile network demand forecasting methodology which yields significant improvements.

Chapter 6

CellDA: Data-Driven Autonomous Hotspot Cell Detection Framework For Operational Mobile Networks

Mobile network traffic demand evolves in unpredictable ways over time, and this unpredictability leads to issues with cell-level over-provisioning and under-provisioning of resources. Under-provisioning is known as a hotspot [92], and this has significant adverse effects on the quality of service (QoS) and quality of experience (QoE), which risks customer churn [148, 149]. This deterioration in service quality not only impacts existing 3G and 4G networks but also future 5G networks and beyond that are designed to accommodate a wide variety of uses, including ultra-reliable and low-latency communications services – for example, connected vehicles and remote surgery. Mobile operators must dynamically detect hotspot cells in order to avoid them and accordingly expand network capacity to minimize customer dissatisfaction. *In this chapter, for the first time, we consider hotspot cells as a network performance problem of operational mobile networks, rather than as an annual network planning issue, and in particular focus on the problem of automatically detecting hotspot cells.*

6.1 Problem Statement

The effective planning and management of network capital expenditure (CAPEX) is an enormous challenge for mobile operators. In general, the resource allocation problem is currently addressed annually via optimization theory in mobile networks, which is one of the key considerations for mobile operators and helps to effectively plan CAPEX in

terms of distributing the resources, investing, expanding, and running cellular wireless networks in response to evolving or predicted demands [90].

Often mobile networks are entirely operated statically on a given set of parameters for the entirety of their operations[150]. However, we believe resource allocation should be seen as a performance problem that must be tackled dynamically by mobile operators. We believe that the hotspot cells must be automatically identified and resolved in a timely manner, ideally prior to becoming noticeable to mobile subscribers

To ensure the mobile service KPIs, the wireless systems are envisioned to be operated proactively by predicting dynamic changes, demand, and required resources [151]. In existing practice, however, mobile operators cannot ascertain when and which cells turn into hotspots causing degradation in QoS and QoE. Most hotspot cell issues are conducted reactively on an event basis and require the analysis of historical data. When there is a significant deterioration in service quality, which is mostly prompted by the mobile subscribers reporting, radio network engineers manually examine copious volumes of multidimensional network KPI data to diagnose the problem, which may take days or weeks, and is extremely labour-intensive and so costly in terms of operating expenditure (OPEX).

The limitations of the present approach to assessing network resource allocation on an annual basis are as follows[96]:

- First it is not known whether the existing resources sufficiently meet user expectations within each cell in the short term.
- Second, the current annual resource planning methodology is a coarse grained and consequently lacks flexibility with respect to adapting to unforeseen circumstances, as it relies on historical data and statistics to project the needs of both customers and the network.

Dealing with them automatically at the cell level requires being proactive, and transitioning from coarse-grained to fine-grained prediction. Proactive network planning is an important element of performance evaluation and optimization in which detected hotspots are used as critical input. A promising way to achieve this is through the implementation of novel data-driven state-of-the-art machine learning (ML) techniques that can accommodate high dimensionality and rapidly provide satisfactory solutions [90]. The appropriate solution should be capable of dealing with unpredictability (i.e. the rapid growth in the number of users and data demand, high mobility, and load variation) and optimizing the annual network planning more frequently and dynamically [152].

The early detection of hotspot cells is arguably one of the most critical steps which can be used as input to dynamic mobile wireless capacity expansions and effective network resource planning that can not only lead to savings in OPEX but also ensure user QoE. This suggests that hotspot cell detection is yet another ideal use case of automation in mobile networks.

In view of the above, we aim at automated hotspot cell detection for operational mobile networks that can automatically and timely detect hotspot cells, then trigger alarms to kick-start downstream resolution and resource planning processes. While this clearly involves reliable detection of all kinds of hotspot cells, we also aim to detect the operation of other unknown performance degradation sources (e.g., malfunctioning mobile networking hardware) that can cause an impact on the network. The advantages of such an automated hotspot cell detection capability are:

- Hotspot cells can be detected in a timely manner and indicate demand for additional resources. This enables operators to effectively steer CAPEX spend and proactively troubleshoot their network to minimize customer churn resulting from diminished QoS and QoE.
- Detected cell under-provisioning could be used as input dynamic network operations and management – e.g. frequent radio resource adjustments and dynamic load balancing.
- Additional data is generated to improve demand forecasts, allowing operators to optimize annual CAPEX spending.

To this end, we present CellIDA, which to the best of our knowledge is the first automated hotspot cell detection framework for operational mobile networks. By treating hotspots as ‘abnormal’ or ‘anomalous’ from the mobile radio access network (RAN) infrastructure side, CellIDA approaches hotspot detection as an anomaly detection (AD) problem. CellIDA is envisioned for operator-side deployment and considers cells at each tower site as measurement vantage points. It continually monitors the time series of various cell-level KPIs to detect anomalous behavior over time.

At the core of CellIDA are three deep learning-based time series anomaly detection methods that we developed, which all work with multivariate KPI data at each cell [99]. In the first method, a multivariate KPI time series using an LSTM autoencoder model trained in a semi-supervised manner with normal cells’ data and the associated reconstruction error over time is compared against a threshold to detect a hotspot cell.

The other two methods, respectively, are multi-variate long short-term memory (LSTM) neural network and hybrid stacked convolutional neural network (CNN) and LSTM models. Both those models are trained with supervised learning approaches to track the variation observed in the cell KPIs to predict whether they stay normal or turn to ‘abnormal’ or ‘anomalous’ (i.e., hotspot).

For the evaluation, we use a large-scale real mobile network data with daily time resolutions over a period of one year, comprising 4000 cells collected across 4 cities with different characteristics by a market-leading mobile operator with more than 40 million subscribers. Using this dataset, we provide evidence on the feasibility of automated and proactive hotspot cell detection. We also extensively and visually elaborates on hotspot cell KPIs to improve and addresses hotspot predictability in mobile networks. To the best of our knowledge, this is the first study that approaches hotspot cell detection as a performance issue and proposes an autonomous hotspot cell detection framework.

The key contributions are listed in (§1.1). Nevertheless, for the convenience of the reader, the key contributions of this study are listed below.

- We illustrate the relationship between physical resource block (PRB) utilization and 4G downlink traffic volume via a heat map, and demonstrate the trade-off between over-provisioning and under-provisioning of the cells.
- We develop a set of deep neural network models for hotspot cell detection and compare their performance.
- For the best performing model, we also assess the time horizon over which a hotspot cell can be detected.

In the next section, we provide a literature survey and describe our dataset and evaluation metrics.

6.2 Dataset

Our study is particularly unique in its use of a real-world mobile network dataset of cellular-level KPIs obtained from a national mobile operator with around 40 million customers. As a result, this dataset was especially suited for hotspot detecting at the cell level. The data was gathered from four different counties across cities with different characteristics and included 4,000 cells, each comprising 365 samples of radio network KPIs measured at a daily time resolution over the course of 2021. The samples were

labeled in binary format, where 1 and 0 indicated the presence or absence of a hotspot respectively. Nowadays, 5G deployment is quite limited, and the bulk of network traffic is transported over 4G; therefore, we focused exclusively on 4G cells in our study. Each of our daily samples bore detailed information on time, date, site, cell, county and city in addition to cell KPI measurements such as uplink and downlink traffic volumes (MB), 4G volume (total uplink and downlink traffic volumes) (MB), average uplink and downlink user throughputs at the packet data convergence protocol (PDCP) layer (Mbps), uplink PRB utilisation, 90th-percentile downlink PRB utilisation, average and maximum number of radio resource control (RRC) connected users, as well as average PDDCH control channel elements utilisation.

6.3 CellDA Framework

In this section, we describe our proposed CellDA framework (illustrated in Fig. 6.1) designed to address the above challenges. We envision CellDA for operator-side deployment, considering cells at each tower site as measurement vantage points to aid in the detection of online hotspot cells. This approach relies on continual monitoring of the time series of various KPIs at each of these cell locations and collecting data at the operator’s radio access network data lake facility. This data is then preprocessed to address dramatic real-world data problems, such as missing values, by imputing neighbouring values through the pipelines prior to using it as input for the CellDA hotspot detection models.

CellDA approaches cell-level hotspot detection in an operational mobile network as a time-series anomaly issue [110, 111, 153], assuming that hotspots manifest as ‘anomalous’. Therefore, CellDA features multiple deep learning based time-series anomaly detection models, as described below, including a LSTM Autoencoder model trained in a *semi-supervised* manner [110], and two models trained in a *supervised* manner – one LSTM based and the other with stacked CNN-LSTM model.

6.3.1 Deep Learning Models for Cell-Level Hot Spot Anomaly Detection

Here we describe the anomaly detection based models that we trained and tested as part of CellDA framework for daily hotspot cell detection. These models take multivariate time series data for radio network KPIs as input but aim to detect anomalous samples in

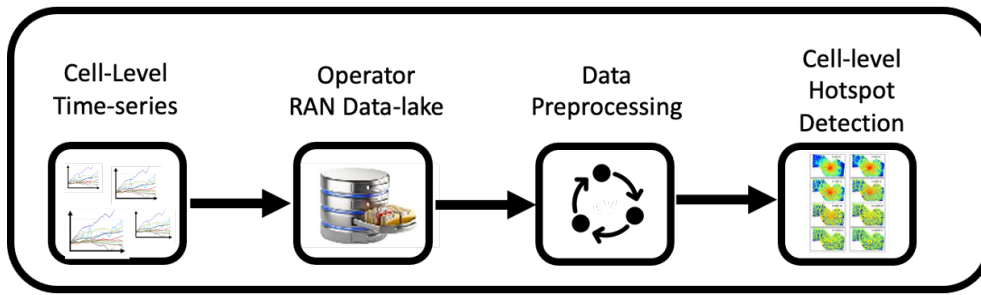


Figure 6.1: Illustration of the CellIDA Framework.

the time series through different approaches, as elaborated below.

Deep Learning Models

In this study, we investigated a diverse and representative set of deep neural network (DNN) models as outlined below. The models take multivariate time series data i.e. radio network KPIs as input but aim to detect anomalous samples through varying approaches, as elaborated below. Since we were dealing with time series data, we used LSTM cells in the architecture of both models – also, combining CNN and LSTM is an oft-used approach.

There exist a large variety of anomaly detection models [153], which broadly fall into three categories: statistical, shallow machine learning (ML) and neural network (NN) models. According to the literature, the statistical approaches are found to perform poorly with mobile network time series data [90, 72, 88]. Hence they are excluded in this study. Furthermore, we have a sufficient amount of data and computation power which have led us to consider a diverse and representative set of deep neural network models as outlined below.

Multi Layer Perceptron (MLP) A basic deep learning model, where all layers in the network are fully connected. Fig. 6.2a) shows our MLP model structure – a specific version for binary classification, which consists of 10 layers i.e. the input layer, four pairs of hidden dense(fully connected) and dropout layers, and finally one binary output layer. Each of these dense layers consisted of 64, 32, 16 and 2 neurons respectively, and as a regularization, the dropout layers drop 20% of the randomly selected neurons are ignored. As a rule, where data is sequential, such as with time series, MLP models perform poorly compared to sequential deep learning models. In our study, we took advantage of the MLP model in order to obtain the baseline results. We implemented binary cross entropy to compute

the cross-entropy loss between true labels and predicted labels and achieved optimization with the rectified linear activation function (ReLU) using a batch size of 64.

Long and Short Term Memory (LSTM) A state-of-the-art RNN for sequential data – i.e. to based time-series forecasting model as proposed by[95, 98, 99]. LSTM enables long-term storage of states and comprises cells with input, output and forget gates. LSTM is often used to detect unusual sequential patterns in data as anomalies. Fig. 6.2b) shows the structure of the LSTM model, which consisted of three LSTM layers (the input layer and two hidden layers) and one fully connected output layer. The LSTM cells in the input layer were equal to the number of features in each input sample. This consisted of three LSTM layers with 32, 16, and 8 neurons respectively, and one dense, fully connected output layer with a single neuron for binary outputs. As with the MLP model, with Adam optimization, binary cross entropy and ReLU are used in all the LSTM layers while softmax activation was used for binary classification in the fully connected layer.

LSTM Auto-Encoder(AE) Fig. 6.2c) illustrates the proposed LSTM autoencoder-based model that takes multivariate time-series data as input. This model relies on the (in)ability to faithfully decode the input sample[99]. When provided with a sufficient amount of data in the form of normal samples, it learns how to reconstruct it through training – that is, it learns how to encode and decode each normal input sample. The reconstruction error as a result of the model’s learning through training will be much higher for abnormal samples than for normal samples; thus, with an empirically optimised threshold, the model will label these samples as anomalies. Root mean square error was used to calculate the reconstruction loss. As with the MLP model, Adam optimization and ReLU were used in all LSTM layers while softmax was used for binary classification in the final fully connected layer.

Hybrid (CNN and LSTM) This model has hybrid architecture as depicted in Fig. 6.2d) and is composed of two main stages. In the first, the convolution CNN Conv1D layer is used to extract the spatial features from the multidimensional inputs with a size 5 kernel. The convolution layer is followed by three LSTM layers with 32,16 and 2 cells respectively, combined with ReLU. Finally, the fully connected layer with its softmax activation function is used for the binary outputs at the output

layer. As with the other models, Adam optimization and binary cross entropy were used,

In addition, all these models were trained for 20 epochs per cell in the training dataset. We empirically optimized the hyper-parameters with a grid search [110].

6.4 Evaluation

6.4.1 Data Analysis

Fig. 6.3 depicts the correlations of cell-level KPIs that were used in this study. We observe that downlink user throughput is negatively correlated with all other KPIs, which demonstrated higher positive correlations – i.e. above 78%.

Fig. 6.4 details the four counties and their associated characteristics, while the plot to the left shows the variations in total 4G mobile service traffic volumes for each county during 2021. It is apparent from this plot that there is a different trend within each county. The volume of *county719* peaks during the summer prove that season is a dominant factor, presumably due to a higher population during this period. Different trends are apparent in *county505* and *county228* where the traffic is lower and remains steady throughout the year – except in *county505* where there is a minor reverse during seasonal months with a relatively small dip. Furthermore, these counties show variations in any given week in terms of total traffic volume peaks on weekdays relative to weekends. This indicates that the data for these counties were concentrated in city centres and rural areas respectively. Finally, the patterns in the data for *county2* are vastly different from those above, it is predominantly rural with relatively low traffic volume and no discernible increase owing to demand or seasonality.

Fig. 6.5 shows the daily variations in 10 selected cells across the four counties. From top to bottom, these heatmaps visualize three important cellular-level KPIs: 4G mobile service traffic volume, UL PRB utilization, and hotspot cell labels. Moreover, for each heat map, the y-axis depicts the cell index, and the x-axis the days of the year. In general, in all cells, we observe the colors change from dark to light on a daily basis. For example, in the top heatmap, the light beige represents high volume, while in contrast, the dark red of the middle map represents poor UL PRB utilization, and this in turn corresponds to the black in the bottom heatmap, which represents congested hotspot cells. The color variations for each cell over the course of the year additionally prove the shifts between cell over-provisioning and under-provisioning over time, on both a daily and monthly

basis. Some cells have become hotspots during the week or weekend while for others, this occurs seasonally, during the winter or summer.

6.4.2 Hotspot Detection Results

Our CellDA framework offers five different AD models: MLP, AE, CNN, LSTM and hybrid (CNN and LSTM) binary classification. We trained these models using the subset of the dataset independent of the subset used for testing.

We first compared each deep AD model's ability to detect hotspot cells in the test data (see Fig. 6.6). The results demonstrate the next-day predictions, which indicate that the MLP model was marginally worse than sequence-to-sequence LSTM models – i.e. LSTM and AE (proposed by [95, 99] respectively), where yields were greater than 0.75 across all metrics. In some cells, we additionally observed that the MLP performed relatively poorly along three measures since it is not appropriate for time-series predictions. Furthermore, as we can observe from the figure, the LSTM layers are able to know what information is to be 'remembered' or 'forgotten' from the previous cell state, using its forget gate. Hence, the semi-supervised deep LSTM-based AE and supervised LSTM binary classification AD models are slightly better than the MLP model. Finally, The hybrid AD (stacked CNN and LSTM-based) model has the best performance results and yields greater than 0.85 across all metrics. The Conv1D layer has learned the spatiotemporal features, and evidently, stacking the Conv1D layer with the LSTM layers also improved the decision of what special feature to be extracted and stored in the present cell state. Since the hybrid AD model performed better than the other models, therefore, we are going to consider this hybrid AD model for further evaluation.

Fig. 6.7 shows the limitations of the prediction, where in the y-axis, it is evident there are different versions of the hybrid model, which was trained to predict 2, 3, 5 and 10 days ahead. Specifically, we empirically examined the pattern that when the number of prediction steps increases to 5 days, the performance of the hybrid model gradually deteriorates. But we found no significant difference between 5 or 10 day ahead predictions.

6.5 Summary

In this chapter, we have addressed the hotspot cell detection problem which we have considered hotspots as a performance optimization problem, and presented CellDA, the first online framework for cell-level hotspot detection in operational mobile networks. Based on a real 4G dataset the results of our study demonstrate the effectiveness of our CellDA framework. Finally, we compared the performance results of the predictions made by the deep NN models with respect to four different time steps.

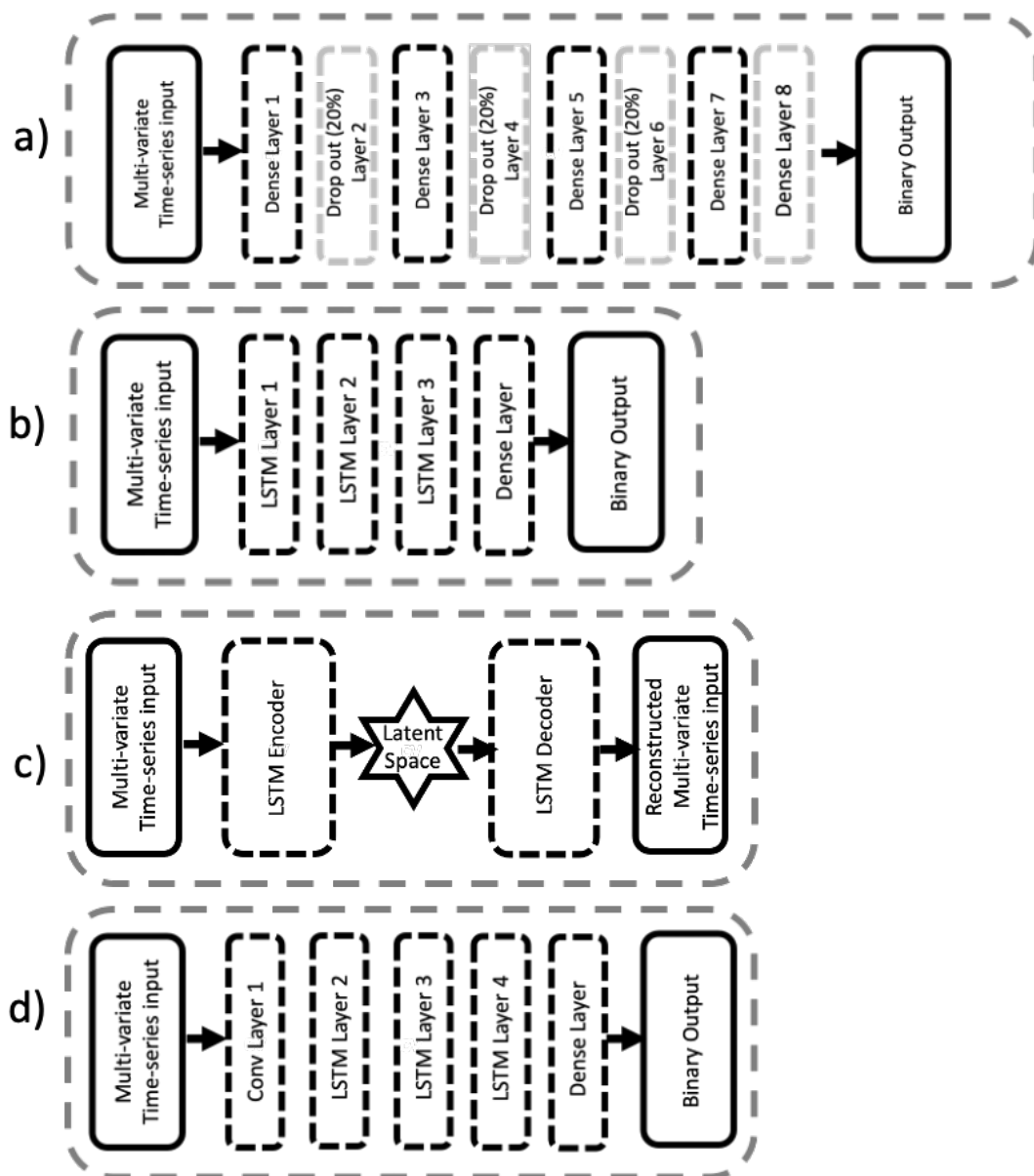


Figure 6.2: DNN models i.e. MLP, LSTM and Hybrid (CNN and LSTM combined) architectures.

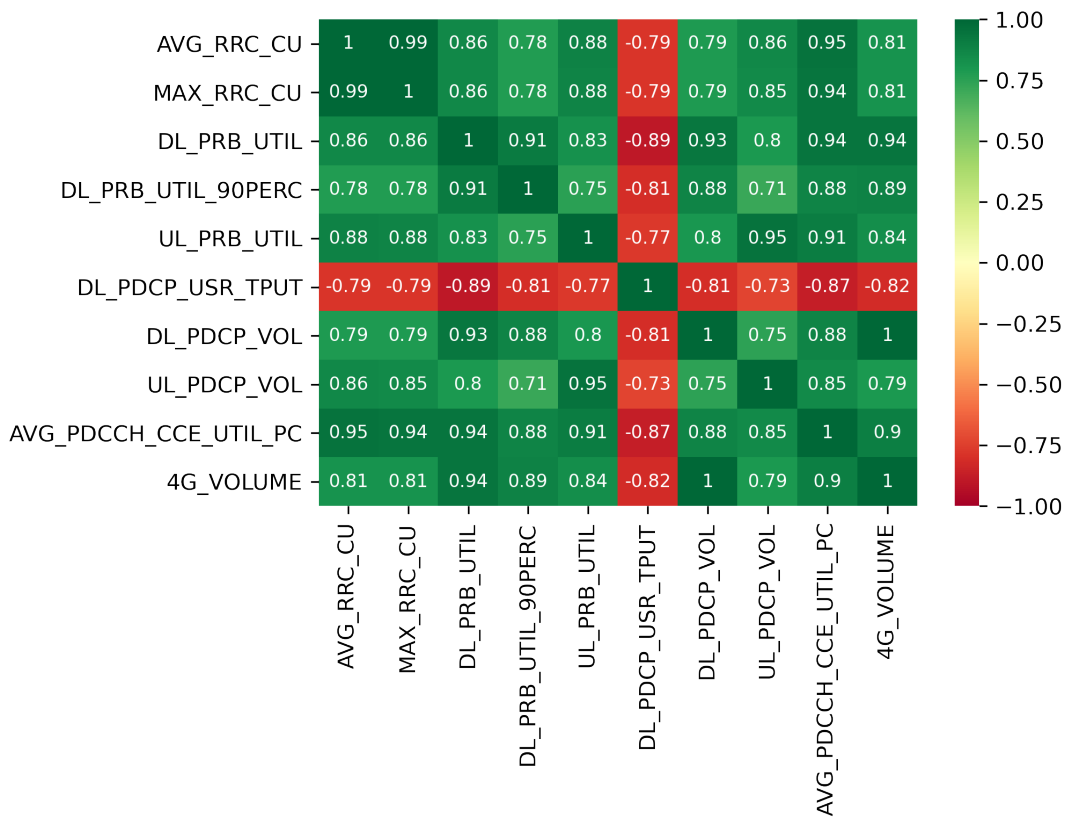


Figure 6.3: Correlation Cell KPIs.

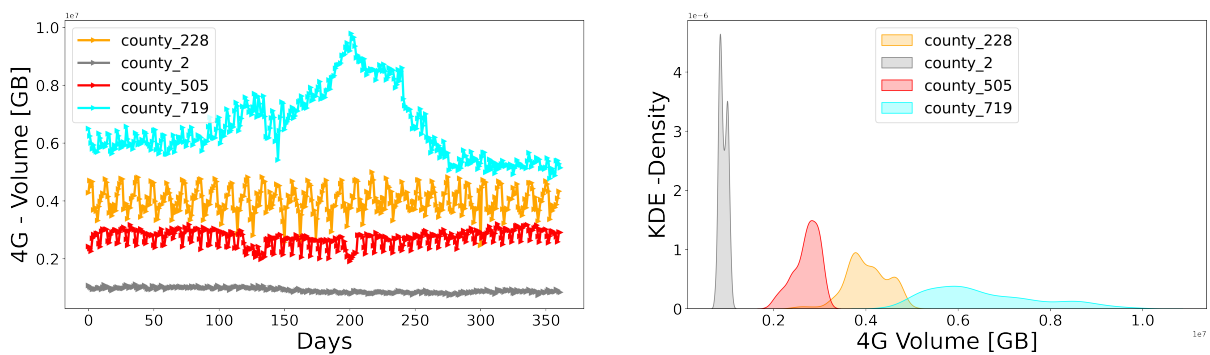


Figure 6.4: 4G Mobile Traffic Volume and Time (days) over 2021 in 4 selected areas (left) and corresponding probability densities (right)

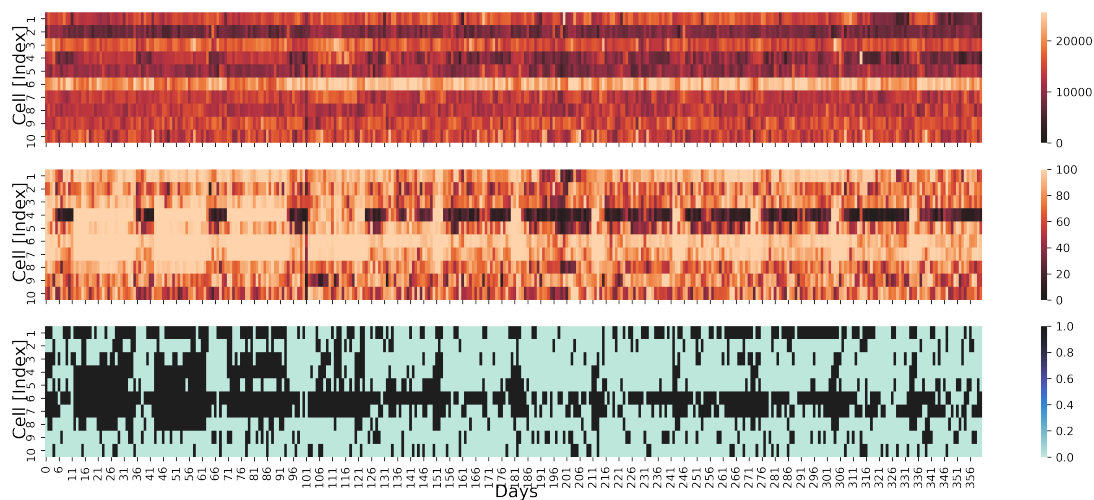


Figure 6.5: Cell KPIs vs Daily Labels.

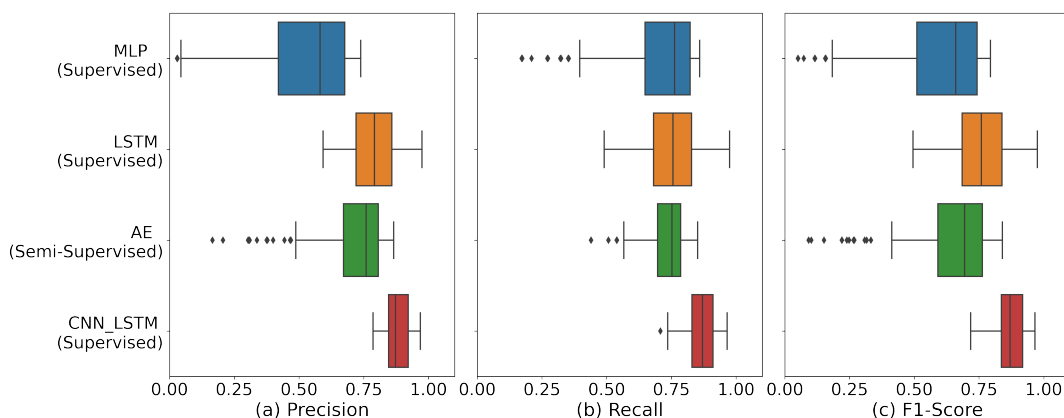


Figure 6.6: The performance of AD models on the testing dataset.

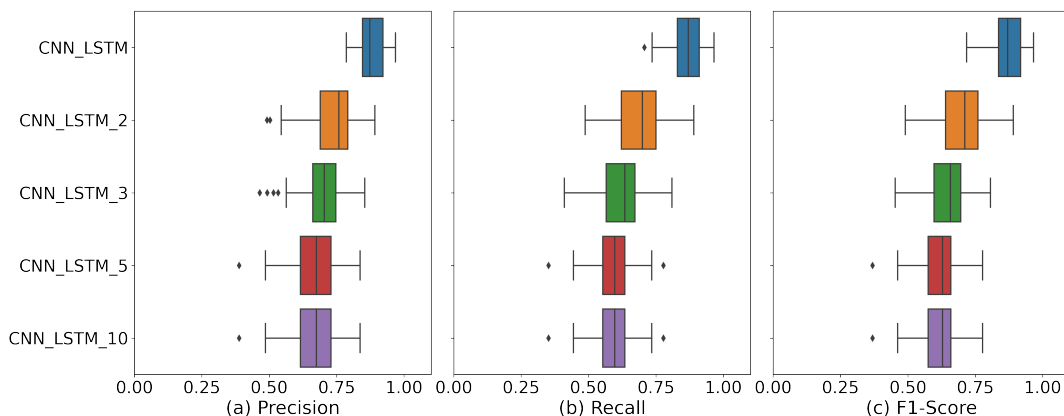


Figure 6.7: Combined CNN and LSTM performance comparison.

Chapter 7

Conclusions and Future Work

7.1 Summary of Contributions

Traditional operations, from network planning to error investigations, are primarily handled manually in operational mobile networks. This leads to inefficiency in CAPEX and OPEX management and causes QoS and QoE degradations, resulting in customer churn. Due to advancements in data storage and computation systems, data has become ‘the new oil’. Machine learning represents a new dimension in the telecommunications industry by optimizing operations and improving the underlying system performance.

In the long term, the problems explored and data-driven solutions provided in this thesis can be viewed as significant contributions to the next generation of data and machine-learning-driven mobile networks. The 6th generation (and beyond) will strongly depend on networking paradigms with automated network anomaly detection and decision-making for optimization and control across network communication layers and the infrastructure components.

This thesis focuses on the network automation concept and four different use cases that can hinder operational mobile networks. We propose data and machine-learning-driven solutions that can overcome obstacles and enable efficient operations. Although each of these solutions focuses on different use cases, they are complementary in terms of providing a holistic view and a better understanding of data and machine-learning-driven paradigms in operational mobile networks. The high-level conclusions for each of these use cases and their solutions are presented in the following subsections.

7.1.1 5G automation concept and data-driven network automation use cases

The 5G automation system will be powered by cutting-edge ML techniques. So, this chapter has also provided a comprehensive background, first as a baseline for autonomous networks elaborated on existing networks' automation framework i.e., LTE SON, then we outlined commonly used ML techniques, namely supervised, unsupervised, reinforcement, semi-supervised, and distributed learning. This chapter also provided an overview of the literature on using the aforementioned ML techniques for the automation of mobile networks.

7.1.2 JADE:Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks

We have presented JADE, an online framework for jammer activity detection in operational mobile networks. At its core, the JADE framework consists of deep learning-based semi-supervised anomaly detection models that solely rely on 'normal' training data. Also, JADE incorporates an adaptive mechanism for addressing the thresholding issue for cell-level anomaly detection. Moreover, the JADE framework utilizes transfer learning to enable itself to scalably work across many cells and multiple frequency bands. We have evaluated the JADE framework on a 4G RAN dataset provided by a multinational mobile network operator with jammer activation events labeled for different types of jammers. Field validation is also conducted, and it shows the effectiveness of the JADE framework in the wild. Lastly, we also provide promising results on the use of jammer detections from JADE for the localization of jammers along with cell site location data.

7.1.3 Demand Characterization and Forecasting for Cost-Effective Operational Mobile Network Planning

In this work, we have conducted a unique mobile network demand characterization and forecasting study with the aim of enabling cost-effective network planning for the operator. To this end, we have used multi-year and nationwide region-level mobile network traffic data. Our analysis reveals several novel insights, including: (1) significant differences among traffic characteristics at the regional level and with national level demand characteristics; (2) the effect of Covid on mobile service demand is not apparent on the region scale traffic characteristics; (3) mobile and FWA services are markedly

different in their characteristics, especially with respect to national level demand. The clustering-driven mobile network demand forecasting methodology we introduced is shown to yield significant improvements in mobile service demand forecasting accuracy by over an order of magnitude compared to the baseline approach while being scalable and also being effective for FWA service demand forecasting.

7.1.4 CellIDA: Data-Driven Autonomous Hotspot Cell Detection Framework For Operational Mobile Networks

The hotspot cells cause significant QoS and QoE degradations for the mobile subscriber. Hotspot cells must be addressed frequently and rapidly to avoid customer churns without losing time. However, in current practice hotspots tend to be seen as a network planning issue and are handled annually. For the first time, in this paper, we have considered hotspots as a performance optimization problem and presented CellIDA, the first online framework for cell-level hotspot detection in operational mobile networks. Instead of the coarse-grain annual resource planning methodology, CellIDA helps to handle the uncertainty in operational mobile networks on daily basis. By enabling the detection of hotspot cells based on the cell KPIs, CellIDA assures whether the existing radio resources sufficiently meet user expectations within each cell daily. The CellIDA framework consisted of deep learning-based anomaly detection models that were trained using supervised and semi-supervised learning approaches. We evaluated the CellIDA framework on a real 4G dataset with hotspot labels provided by a multinational mobile network operator. The results of our study demonstrate the effectiveness of our CellIDA framework. Finally, we compared the results of the predictions made by the deep NN models with respect to four different time steps.

7.2 Limitations and Directions for Future Work

This section summarizes the limitations of the contributions presented in this thesis, and suggests directions for future work.

7.2.1 JADE: Data-Driven Automated Jammer Detection Framework for Operational Mobile Networks

JADE is versatile in detecting both intentional and unintentional jammer-like activity affecting mobile network operations. However, regardless of the cause of the problem, all detected anomalies are labeled as jammer activation, even when no actual jammer is present. This mislabeling leads to higher false alarm rates. To minimize these, and to clarify the root cause of the problem of the detected cell-level anomalies, JADE must be extended with a probabilistic function so that the source of the problem can be identified with a probability value. Furthermore, this probabilistic approach requires representing multi-label data for training, e.g., a classification model for each anticipated cause of the cell-level anomalies.

As noted, jammers may exhibit complex discontinuous activation patterns that can have a slightly disambiguated effect on the dynamics of different network frequency bands, which is induced by anticipated behavior, depending on the distance. Sometimes, distinguishing this ambiguous effect from the natural noise on wireless signals may be impossible. Therefore, JADE could miss the detection of a specific jammer activation. This is, however, an exciting aspect that requires investigation and may further help in understanding the behaviors of jammers.

JADE jammer detection capabilities are limited to 4G networks since the deep learning JADE models are trained with 4G network KPI data. However, JADE's jammer detection capability can be expanded to detect jammer activations in other wireless access networks, such as 5G. The new version of anomaly detection models, in particular, must be trained with corresponding 5G network KPI data collected during periods with no jammer activation. Furthermore, the performance of 5G models must be validated with jammer cases detected in 5G networks.

7.2.2 Demand Characterization and Forecasting for Cost-Effective Operational Mobile Network Planning

A real 4G nationwide dataset with weekly granularity is used in this study. However, in mobile network data, many interesting and significant statistical patterns arise at a higher time granularity, i.e., 1 h or 15 minutes. Therefore, the obvious next step is to extend our work with much finer time granularity data.

Additionally, the nationwide real 4G networks, including FWA data considered

in this study, were provided by the market-leading mobile operator, with 40 million subscribers, covering half of the population in Turkey. However, our study only highlights the demand characterization and forecasting in this specific operator's 4G networks and subscriber demand. Furthermore, our findings may vary to some degree for other operators' data because they may employ different marketing strategies, e.g., focusing on different wireless access technologies such as 5G, as well as targeting customer groups in marketing campaigns (teenagers or public workers). Furthermore, since we do not have access to other operators' data, our study cannot characterize 100

In addition, our study's notion of mobile demand is based on traffic volume, while other wireless access technologies (2G, 3G, and 5G) were ignored since 2G and 3G are downgraded, and 5G is relatively new and does not generate huge amounts of traffic volume. Finally, our work is limited because it is only based on 4G network KPI data. To obtain a more comprehensive demand characteristics analysis, our study should be enlarged with complementary statistical data of the mobile subscriber, e.g., education level, occupation, and age.

7.2.3 CellIDA: Data-Driven Autonomous Hotspot Cell Detection Framework For Operational Mobile Networks

In this study, we demonstrated that the cells shift their status from over-provisioning to under-provisioning over time and become hotspot cells or vice versa on both a daily and monthly basis and during weeks, weekends, or summer. However, when CellIDA detects these particular hotspot cells, they must be addressed by allocating additional network resources to ensure optimum network coverage and capacity by the mobile operators. Allocating additional resources will cause inefficient network planning and infrastructure investments because the resources added to prevent the hotspots at certain times (days) of the year will become significantly redundant and transform into over-provisioning on other days of the year. In addition, we only developed the CellIDA framework for operational 4G networks. As with the additional use cases noted above, our CellIDA study could be expanded; the new hotspot detection models must be trained with the corresponding 5G network cell-level KPIs data.

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