



Resilience-as-a-service for 5G RAN driven by machine learning methods

Soumeya Kaada

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*Mathématiques, Télécommunications, Informatique, Signal, Systèmes,
Électronique*

Spécialité : *Informatique*

Par

« Soumeya KAADA »

« La résilience en tant que service à la demande des réseaux 5G
dirigée par le Machine Learning »

Thèse présentée et soutenue à « Rennes », le « 23 Sept 2024 »

Unité de recherche : Inria et Nokia Bell Labs France

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I would like to dedicate this thesis to my loving parents, my dear sisters, and to the memory of my grand parents, as well as to all the people who passed away during this journey.

DECLARATION

This is to certify that:

- the contents of this thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.
- this thesis is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.
- all main sources of help have been acknowledged.
- the source is always given when quoting from the work of others.

Soumeya KAADA

May 2024

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Abstract

The Fifth Generation of mobile communications (5G) networks are expected to meet the ever-growing number of demands for faster and more reliable connectivity, increased network capacity, low latency capabilities, high data rate transfer and improved user experience. However, the 5G-Radio Access Network (RAN) can likely be disturbed or shutdown due to unfortunate events despite designing reliable 5G Base Station (BS) systems. Recently, operators started to take an interest in improving the resilience of communication networks. Broadly speaking, resilience refers to the ability of a network to maintain a good level of service under outage from the user's perspective. Instead of traditional costly and static approaches, such as redundancy, the resilience requires a comprehensive understanding and a rigorous analysis of network elements to accurately predict the failures and undertake the optimal actions to face incoming challenges. In this context, we address, in this thesis, the following problems: 1) how to characterize the resilience of the 5G-RAN based on collected Key Performance Indicators (KPIs) and radio data in order to analyse and measure current and future levels of resilience, 2) how to reactively and proactively face unpredictable network outages by deploying adaptive mechanisms automatically in order to optimize the network resilience, 3) how to enable an end-to-end, on demand resilience strategy within future wireless systems that utilizes data driven solutions to ensure automatic network management through resilience analysis and optimization, and 4) how can data-driven solutions cope with deployment challenges and implementation limits in real networks regarding the availability of collected data to ensure efficient network management.

In the first contribution of the thesis, we start by performing a rigorous resilience analysis of network issues. By modeling the network status with Markov chains based on coverage and Quality of Service (QoS) indicators, we can provide resilience quantification throughout several metrics. To validate the proposed method, a standardized simulator is used to obtain radio data in different network configuration to test the analysis method. The experiments show that the proposed analysis can successfully forecast the average behaviour of a given RAN area, as well as its correspondent resiliency levels. Besides, we investigate the possibility of developing a resilience strategy for 5G and beyond RAN through a resilience framework deployment within a virtualized RAN.

Our second contribution tackles the resilience optimisation for automated cell antenna

reconfiguration. We formulate a multi objective optimization to improve quality of service while ensuring coverage and service availability constraints. By leveraging the power of Reinforcement Learning (RL) and Deep Learning (DL), we are capable to learn a multi-agent Deep Reinforcement Learning (DRL) models for large scale network optimizations. A simulator is used to evaluate the proposed solution and the results demonstrate that we can mitigate outage induced performance and enhance the resilience in face of various abnormal network behaviour.

Finally, the third and last contribution addresses a fundamental challenge encountered in the real world when applying data-driven solutions in the wireless communication domain: the scarcity of collected data. By leveraging the capabilities of generative Machine Learning (ML), we use real collected data to learn their distribution and to generate synthetic radio data for training multiple network performance analysis use cases. The results show that we are able to achieve the same accuracy when using synthetic data instead of real data, proving the quality of the synthetic data and their potential to solve storage and data transportation issues in real networks.

Keywords

5G, Radio Access Network (RAN), network resilience, coverage, Quality of Service (QoS), Markov chains, Deep Reinforcement Learning (DRL), outage mitigation, multi-agent systems, generative models, environment sensing.

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1G	First Generation of mobile communications	22
2G	Second Generation of mobile communications	22
3G	Third Generation of mobile communications	22
3GPP	Third Generation Partnership Project	viii
4G	Fourth Generation of mobile communications	22
5G	Fifth Generation of mobile communications	iii
6G	Sixth Generation of mobile communications	22
AI	Artificial Intelligence	15
AR	Augmented Reality	22
ARCEP	Authority for Electronic Communications, Posts and Press Distribution	15
BBU	BaseBand Unit	28
BIRCH	Balanced Iterative Reducing and Clustering using Hierarchies	xi
BS	Base Station	iii
BSS	Business Support System	31
C-RAN	Cloud Radio Access Network	24
CN	Core Network	27
COC	Cell Outage Compensation	39
COD	Cell Outage Detection	39
CPRI	Common Public Radio Interface	29
CSI	Channel State Information	62
CTMCs	Continuous Time Markov Chains	20
CU	Central Unit	29
DEC	Deep Embedded Clustering	xi
DL	Deep Learning	iv
DQN	Deep Q-Network	x
DRL	Deep Reinforcement Learning	iv
DU	Distributed Unit	29

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eMBB	enhanced Mobile Broadband	23
EMS	Element Management System	31
eURLLC	extremely-Ultra Reliable Low Latency Communications	33
FeMBB	Further-enhanced Mobile BroadBand	33
GAN	Generative Adversarial Network	xi
GMM	Gaussian Mixture Model	xi
gNB	Next Generation Node-B	27
IOD	Indoor-Outdoor Detection	55
IoT	Internet of Things	22
JSD	Jensen-Shannon Divergence	xi
KLD	Kullback-Leibler Divergence	67
KPI	Key Performance Indicator	iii
LTE	Long Term Evolution	22
MDT	Minimization of Drive Test	118
MDP	Markov Decision Process	94
ML	Machine Learning	iv
mMTC	massive Machine Type communications	23
MS	Mobile Station	87
MTTF	Mean Time To Failure	67
MTTR	Mean Time To Repair	67
NMS	Network Management System	30
NP-hard	Non-deterministic Polynomial-time hard	85
O-RAN	Open-Radio Access Network	14
OAM	Operations, Administration, and Maintenance	30
OSS	Operation Support System	31
PRB	Physical Resource Block	90
PRD	Precision and Recall for Distribution	127
QoS	Quality of Service	iii
RAN	Radio Access Network	iii
RB	Radio Resource Blocks	63
RCA	Root Cause Analysis	38

RIC	Radio Intelligent Controllers	34
RL	Reinforcement Learning	iv
RRH	Remote Radio Head	28
RRM	Radio Resource Management	35
RRU	Remote Radio Unit	25
RS	Reference Signal	62
RSRP	Received Signal Reference Power	ix
RSRQ	Received Signal Reference Quality	xi
RU	Radio Unit	29
SDN	Software Defined Networking	24
SLA	Service Level Agreement	15
SMO	Service Management and Orchestration	35
SON	Self Organizing Networks	14
UAV	Unmanned Aerial Vehicle	51
UDN	Ultra Dense Network	14
UE	User Equipment	ix
UED	User Environment Detection	121
UMi	Urban Micro	87
umMTC	ultra-massive Machine-Type Communications	33
URLLC	ultra Reliable Low Latency Communications	14
UT	User Terminal	87
V-RAN	Virtualized Radio Access Network	24
VAE	Variational AutoEncoder	xi
VNF	Virtual Network Function	24
VR	Virtual Reality	22
WGAN	Wasserstein Generative Adversarial Network	xi

RÉSUMÉ DE LA THÈSE

0.1 Introduction

Dans cette thèse, nous nous sommes intéressés à la gestion de résilience dans un réseau radio 5G et au-delà. Dans ce chapitre, nous résumons le contexte et les contributions de cette thèse. Nous commencerons par le contexte et les motivations de nos travaux. Puis, nous décrirons les approches qu'on a proposées et les principaux résultats obtenus.

0.2 Contexte et motivations

La 5G est vue par la majorité des acteurs des télécommunications comme la prochaine génération de réseaux mobiles qui doit être à la fois économiquement intéressante et génératrice de bénéfices en termes de dépenses d'investissement (CAPEX) et d'exploitation (OPEX). Les réseaux 5G et au-delà doivent apporter qualité et économie aux nombreux «clients-rois » qui sont de plus en plus exigeants pour des services peu chers et très satisfaisants. Pour répondre aux demandes exigées par les clients, la résilience est vue, dans cette optique, comme une fonctionnalité importante des réseaux futurs au delà de la 5G pour leur fonctionnement général et pour la qualité des services offerts aux clients de l'opérateur. D'une manière générale, la résilience est définie par la capacité d'un système à résister, à s'adapter et à rebondir rapidement après avoir été confronté à des défaillances, des perturbations ou des challenges, afin de maintenir un niveau acceptable de qualité de service du point de vue des utilisateurs. Alors que les réseaux mobiles évoluent pour répondre aux exigences des réseaux 5G et au-delà, des initiatives telles que le réseau d'accès ouvert (Open Radio Access Network - ORAN) ont fait évoluer les architectures de réseaux mobiles vers de nouvelles topologies caractérisées par la désagrégation et la virtualisation afin d'assurer une meilleure rentabilité pour les opérateurs et des performances accrues pour les utilisateurs. La transparence offerte par le réseau d'accès radio ouvert (O-RAN), ainsi que d'autres propriétés telles que la flexibilité, l'interopérabilité et la virtualisation, renforceront la sécurité et la fiabilité du système cellulaire sous divers aspects, notamment la sécurité des interfaces et des logiciels, ainsi que l'assurance d'une

disponibilité du système 24 heures sur 24 et 7 jours sur 7.

Les concepteurs des systèmes radio visent principalement à réduire autant que possible les défaillances du système et leur impact négatif, en particulier dans le contexte des systèmes de communication ultra-fiable à faible latence (Ultra-Reliable Low-Latency communication - URLLC) et des réseaux ultra-denses (Ultra Dense Networks - UDNs). Cependant, réduire le nombre de défaillances à zéro reste un véritable challenge qui nécessite une compréhension globale de toutes les caractéristiques du système de communication, de ses composants et de ses rendements, afin de fournir des communications radio sans défaillance. En effet, malgré l'utilisation de procédures agiles et optimisées, les réseaux du futur demeurent vulnérables aux défaillances en raison de la complexité croissante engendrée par l'innovation et le déploiement intensif d'équipements réseaux dans un environnement radio qui est de nature instable. Ceci peut entraîner une augmentation considérable des coûts d'entretien dû aux opérations de rétablissement, tant en délai de traitement et qu'en ressources, pour gérer les événements perturbateurs. Dans cette optique, le paradigme de la résilience a vu le jour avec la montée de la complexité de la gestion des systèmes et la limite des approches traditionnelles de gestion tels que le domaine de sûreté de fonctionnement.

Les méthodes de sûreté de fonctionnement appliquées aux réseaux cellulaires sont spécifiées en fonction de la disponibilité et de la fiabilité requises. Elles sont quantifiées à l'aide d'indicateurs clés de performance (Key Performance Indicator - KPI), représentés généralement par des valeurs réelles supérieures à 90% [104]. Dans la pratique, lorsque des défaillances surviennent, les opérateurs de télécommunications mobiles procèdent à des réparations en envoyant, la plupart du temps, une équipe technique pour réparer manuellement les stations de base (Base Stations - BSs) défaillantes ou dégradées. Il existe tout de même sur le terrain des fonctions automatisées d'autoréparation, activables à distance sur site et sans intervention humaine, qui ont été proposées pour les réseaux RAN émergents tels que les réseaux auto-organisés (SON). Dans tous les cas, les opérations de réparation prennent un temps excessif et incontrôlé, ce qui peut entraîner une panne persistante du réseau, provoquant l'effondrement de tous les services sensibles. En effet, selon l'Autorité de Régulation des Communications Électroniques, des Postes et de la distribution de la presse (ARCEP), un délai moyen de réparation de 46 heures a été constaté en 2021 pour 85% des anomalies rapidement détectées [31]. Cela signifie que des perturbations inévitables se produiront quelles que soient les méthodes de sûreté de fonctionnement du RAN mises en place, les techniques d'optimisation utilisées et les fonctions

de guérison. En outre, nombre de ces mécanismes sont incapables d'évoluer dynamiquement pour répondre à une exigence spécifique du RAN. C'est pourquoi nous pensons qu'une solution de résilience auto-évolutive devrait être envisagée dans ce contexte. Ces solutions permettraient d'analyser automatiquement l'état actuel du système et d'agir dynamiquement en fonction des observations, en s'adaptant aux changements des conditions sous-jacentes du réseau. Cette solution devra ainsi prendre en compte l'évolution des besoins utilisateur dans le temps, tout en en faisant face aux limites de déploiement imposées par le réseau lui-même. Une gestion automatique de la résilience aura pour but de réduire le temps d'interaction homme-machine afin d'accroître l'efficacité opérationnelle et d'assurer la continuité des services.

Cette thèse aborde le problème d'une gestion efficace de la résilience des réseau d'accès radio (RAN). Nous étudions le concept de la gestion de la résilience dans un RAN avec une stratégie proactive basée sur l'analyse de service et la collecte de données en temps réel. Nous supposons qu'à l'avenir, les fournisseurs de réseaux ou les opérateurs devront définir les exigences de performances du RAN en termes de résilience du réseau, au sein de contrats de niveau de service (Service Level Agreement - SLA) sur la base d'attributs ciblées. Cette approche requière dans une première étape de réaliser une étude approfondie de la résilience [68]. Le plus souvent, la résilience des systèmes est analysée à l'aide de données historiques en utilisant des méthodes quantitatives. Les mesures de résilience extraites à partir de ces données sont établies le plus souvent avant le déploiement du réseau et des sites des stations de bases [38]. Cette approche fait partie du domaine de l'analyse des performances des réseaux et des systèmes, où les données jouent un rôle crucial permettant de faciliter une compréhension précise des systèmes et d'élaborer des solutions efficaces. Dans la thèse, nous proposons dans un premier temps de nous appuyer sur la technique de modélisation des chaînes de Markov pour analyser, quantifier et prédire en moyenne le comportement du réseau. Cette approche nous permettra de caractériser le comportement du système réseau, nous indiquant si le réseau est susceptible de satisfaire les contraintes requises, ou s'il existe une probabilité de non-satisfaction. Ensuite, sur la base des observations obtenues avec l'analyse, nous abordons le problème de l'optimisation de la résilience afin de compléter l'étude de notre approche sur la gestion efficace de la résilience. L'optimisation de la résilience aura pour but d'assurer la satisfaction de ces contraintes en fournissant un fonctionnement normal du réseau dans des conditions défavorables. Pour cela, on tirera parti de la puissance de l'apprentissage profond (Deep Learning - DL) et de l'apprentissage par renforcement (Reinforcement Learning - RL), nous

visons à introduire du dynamisme et de l'adaptation dans l'optimisation de la résilience pour faire face à diverses situations de panne et ainsi atténuer leur degré de sévérité du point de vue de l'utilisateur final. Nous nous appuyons sur l'apprentissage profond multi-agent pour améliorer les indicateurs clés de performance du réseau et l'expérience de l'utilisateur dans l'ensemble de la zone de déploiement. Cette approche, qui considère les cellules de la zone comme une entité cohésive avec des liens indissociables entre elles, impliquera la participation de toutes les cellules de la zone dans la gestion de la résilience. Ceci permettra d'enclencher des analyses et des optimisations ciblées par zone de couverture et de service, offrant une gestion de la résilience de bout en bout sur des endroits ciblés par l'opérateur. Ceci garantira une atténuation efficace des pannes réseau quelque soit le scénario de panne et son degré de sévérité sur le réseau. Enfin, nous nous concentrons sur les défis rencontrés lors de l'application de nos méthodes dans un réseau réel, comme le problème des coûts de partage et de stockage des données. Lorsqu'il s'agit d'analyser les performances d'un système, les données sont un élément essentiel pour effectuer une évaluation précise et élaborer un examen détaillé des comportements du réseau et des utilisateurs. En réalité, le manque de données dans l'industrie des télécommunications est un problème courant (i.e., data scarcity). Le manque de ces données peut constituer un obstacle au développement d'une analyse efficace des performances. Pour cela, nous proposons d'exploiter l'utilisation de données synthétiques pour compenser le manque des données, un problème communément appelé rareté des données ou data scarcity. Afin d'évaluer le rendement de l'utilisation des données synthétiques, on teste cette approche dans le cas de la détection de l'environnement de l'utilisateur. C'est un des cas d'étude axé sur l'analyse de l'état du réseau, étant donné que le comportement de l'utilisateur peut influencer les performances du système réseau. Dans ce qui suit, nous résumons les différentes contributions dans la Section 0.3. Ensuite, nous présentons l'organisation de cette thèse dans la Section 0.4.

0.3 Contributions

Nous avons abordé dans cette thèse, les problèmes suivants : 1) comment analyser et quantifier la résilience d'un réseau d'accès radio sur la base d'indicateurs collectés par les stations de bases afin de caractériser le comportement global du système radio, 2) comment optimiser les attributs et les mesures de la résilience en s'appuyant sur l'apprentissage par renforcement profond, 3) comment faire face aux défis d'implémentations de nos méth-

odes dans un réseau réel 5G et au-delà, en adressant le problème de manque de données dans un contexte de surcoût de stockage et de transfert de données avec l'utilisation des données radio synthétiques, et 4) comment exécuter cette stratégie dans une architecture virtuelle telle que le réseau d'accès ouvert (ORAN). Ces problèmes sont présentés en trois contributions comme suit:

0.3.1 Analyse de la résilience basée sur les modèles de Markov à temps continu et les indicateurs de performance réseaux

Notre première contribution consiste à proposer une méthode proactive d'analyse quantitative de la résilience pour un réseau d'accès radio 5G-RAN et au-delà. Plus précisément, la solution que nous proposons utilise les chaînes de Markov pour modéliser l'état du réseau sur la base d'indicateurs clés de performance du réseau. En se basant sur l'intensité du signal reçu et sur le débit de données reçu par l'utilisateur, nous définissons deux modèles afin de prédire la couverture radio et l'état des services à l'aide de divers métriques de résilience. Ensuite, nous validons l'analyse en utilisant des données extraites d'un environnement simulé en utilisant un simulateur de réseau 5G [110, 109]. Nous effectuons une analyse numérique par le biais de simulations dans différents types de réseaux et type de scénarios de fonctionnement du réseau normal ou défaillant. Pour montrer la faisabilité de l'approche, nous schématiserons un système de gestion de la résilience afin d'appliquer notre méthode au sein de l'architecture 5G et au-delà. Les résultats expérimentaux montrent que cette approche proactive peut aider à prévoir efficacement le comportement moyen des états du réseau mobile, soit à prédire en moyenne les défaillances dans le temps ainsi que le niveau de résilience correspondant, à court ou à moyen terme. En outre, la quantification de la résilience du réseau basée sur des multiples mesures de plusieurs indicateurs clés de performance permet de déterminer séparément l'impact de chaque indicateur sur la résilience. Cela permet de prendre des décisions anticipées appropriées pour améliorer le réseau en activant les mécanismes de résilience. Cette contribution a fait l'objet de deux publications, dans la conférence Network Of Future (NoF) [48] et dans le symposium IEEE/IFIP Network Operations and Management Symposium (NOMS) [49].

0.3.2 Optimisation de la résilience basée sur l'apprentissage par renforcement profond

Dans la seconde contribution, nous abordons le problème de l'optimisation de la résilience au sein d'un réseau dense. Plus précisément, on développera un algorithme basé sur l'apprentissage automatique pour la reconfiguration automatique de l'angle de l'inclinaison de l'antenne dans l'espace vertical ainsi que de la puissance de transmission du signal. On s'intéresse à un scénario dans lequel une ou plusieurs stations de base peuvent subir une panne. En réalité, la 5G utilise des réseaux ultra-denses avec de multiples déploiements de petites cellules dans des environnements internes ou externes. L'explosion du trafic des utilisateurs et de leurs données rend plus complexe la gestion des défaillances dans ces zones, et l'ajout d'autres petites cellules comme redondance augmentera le coût lié à la planification des cellules. Malheureusement, avec la complexité croissante du réseau, la mobilité et la diversité des utilisateurs, il devient difficile d'adapter les techniques actuelles de gestion de la résilience, qui reposent sur des optimisations locales, à de vastes déploiements des réseaux denses. Pour relever ce défi, nous proposons d'optimiser globalement la résilience d'un réseau multi-cellulaire dense en temps réel sur la base d'un algorithme d'apprentissage par renforcement multi-agents. Plus précisément, la solution que nous proposons permet à la fois, d'incliner dynamiquement l'angle des antennes et de reconfigurer la puissance de transmission du signal des cellules avoisinantes et proche de la zone de défaillance afin d'atténuer la panne et d'augmenter la couverture et la disponibilité du service. Contrairement aux études d'atténuation des pannes proposées précédemment, notre approche vise à impliquer toutes les cellules de la zone visée par l'optimisation dans le processus de reconfiguration afin d'atteindre l'équilibre optimal pour l'optimisation de la résilience. Cela permet au déploiement de petites cellules d'améliorer efficacement la couverture et la disponibilité du service, et de fournir une expérience utilisateur acceptable en cas de comportement anormal du réseau. Pour cela, nous formulons un problème d'optimisation multi-objectifs pour satisfaire simultanément les contraintes de couverture et de résilience du service tout en maximisant la qualité de service dans la zone du réseau afin de minimiser l'impact des pannes sur les cellules voisines. Pour évaluer notre approche, nous étudions des modèles entraînés dans des scénarios de panne dynamiques générés par un simulateur standardisé et montrons que le mécanisme proposé peut atténuer efficacement les défaillances de cellules. Les résultats de la simulation montrent que la disponibilité moyenne du service en termes de débit de l'utilisateur peut être aug-

mentée de 50-60% en moyenne, tout en atteignant une disponibilité de couverture de 99% dans les meilleurs cas. Cette contribution fera l'objet prochainement d'une publication dans une revue.

0.3.3 Challenges liés à l'implémentation dans un réseau réel : le problème de manque des données

La troisième contribution aborde certains problèmes qui peuvent être rencontrés lorsque nous voulons appliquer nos méthodes dans un réseau réel et les limites de mise en œuvre qui en découlent. Plus précisément, nous nous concentrons sur le coût élevé du partage/stockage de données lié à leur collecte dans le réseau. En réalité, dans les infrastructures mobiles basées sur la détection, le réseau lui-même agit comme un capteur global qui permet la collecte des données radio et des signaux ainsi que leur exploitation au niveau des stations de base. Généralement, ces données sont exploitées par des solutions data-driven qui regroupent non seulement l'apprentissage automatique, mais aussi la modélisation statistique, ainsi que des techniques d'optimisation pour apprendre, évaluer et analyser les performances pour des besoins de gestion du réseau, notamment la gestion de la résilience. Par exemple, l'analyse des performances du réseau est un cas d'utilisation crucial qui nécessite des données complètes pour tenir compte à la fois de l'état du réseau et du comportement des utilisateurs. Néanmoins, des données qualitatives à grande échelle sont nécessaires pour obtenir un apprentissage de haute précision. Cependant, leur phase d'apprentissage entraîne des coûts prohibitifs et de lourdes contraintes en matière de collecte et de stockage des données, ce qui n'est pas souhaitable pour l'opérateur. Ce manque de données collectées dans l'industrie des télécommunications est appelé le défi de la rareté des données (i.e., data scarcity). Pour surmonter ce problème, nous proposons d'utiliser des données synthétiques à la place des données réelles, afin d'éviter les coûts élevés de partage/stockage des données. Contrairement aux méthodes conventionnelles d'augmentation des données qui visent à améliorer la précision de la classification en ajoutant des données synthétiques aux ensembles de données existants, cette approche se concentre principalement sur la génération de données synthétiques pour imiter le comportement des données réelles lorsque celles-ci sont rares ou indisponibles en raison de contraintes liées au coût du partage des données. Dans cette contribution, nous nous intéressons à la détection de l'environnement réseau dans un contexte de partage limité des données. En se basant sur les données réelles disponibles

comme l'intensité et la qualité du signal, nous apprenons leur distribution à l'aide des modèles génératifs. Nous menons une étude comparative sur les modèles génératifs, qui sont capables de générer des données radio 3GPP synthétiques avec une distribution similaire à celle des données sources. On étudie la qualité de ces données radio synthétiques générées selon trois dimensions : la similarité de la distribution, la variabilité des données et la capacité de détection. Pour tester l'étendue de notre solution, nous nous appuyons sur le cas de la détection de l'environnement de l'utilisateur en tant qu'exemple candidat de l'analyse des performances du réseau. Ce cas d'étude vise à détecter le comportement des utilisateurs en déterminant si un utilisateur connecté au réseau se trouve à l'intérieur ou à l'extérieur d'un bâtiment (i.e., Indoor-Outdoor). Ainsi, ces informations seront précieuses pour déterminer des modèles de trafic susceptibles d'influencer les performances du réseau et pour détecter divers problèmes sous-jacents qui peuvent contribuer directement ou indirectement à l'analyse de la résilience. Nous utilisons des modèles de classification d'apprentissage automatique non supervisés entraînés avec des données synthétiques et nous les testons dans un contexte réel pour classer les utilisateurs en environnement interne ou externe. L'étude montre des résultats convaincants avec une performance de classification allant jusqu'à 80% du $F1 - score$ similairement aux scénarios d'entraînement sur des données réelles seulement. Cette contribution a fait l'objet d'une publication dans la conférence internationale Vehicular Technology Conference (VTC) [47] et est également décrite dans un brevet d'invention [66].

0.4 Organisation de la thèse

Cette thèse est organisée en 7 chapitres. Les chapitres de base sont dérivés de différentes publications de recherche publiées au cours des travaux de doctorat comme suit:

Chapitre 2 Fournit un aperçu de l'architecture, des défis et des concepts de la 5G, en mettant davantage l'accent sur les composants de gestion du réseau. Il donne ensuite un aperçu des principaux indicateurs clés de performance (Key Performance Indicator - KPI) des réseaux futurs et des défis à relever. Enfin, il souligne l'importance de mettre en place une stratégie de résilience pour les futurs réseaux mobiles.

Chapitre 3 Présente le contexte de la résilience et l'état de l'art, dans lequel nous relevons la relation de la résilience avec le domaine de la sûreté de fonctionnement et de la

gestion des réseaux, en fournissant une taxonomie et en passant en revue les problématiques de notre thèse. Nous identifions les lacunes et proposons notre vision de la résilience et nos contributions.

Chapitre 4 Développe une méthode d'analyse de la résilience. Plus particulièrement, présente notre première contribution, intitulé mesure de la résilience à l'aide de la modélisation avec les chaînes de Markov à temps continu (Continuous Time Markov Chains - CTMCs) en se basant sur les indicateurs de qualité de service et de couverture.

Chapitre 5 Aborde le problème de l'optimisation de la résilience d'une zone d'un réseau d'accès qui dessert de multiples utilisateurs et qui peut subir des défaillances au niveau des stations de base. Plus précisément, nous présentons notre deuxième contribution sur l'apprentissage par renforcement profond pour reconfigurer le réseau dynamiquement afin d'atténuer l'impact des pannes et améliorer la qualité de service. Cette solution sera également évaluée sur un simulateur dynamique et standardisé.

Chapitre 6 Aborde le problème de la rareté des données dans le cadre du déploiement des solutions d'analyse de performance du réseau dans des réseaux réels. On mettra l'accent sur l'apprentissage automatique génératif pour le partage et le stockage des données.

Chapitre 7 Conclut cette thèse, en synthétisant ses objectifs et les contributions associées, et présente une perspective pour des travaux futurs.

INTRODUCTION

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1.1 Context and motivation

THE original 5G vision that rely on supporting a wide range of devices, services, and deployment scenarios, also includes the support of a robust and secure system. Mobile networks are seen as part of critical national infrastructure and thus authorities want to ensure high level of resilience. Generally speaking, network resilience is thought of as the ability of a network suffering from disruptive events to keep an acceptable level of service from users perspective. As mobile networks evolve to meet the demands of the 5G and beyond networks, initiatives like the Open-Radio Access Network (O-RAN) have moved mobile network architectures towards new topologies featuring disaggregation and virtualization in order to ensure scalability and cost-effectiveness, for operators and provide enhanced performance for users. The transparency provided by O-RAN, among other properties like flexibility, interoperability and virtualization, will strengthen the cellular system security and dependability in various aspects, including interface and software security and the adoption of 24/7 system availability.

The radio system designers primarily aim at reducing as much as possible system's failures and their associated negative impact, especially in the context of ultra Reliable Low Latency Communications (URLLC) systems and Ultra Dense Networks (UDNs). This is a real challenge requiring a comprehensive understanding of all system features, its inputs and outputs, in order to provide failure-free radio-based communications. Despite using agile, complex, and optimized procedures, future networks are still failure-prone environments due to the growing complexity generated by innovation and the massive deployment of network equipment in a radio environment that is by nature unstable. This results in a dramatic increase of the recovery cost, in both time and resources, in order to manage disruptive events. From that perspective, the paradigm of resilience has emerged in the context of the growing complexity of system management and the limitations of traditional management approaches such as the dependability.

In wireless network systems, dependability methods are specified as a function of the required availability and reliability quantified using the KPIs. These are usually represented by means of float numbers in general constrained to be greater than 90% [104]. Practically, when failures occur, Mobile telecom operators perform healing by sending, most of the time, a technical team that manually fixes failed or degraded BSs. It is worth here to mention that automated self-healing functions have been proposed in the literature for emerging RAN, such as Self Organizing Networks (SON). In all cases, repairing oper-

ations take an uncontrolled and excessive time which may result in a persistent network blackout causing the collapse of all sensitive services. In fact, according to the Authority for Electronic Communications, Posts and Press Distribution ([ARCEP](#)), an average repair time of 46 hours was recorded in 2021 for 85% of quickly detected anomalies [\[31\]](#). This fact means that inevitable disruptions will occur whatever installed [RAN](#) dependability methods, used optimization techniques and healing functions. Moreover, many of these mechanisms are unable to dynamically evolve in order to follow a specific [RAN](#) requirement. That is why, we believe that a self-evolving resiliency solution should be considered in the context of a [RAN](#). These solutions will dynamically analyze the current system state and adapt based on these observations, responding to changes in the underlying network. Consequently, this solution will need to consider users' requirements and how they evolve over time, while also adhering to the deployment limits imposed by the network itself. Automating resilience management will decrease human-machine interaction, thereby, enhancing operational efficiency and ensuring service continuity.

In this context, this thesis addresses the problem of an efficient network management for building a resilient [RAN](#). We investigate the concept of resilience management in [RAN](#) with a double step strategy, during service delivery, based on real time data collection. We assume that, in the future, network providers or operators will need to define the network resilience requirements in Service Level Agreement ([SLA](#)) contracts based on target attributes. For the sake of effective resilience management, the first and crucial step to be done is resilience analysis [\[68\]](#). Frequently, the resilience of systems is analyzed using historical data and provide resilience measurements using quantitative methods before [BSs](#) sites deployment [\[38\]](#). This falls within the domain of network performance analysis, where data plays a crucial role in facilitating accurate analysis and the development of efficient solutions. As a first step in this thesis, we propose to rely on Markov chains modeling technique to analyse, characterise and predict the average behaviour of the network. This approach will allow us to characterize the behavior of the network system, indicating whether the network is likely to satisfy the required constraints, or whether there is a probability of non-satisfaction. Then, based on the analysis observations, we address the problem of resilience optimization in order to complete the study of our approach of resilience management. The optimization aims to ensure that the resiliency constraints are met using an outage mitigation technique to provide a normal network operation from the users' perspectives. By leveraging the power of Artificial Intelligence ([AI](#)) with [DL](#) and [RL](#), we aim to introduce dynamism and adaptation in the resilience optimization process

to face various outage situations. We rely on multi-agent **DRL** to enhance the overall network **KPIs** and user experience across an entire network area. This holistic approach, that considers the cells of a given serving area as a cohesive entity, with dependant links between them, will involve the participation of all these cells in the resilience management process. This will enable targeted analysis and optimization per coverage and service areas, offering an end-to-end resilience management at targeted locations by the operator. Finally, we focus on the challenges met when applying our methods in a real network like data sharing/data storage cost problems. When it comes to network performance analysis, data is an essential fuel for performing accurate analysis and elaborate a detailed examination of network and user behaviors, as well as evaluating system performance metrics. The lack of this data in the telecommunication industry is a common issue known as the data scarcity challenge. A lack of data can pose a barrier for developing efficient performance analysis. For that, we propose investigating the usage of synthetic data to address the data scarcity issue. As user behavior can influence network performance, we evaluate the usability of synthetic radio data on an environment sensing and user behaviour detection use case. In what follows, we summarize the different contributions in Section 1.2. Then, we present the organization of this thesis in Section 1.3.

1.2 Contributions

This thesis contributions can be broadly classified into 3 major categories. The first contribution addresses measuring resilience of a **5G-RAN** and beyond networks based on Markov chains and network performance indicators. The second contribution aims to optimise resilience attributes and metrics based on **DRL**. The last contribution extends our network management study to the possible challenges that can be met when applying network management methods and specifically network performance analysis methods into a real network, by producing synthetic data to tackle the data scarcity challenge. In what follows, we present in a nutshell these contributions.

1.2.1 Measuring and analysing resilience based on network performance indicators and modeling techniques

As a first contribution, we propose a proactive quantitative resilience analysis method for a **5G-RAN** and beyond networks. Specifically, our proposed solution uses Markov

chains for modelling network status based on network performance indicators. Specifically, we track network status using received signal strength and user received data rate. Then, based on two models, we predict radio coverage and service status, and propose metrics to quantify the level of network resilience. Afterwards, we validate the analysis using data extracted from a simulated environment using a 5G network simulator [110, 109]. We conduct a numerical analysis through simulations in different network types, use cases and failure scenarios. To show the usability of the approach, we propose to enable a resilience management scheme in order to apply our method on 5G and beyond networks architecture. Experimental results show that this proactive approach can help to efficiently forecast the average behaviour of mobile networks, at the level of outages and resilience, in short or mid-term duration. Besides, quantifying network resilience with multiple metrics for each KPI allows to determine the impact on these indicators separately and take suitable anticipated decisions to improve the global system behaviour by activating resilience mechanisms. This contribution is the object of two conference publications in the Network Of Future Conference (NoF) [48] and the IEEE/IFIP Network Operations and Management Symposium (NOMS) [49].

1.2.2 Resilience optimisation based on Deep Reinforcement Learning (DRL)

As a second contribution, we address the problem of resilience optimization within a dense network. Specifically, we develop a learning algorithm for automated cell antenna tilting and transmit power reconfiguration using DRL. We are interested in a scenario where one or multiple BSs can experience an outage. 5G utilizes small cells with multiple deployments within dense networks in both indoor and outdoor areas. The explosive users data traffic adds complexity to the outage management in these areas, and adding more BSs as redundancy will increase the cost related to cell planing. Unfortunately, with the growing network complexity, user mobility, and user diversity, it becomes challenging to scale current resilience management techniques that rely on local optimizations to large dense network deployments. To address this challenge, we propose to globally optimize the resilience of a dense multi-cell network in real time based on multi-agent DRL. Specifically, our proposed solution can dynamically tilt cell antennas and reconfigure transmit power to mitigate the outage and increase both coverage and service availability. In contrast to previously proposed outage mitigation studies, our approach aims to engage all

cells in the reconfiguration process to achieve the optimal balance for resilience optimization. This offers small cells deployment an efficient coverage and capacity enhancement and provide an acceptable service quality and user experience under abnormal network behaviour. For that, we formulate a multi-objective optimization problem to simultaneously satisfy coverage and service resiliency constraints while maximizing the **QoS** in the network area in order to minimize the impact of outages on neighbouring cells. To assess the optimization capability of our approach, we evaluate the trained **DRL** models in a standardized simulator and show that the proposed mechanism can effectively mitigate the cell outages. Extensive simulations then demonstrate that with our proposed solution, the average service availability in terms of user throughput can be increased by up to 50-60% on average, while reaching a coverage availability of 99% in best cases. This contribution will be the object of a paper presently in preparation.

1.2.3 Real-world implementation challenges: data scarcity

As a third contribution, we propose to tackle some of the problems that can be encountered when we want to apply our methods on a real network and the related implementation limits. More specifically, we focus on the high cost data sharing/storage related to network data collection. In fact, in sensing-enabled mobile infrastructures, the network itself acts as a whole sensor by leveraging radio data or signals collected within **BSs**. This data is exploited for the development of data-driven solutions to augment network's capabilities. Typically, data is fed into these solutions that encompass not only **ML** but also statistical and simulation modeling, along with optimization techniques to learn, analyse and assess an accurate network performance analysis for various network management tasks, and particularly the resilience management. For instance, network performance analysis is a crucial use case requiring comprehensive data to analyze both network and user behaviors. Nevertheless, large-scale qualitative data is required for achieving high accuracy learning. However, acquiring voluminous data leads to prohibitive cost and heavy constraints on data collection and storage that are not desirable for network. This lack of collected data in the telecommunication industry is called the data scarcity challenge. To overcome this problem, we propose to use synthetic data instead of real data for training data-driven solutions to avoid the high cost of data sharing/storage. Unlike traditional data augmentation methods that aim to improve classification accuracy by adding synthetic data to existing datasets, this approach focuses solely on generating synthetic data to mimic the behavior of real data when actual data is scarce or unavailable due to cost-

related constraints on data sharing. In this contribution, we are interested in real-life environment sensing networks in a context of limited data amount sharing. Based on real radio data available of signal strength and quality patterns, we learn their distribution using generative models. We conduct a comparative study on generative models, that are able to generate synthetic **3GPP** radio data with similar distribution than the source data. We investigate the quality of these synthetic generated radio data according to three dimensions: distribution similarity, data variability and detection capability. To test the extent of this solution, we rely on environment detection as a candidate use case for network performance analysis. This use case aims to detect user behaviour by inferring whether a user connected to the network is inside or outside a building. Thus, provides valuable insights about traffic patterns that may influence the network performance and allow detecting various underlying issues that contribute in a direct or indirect way to resilience analysis. We use unsupervised **ML** classification models trained with synthetic generated data and test them in real-life context to classify indoor and outdoor users. The study shows convincing results with an Indoor/Outdoor unsupervised classification performance up to 80% of $F1-score$ like in real-life data training scenarios. This contribution is the object of a conference publication in the Vehicular Technology Conference (VTC) **[47]** and is also described in a patent **[66]**.

1.3 Outline

This thesis is organized in 6 chapters. The core Chapters are derived from different research publications issued during the PhD works as follows:

Chapter 2 First, provides an overview of the **5G-RAN** architecture, challenges and concepts, with more focus on the network management components. Then, it provides an overview of the most important future network **KPIs** and challenges. Finally, it highlights the importance of enabling a resilience strategy for future networks.

Chapter 3 Presents the resilience background and the State of the Art, in which we highlight the relation of resilience with the dependability domain and the network management, provide a taxonomy and review the problematic of our thesis. We identify the shortcoming and propose our resilience vision and contributions.

Chapter 4 Develops the resilience analysis method. More specifically, we present our first contribution, namely, measuring 5G-RAN and beyond networks resiliency based on Continuous Time Markov Chains (CTMCs) and using network KPIs, namely, coverage and QoS indicators.

Chapter 5 Investigates adaptive data driven solutions for RAN resiliency. More specifically, we present our second contribution on resilience optimization of a serving area for mitigating cell outage problems. A reactive and adaptive solution based on multi-agent DRL is developed and evaluated on a dynamic and standardized simulation environment.

Chapter 6 Addresses the data scarcity challenge on the real network deployment and implementation with focus on generative ML for data sharing and data storage problem.

Chapter 7 Concludes this thesis, synthesizes the thesis objectives and the associated contributions and presents a perspective for future works.

5G AND OPEN RADIO ACCESS NETWORK (O-RAN) CHALLENGES AND TECHNOLOGIES: BACKGROUND

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2.1 Introduction

THE fifth network generation 5G tends to be a multi-layered, multi-actor, and multi-access mobile network in order to fulfill the stringent availability, security, privacy and resilience requirements. This chapter is dedicated to the context and overview of 5G-RAN architectures, Open RAN paradigm and its challenges. The network management components and the resilience importance are also described.

2.2 5G requirements and challenges

Mobile communication technologies have become an integral part of our daily lives, revolutionizing the way we communicate, access information, and perform various tasks. From focusing only on providing voice calls with First Generation of mobile communications (1G) and text messaging with Second Generation of mobile communications (2G) (e.g., Global System for Mobile Communications - GSM), passing by the Third Generation of mobile communications (3G) (e.g., Universal Mobile Telecommunications System - UMTS and CDMA2000) that enabled internet access, video calling and multimedia messaging (MMS), to the latest massively deployed nowadays Fourth Generation of mobile communications (4G) (Long Term Evolution (LTE), LTE advanced and WIMAX) that offers more advanced data services like faster internet access, high-definition video streaming and advanced mobile gaming [95]. 5G is already here to be adopted for supporting emerging technologies like the Internet of Things (IoT), autonomous vehicles, Virtual Reality (VR), and Augmented Reality (AR), while the Sixth Generation of mobile communications (6G) is still under development and research to go beyond the capabilities of 5G to cover other technologies that may not be fully realized or feasible with current network infrastructure [78]. The mobile communication technologies are pervasive and growing such that each subsequent generation of mobile networks was build upon the previous one. Historically, the evolution of cellular network generations is influenced primarily by improving and enhancing network capabilities, and offering higher speed and capacity. While 1G to 4G focused primarily on human-centric communication, 5G expands the scope to include massive machine-to-machine communication and support for a wide range of applications beyond traditional mobile devices [91].

Future networks, with 5G as an example in this thesis, are designed to handle the continuous growth in wireless user devices, data usage, and to provide the support for a

wide range of new applications and services compared to previous generations of wireless networks while improving the quality of user experience. Specifically, 5G aims to provide the following three key use cases as depicted in Figure 2.1:

- (i) enhanced Mobile Broadband (eMBB) services that focus on delivering significantly enhanced data speed and capacity, to meet the growing demand for high-bandwidth applications and services, such as ultra-high-definition video streaming, VR, AR, and other data-intensive applications.
- (ii) URLLC services that focus on delivering low latency precise synchronization and high reliability for mission-critical applications that require real-time responsiveness such as public safety, remote surgery, emergency response, autonomous driving, industrial automation and control systems.
- (iii) massive Machine Type communications (mMTC) services that enable scalable and efficient communication in scenarios where billions of devices are interconnected, while ensuring low power consumption and optimized data traffic for wide range of applications such as IoT devices, smart sensors, wearable devices, industrial machinery in agriculture, healthcare, logistics, smart cities and various industries.

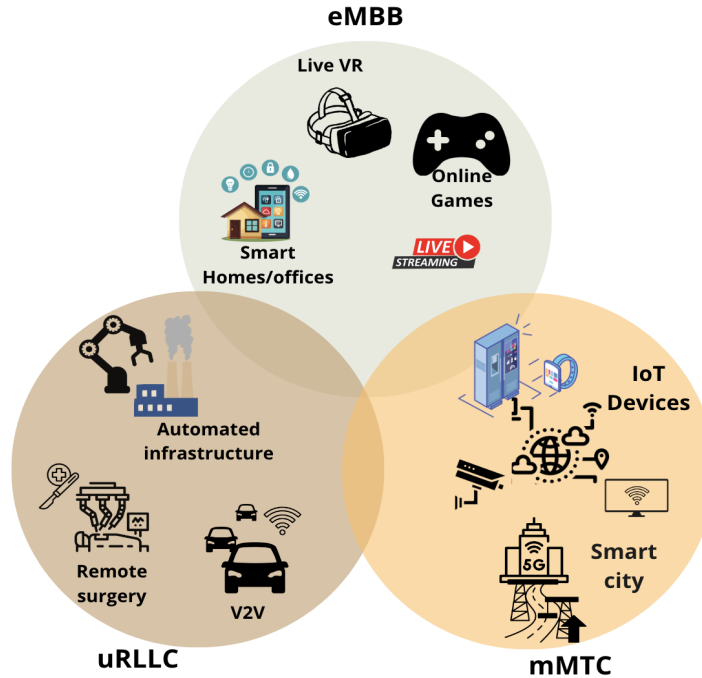


Figure 2.1 – Three main 5G use cases.

To allow deploying efficiently these use cases, 5G brings a specific number of features

with its associated number of challenges, including:

- **Improved Spectral Efficiency:** with massive Multiple-Input Multiple-Output (MIMO) technology and more efficient modulation schemes by using large number of antennas at the BSs. This allows more data to be transmitted over the available spectrum, increasing the overall network capacity. However, it results in increased complexity of spectrum utilization, interference management and power consumption.
- **Spectrum Availability:** with millimeter Wave (mmWave) that allows using higher-frequency bands, including mmWave spectrum, to achieve faster data speed. However, this type of signals are more subject to blockage by physical objects since they have shorter range, which creates challenges in terms of signal propagation, coverage, and deployment of small cells.
- **Beam Management** with beamforming techniques to focus signals towards specific users or devices for improving signal quality and capacity. However, beam management presents challenges in terms of beam tracking, synchronization, and handover between beams, especially in dynamic environments and in the deployment of numerous small cells.
- **Network Slicing:** with the concept of network slices, that allows the creation of multiple virtualized networks with different performance requirements on a shared physical infrastructure, allowing for the flexible allocation of computational resources based on demand. This brings challenges in terms of ensuring effective management and coordination of network slices, maintaining QoS, and deals with security and scalability issues.
- **Virtualization and Cloud Computing:** with Virtual Network Function (VNF) and Software Defined Networking (SDN) concepts to virtualize the network infrastructure, separate the control and data planes and centralize the computational resources in large data centers respectively. This offers flexibility and scalability in network deployments. The challenges include robust orchestration, efficient resource allocation, and maintaining service continuity in virtualized environments.
- **Cloud-RAN:** 5G promotes the shift towards a centralized and virtualized RAN architecture through Cloud Radio Access Network (C-RAN), Virtualized Radio Access Network (V-RAN) and Open RAN concepts, to centralize the computational resources in large data centers that are geographically distributed. This adds latency in data transmission and processing due to the distance between end-users/devices

and the cloud data centers. The challenge is to ensure high-capacity and low-latency fronthaul connections to transport data with least cost between Remote Radio Units (RRUs) and central processing units.

- **Edge Computing:** 5G brings computing resources closer to the network edge to enable faster data processing and reduced latency, for real-time and latency-sensitive applications. However, it offers limited scalability compared to cloud computing, limited computing power, storage capacity, and energy resources of the end devices. Besides, the data processing and storage is spread across various locations which poses challenges in terms of coordination, orchestration, and management complexity.
- **Interoperability and Coexistence with Legacy Networks:** 5G is a complex ecosystem that involves various vendors and technologies. Thus, ensuring interoperability is a challenge in terms of compliance with various regulatory and legal frameworks. The Open RAN paradigm aims to enable smooth coexistence, and privacy regulations with national security considerations. It requires efficient interworking, smooth handovers, and backward compatibility for users and applications.

With the proliferation of connected devices and increasing data demand and traffic coupled, enabling all these features together within the network raise many concerns tackled in hot topics of research through: energy efficiency and sustainability, spectrum and network management, orchestration and resource allocation, scalability and interoperability, security and privacy, resiliency and reliability and many more [103].

2.2.1 Resilience aspects in 5G networks:

Resilience is an important factor of 5G and beyond networks, as it ensures that the network maintains its performance and functionality even in the face of various disruptions [15, 63]. Resilience encompasses tackling a certain number of aspects comprising:

- **Network Reliability and Spectrum Availability:** 5G networks should provide high reliability communications especially for critical services such as autonomous vehicles and healthcare systems through maintaining consistent connectivity, minimizing downtime, and building a redundant network infrastructure. Besides, as the demand for wireless connectivity grows, ensuring efficient spectrum management and allocation of shared radio resources among different services and operators become crucial.

- **Network Security and Privacy:** Factors like virtualization or automation can bring new security risks. In particular, when a network resides in software, there is a danger of cross-contamination or data leakage and automation can also speed up the spread of bad decisions and malware. This can be worsen by the increasing number of connected devices which enables a larger attack surface, the heterogeneity and coexistence of multiple network technologies and the support of critical applications. Ensuring the security of 5G networks and IoT ecosystems against cyber threats, unauthorized access, data breaches, and addressing privacy concerns associated with the collection and processing of massive amount of data become a crucial challenge.
- **Resilience to Environmental Factors and Disasters:** environmental conditions are important factors that may breakdown the network operational state. Events like extreme weather, natural disasters, or physical obstructions can impact signal propagation, coverage, and overall network availability. Considering environmental factors during network planning and be prepared to any extreme condition is essential to design a resilient infrastructure.
- **Sustainability Through Energy Efficiency:** as 5G will support a wide range of power-constrained devices and applications, it may create power-related issues, like overheating or power outages. By minimizing power consumption of network elements like BSs, edge devices, and data centers, it contributes to a better resource utilization, to extend the battery life of these devices, maintain consistent performance and minimize disruptions leading to maximize the efficiency of operators infrastructure. Energy-efficient practices like sleep and power-saving modes mechanisms, dynamic power management, and the reduction of unnecessary signaling and energy waste and thus carbon footprint, will contribute to a more sustainable ecosystem. This leads to cost savings and improved network resilience that align with global efforts to mitigate climate change and promote a greener future.
- **Network Scalability:** The massive number of devices and diverse applications supported by 5G networks leads to increased network scalability requirements. Adopting practices like efficient resource management (e.g., bandwidth, processing power, storage) and optimization of energy consumption, operators can handle the growing demands of network expansion without compromising performance or introducing exponential growth in power requirements. This enables more cost-effective scaling of network infrastructure making it easier to deploy and manage resilient 5G network.

Overcoming the resilience challenge has become a crucial aspect for future networks. To this end, researchers are developing various solutions to address each different aspect of resilience. This thesis aims to provide a proactive resilience strategy for 5G-RAN architecture, from the reliability and availability aspects to the enhancement of network performance.

2.3 Detailed architecture of 5G Radio Access Network (RAN)

5G as the previous mobile network generations is composed of two major parts: the RAN that connects multiple end UEs such as smartphones, tablets or IoT devices, to the Core Network (CN) (i.e., called Evolved Packet Core (EPC) in 4G and 5GC in 5G). The CN is usually responsible for controlling, managing, and routing the traffic within the 5G network.

- **The RAN** consists of BSs, also known as gNodeBs for Next Generation NodeBs (gNBs), responsible for radio signal transmission and reception between antennas and UEs, as well as multiple radio functions like beamforming and handovers.
- **The Core or 5GC** comprises multiple components that are responsible for authentication, mobility management, control and data plane management, subscriber-related data management and network resource usage as well as policy rules related to network access, QoS, and SLAs.

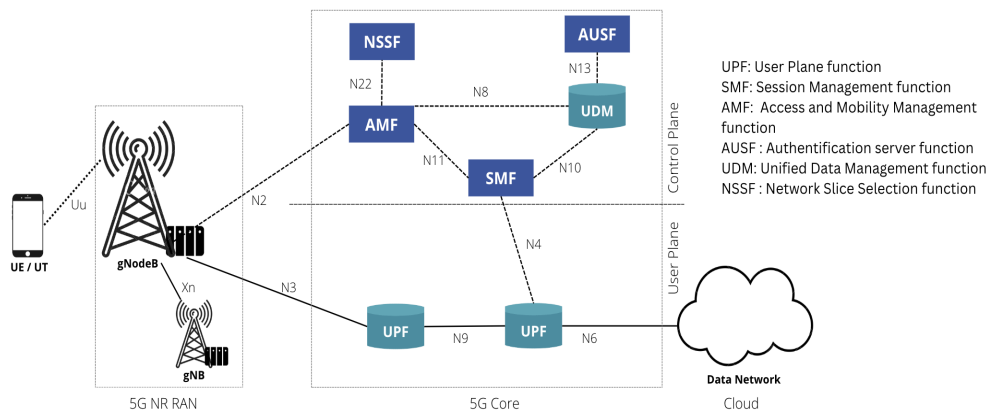


Figure 2.2 – 5G architecture [14].

Currently, most 5G deployments are ‘Non-StandAlone’ (NSA), that connect a 5G-

RAN with an existing 4G LTE infrastructure as defined by 3GPP release 15 [6]. However, the industry is trying to unlock 5G's full potential by deploying it in a 'StandAlone' (SA) mode which means both the 5G core and 5G RAN are executed together with legacy networks in the industry.

2.3.1 5G Radio Access Network (RAN) components

The access network deployment has evolved throughout the years to handle the growing number of UEs and rising user demands. The first version of RAN is Distributed RAN (D-RAN), in which, the traditional BS functionality is splitted into centralized BaseBand Unit (BBU) and the Remote Radio Head (RRH), and are co-located in the same physical location for each cell site. Later, an enhanced version called C-RAN, also known as Centralized RAN or Cloud RAN, was developed in which the BBU is separated from the RRH geographically. This setting allowed to create a centralised location where multiple BBUs are in the same physical location. So that, the resources can be shared dynamically within what is called a BBU Pool or a BBU Hotel. The BBU functions can be implemented on servers and executed in a virtualized environment, that makes it possible to be pooled in a cloud data center [13].

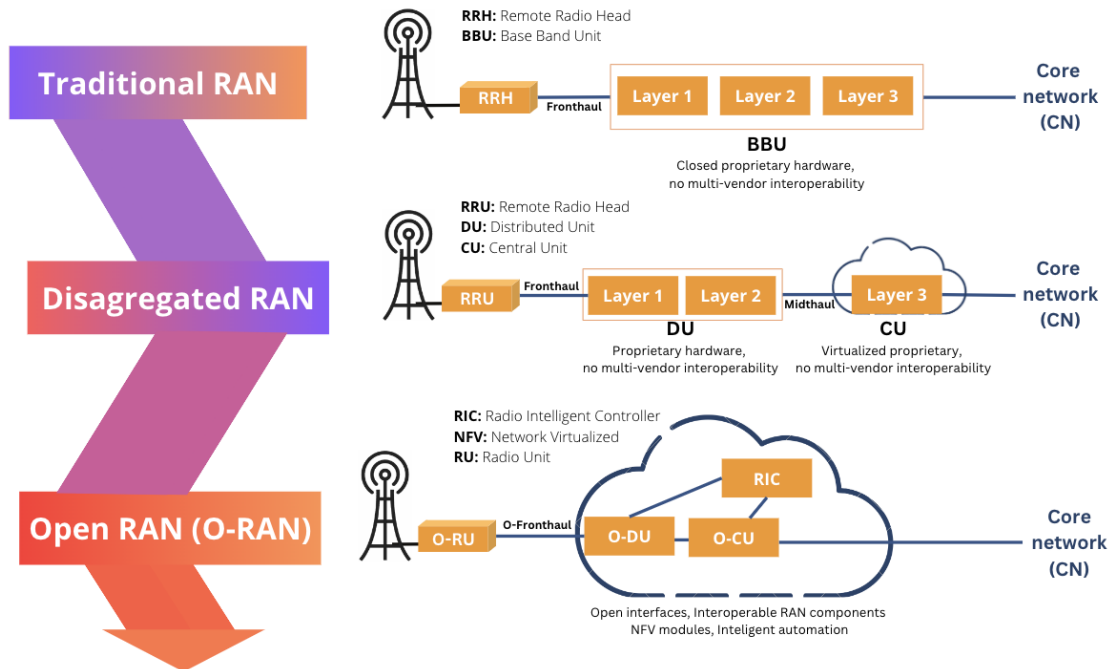


Figure 2.3 – RAN components evolution [71].

Lastly, **V-RAN** architecture was proposed to run **5G** capabilities. It is almost like **C-RAN** but there is no hardware dependency on some major entities of the **RAN** architecture. Furthermore, to reduce the high data load between **RRH** and **BBU** for processing, the **3GPP** proposed functional splits of **RRH** and **BBU** into three components: Radio Unit (**RU**), Distributed Unit (**DU**) and Central Unit (**CU**). In this case, **RU** is located in the cell site whereas **DU** and **CU** can be co-located or not into the same **BBU** pool, as a software package and run on a Commercial Off The Shelf (COTS) server as a **VNF**. In this case some major processing can be done in **DU** layers (e.g., RLC, MAC, PHY) and in **CU** layers (e.g., RRC, PDCP and SDAP in **5G** scenario) [40].

The **5G-RAN** components are interconnected with different interfaces such as the Common Public Radio Interface (**CPRI**) that enables efficient transmission of digitized radio signals and control information between **RU**, **DU** and **CU**, over the fronthaul connection that is based on optical fiber links to transport large amount of data and collected digitized radio signals sent from the **RUs**. The F1 interface connects **CU** and **DU** units carrying both control and user plane data over the midhaul connection. Finally, the New Generation (NG) interface connects the **RAN**, or more specifically, the **5G gNB**, to the **CN** over the backhaul connection. There are many more interfaces, but some are interesting to consider for enabling the contributions in this thesis like, the X2 interface that connects neighboring **BSs** to enable handover management, interference coordination, and neighbor cell measurements [8].

2.3.2 Network cell deployment

5G is expected to support different ranges of frequencies from below 6GHz to mmWave above 24GHz. For that, there exist different deployment options for **BS** cells from macro to small cells (see Figure 2.5).

- **Macro Cells:** present in previous network generations, macro cells provide coverage for a large geographical area. Usually deployed for outdoor and rural environments. The cell radius for macro cells typically ranges from several hundred meters to several kilometers. Coupled with Massive MIMO, they expect to allow large transmission and reception of data.
- **Small Cells:** will play a crucial role in **5G** deployments, particularly in dense urban areas and indoor environments with high user densities. They include various types such as femtocells, picocells, and microcells, each tailored to cover specific ranges

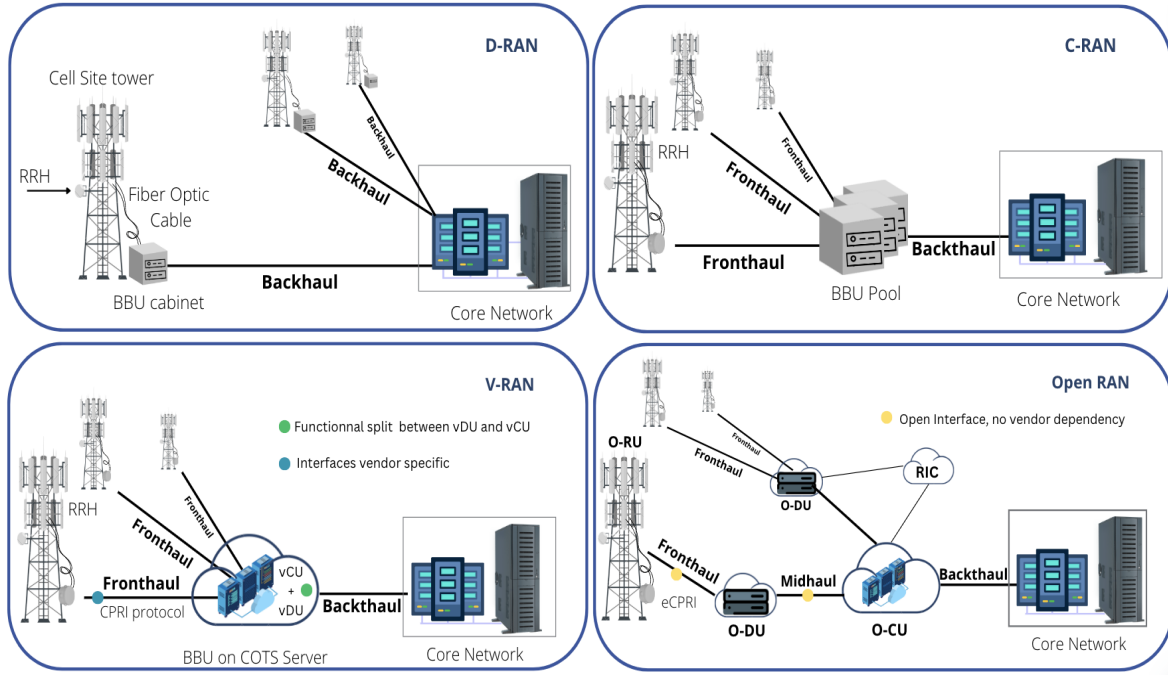


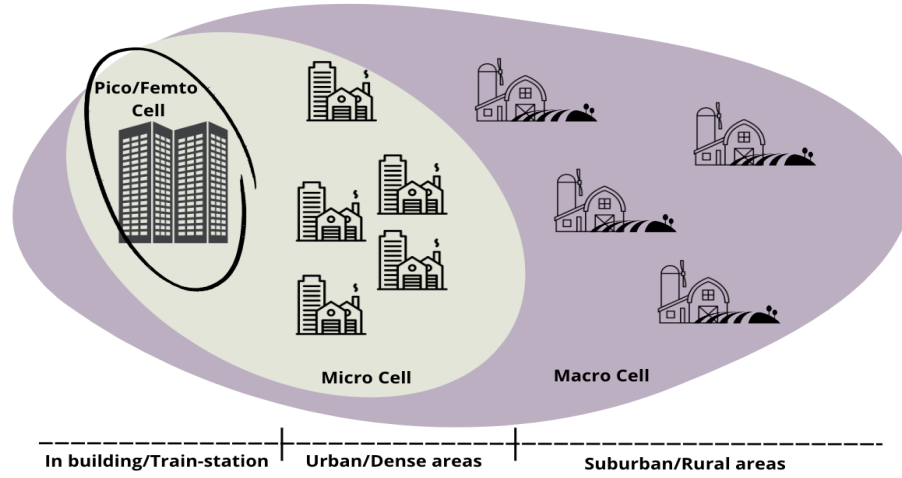
Figure 2.4 – RAN architecture versions: D-RAN, C-RAN, V-RAN and Open RAN [108].

and serve different use cases. The cell radius for femtocells typically ranges from 10 meters to 100 meters, the radius for picocells ranging from 100 meters to a few hundred meters, and the radius for microcells ranges from a few hundred meters to a kilometer. Small cells will allow deploying cell sites in strategic locations and offer higher capacities in targeted small coverage areas. Small cells are deployed both with and without macro coverage, both outdoor and indoor and both sparse and dense areas [2, 53].

2.3.3 5G Radio Access Network (RAN) management entities

A set of management functions and entities are provided to facilitate the Operations, Administration, and Maintenance (OAM) of a 5G-RAN network, including:

- **Network Management System (NMS):** is a central entity for the overall management and control of the 5G-RAN. It provides end-to-end management including fault management, performance management, configuration management, reporting and analytics as well as security management functions and the coordination of network elements and functions. It is vendor specific and it interacts with differ-



BS Type	Number of users	Coverage (km)	Location
Femtocell	1 to 30	0.010 to 0.1	Indoor
Picocell	30 to 100	0.1 to 0.2	Indoor/Outdoor
Microcell	100 to 2000	0.2 to 2	Indoor/Outdoor
Macrocell	>2000	2 to 32	Outdoor

Figure 2.5 – Base Station (BS) cell types [53].

ent management entities and protocols to collect data, and to perform analysis for various types of operations.

- **Element Management System (EMS)**: is an entity that focuses on the management of individual network elements within the 5G-RAN vendor specific. When it manages a group of devices of the same type, it treats all the devices within the group as a single device and does not consider inter-relationship between individual devices like the NMS.
- **Operation Support System (OSS)**: is a set of various software applications and systems that interact with individual NMS to manage multiple vendors equipment and provide one dashboard for FCAPS management that stands for (Fault, Configuration, Accounting, Performance, and Security) management for the access network and the CN. It is also responsible for managing all network entities, including transport network that connects the RAN to the CN, along with the service management in the upper layers. It handles performance monitoring across all network segments to provide a single view of the entire network.
- **Business Support System (BSS)**: is a set of software applications and systems that support the business operations and activities of a telecommunications service

provider. it handles Customer Relationship Management (CRM), billing and revenue management and other business-related operations to fulfill the service commitments outlined in SLAs. The management scope of BSSs/OSSs covers and provides end-to-end service and networks.

2.3.4 Types of failures

There exist many events that may destabilize the network normal functions due to various reasons. It is important to understand the types of failures to cope with them correctly and activate an effective network management to detect and mitigate network failures promptly. Here is a non exhaustive list of network failures types that may be encountered by the RAN [102]:

- **Physical Link Failure or Radio Link Failure (RLF):** physical or logical links that connect equipments like cables or optical fibers, can be damaged due to various reasons such as environmental changes, power outages, or configuration errors.
- **Equipment or node failure:** dis-function of routers, switchers, and servers can breakdown due to malfunction, software bugs, overheating, etc., that leads to component failures.
- **Power failure:** overheating can damage networking components causing power outage and network connectivity disruption, especially if there is no backup power resources.
- **Software failure:** network operating systems, firmware, or software applications can crash or encounter bugs resulting in service interruption or performance degradation.
- **Human errors and configuration failures:** human errors like misconfigurations (incorrect routing tables, firewall rules, or IP address assignments), accidental disconnections, improper handling of equipment, or incorrect software updates can lead to connectivity problems, security vulnerabilities and thus network failures.
- **Environmental factors and disasters:** Environment is a huge factor for several hardware network breakdowns like hurricanes, storms, earthquakes, fires, tsunamis, etc. Other weather factors like extreme temperatures, humidity, or electromagnetic interference can cause problems in signal propagation and the air interface which leads to performance degradation.

- **Security and network attacks:** Network vulnerabilities can be exploited by several cyber-attackers to perform unauthorized access, intrusion, or attacks on the network like Distributed Denial-of-Service (DDoS), malware infections, or phishing. Cyberattacks can compromise network availability, integrity, and confidentiality and disrupt network functionality.
- **Congestion or performance degradation:** traffic fluctuation at peak hours or due, for instance, to social events, can exceed the capacity of network links or devices impacting network performance with increased latency and packet loss or reduced throughput.
- **Socio-political and human-made disaster:** deliberate human actions can collaterally damage communication networks due to terrorism, pandemics, political disputes, cable cuts or space debris. These events can threaten the network that leads to service interruption.

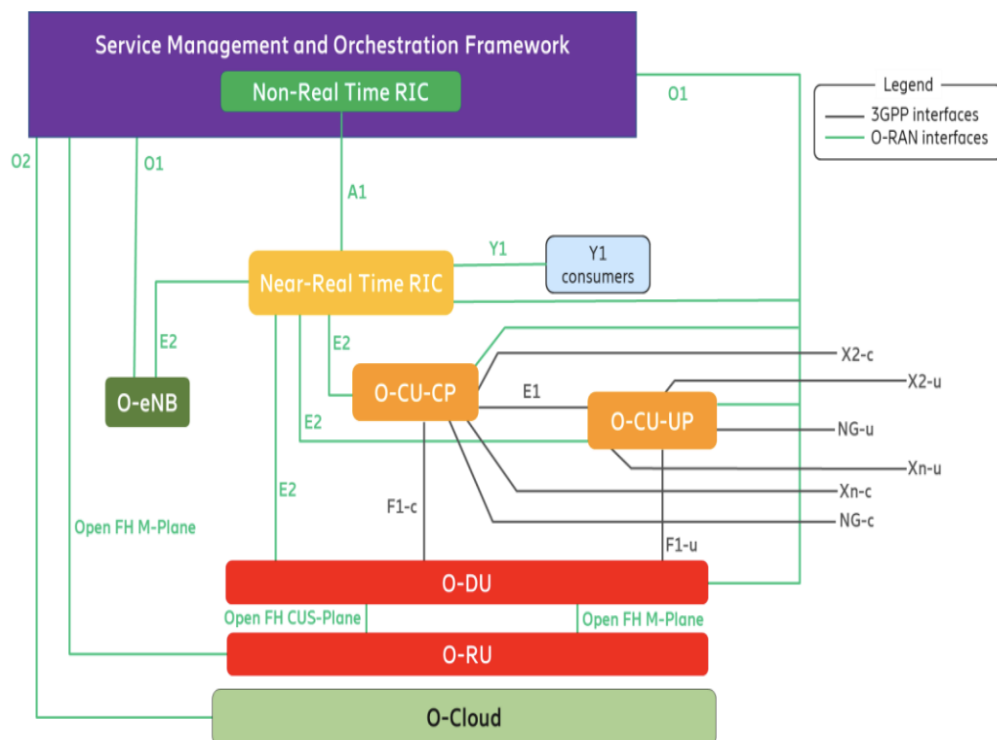
2.4 Open-Radio Access Network (O-RAN) principles

2.4.1 From 5G-RAN to Open RAN: concept

To meet the expectations of the current 5G network requirements, the current V-RAN solution faces limitations in terms of flexibility and scalability. In fact, the 5G components and interfaces are still vendor proprietary specific. The next generation of RAN is looking to opening the interfaces in the RAN ecosystem. The O-RAN or Open RAN concept is proposed as an evolution of the V-RAN [113]. The O-RAN Alliance is a consortium that drives the O-RAN project by grouping the efforts of multiple manufacturers, vendors, operators, and researchers to specify and define the opened architectural concept, and virtualized RAN solutions in the RAN ecosystem. Open RAN brings openness and intelligence compared to the traditional closed and proprietary RAN technology to offer flexibility, performance improvement, and cost-efficient deployments [21, 113].

The openness and intelligence brought by Open RAN aim to deploy improved use cases such as Further-enhanced Mobile BroadBand (FeMBB), ultra-massive Machine-Type Communications (umMTC), extremely-Ultra Reliable Low Latency Communications (eURLLC), and with extremely low power communications, with performance requirements quite beyond current 5G capabilities (e.g. peak data rates > 1 Tbps or latency of 10-100 μ s) [111]. Satisfying these requirements, is essential for delivering the 6G appli-

2.4.2 Open-Radio Access Network (O-RAN) architecture



2.4.3 Open-Radio Access Network (O-RAN) management challenges

Open **RAN** may bring several challenges for effective management of an Open **RAN** ecosystem. This transition requires more complex management systems, including softwarization of network resources and real-time management based on decision-making techniques analyzing historical, temporal, and frequency network data [76]. In fact, most telecom operations are complicated, thus operators highly rely on **OSS** and **BSS** systems. In Open **RAN** ecosystem, the Service Management and Orchestration (**SMO**) framework is defined by **O-RAN** Alliance to focus on the management of multiple vendor entities within the RAN, as illustrated in Figure 2.6. It is located under the E2E management and orchestration provided by the **OSS** component. The **SMO** uses the collected data via the O1 interface to deliver intelligent optimization for **RAN** and **AI/ML** analytics based management using the Non-RT **RIC** [113]. The **O-RAN** alliance tries to address different management challenges such as: ensuring interoperability, new security risks vulnerabilities, Data Collection Explosion (DME), cloud management or network slicing orchestration and automation. Many specifications are under development to shape the next generation of the access network [21].

In this thesis we will make use of the data collection within the **RAN** to enable a resilience framework. Components such as **DU**, **CU** or (**O-DU**, **O-CU**), as well as **NMS**, **OSS**, **RIC** will be used to support our resilience analysis and enhancement solutions.

2.5 Network management and resilience

In what follows, we describe some **OAM** functions and different paradigms used for the management of a **5G-RAN** and beyond networks that participate to enhance the resilience of mobile networks.

2.5.1 Radio Resource Management (RRM)

Radio Resource Management (**RRM**) techniques in **5G-RAN** include intelligent algorithms and mechanisms to optimize radio resource allocation and usage. They involve tasks such as Radio Frequency (RF) planning, interference management, load balancing, handover optimization, and spectrum management. **RRM** techniques ensure efficient utilization of available radio resources and improve network capacity, coverage, and quality.

Some **RRM** algorithms adjust radio resource allocation based on real-time measurements like the maximum amount of services to be derived from a given amount of spectrum and network conditions taking into account the Frequency Domain (FD) and Time Domain (TD). Knowing these measurements can help to define efficient algorithms or multi-objective optimization techniques for resource management [60]. For example, graph theory or linear programming were used to improve Energy Efficiency (EE), Spectral Efficiency (SE) and fairness, by using the throughput as a performance metric in [112, 55]. [117] proposed a Monte-Carlo tree search-based Q-learning algorithm to reduce resource utilisation by considering **QoS** metrics and models throughput while used Markov queuing system to reduce spectrum bandwidth [54]. In [114], a distributed resource allocation method was proposed for multiple users in a cognitive network to maximize the system throughput while considering cross-tier interference and limiting the transmitting power of the small mmWave **BS**, so as to reduce the effect on macro cells. The optimization problem was resolved using the Lagrange dual decomposition. Another work [121] proposed a joint beam and power allocation in a mmWave small through formulation of the nonconvex problem into Mixed Integer NonLinear Programming (MINLP). By first selecting the beam using cooperative games, and then, the power allocation scheme was solved by the Lagrange duality and iterative water-filling algorithm.

RRM techniques can deal also with interference management through fractional frequency reuse [27] to mitigate interference, or with convex relaxation approach [115] to guarantee **QoS** by using Co-tier and cross-tier interference performance metrics. The system throughput was also considered as a performance metric to achieve a robust allocation scheme and reduce interference through non-linear optimization and Lagrange dual methods [116]. Besides, some **RRM** techniques deal with efficient user association. In [122], a non-linear and mixed integer optimization or in [17], a **ML** based game theory methods were proposed using energy efficiency as a performance metric to improve the load balancing, overall throughput and power consumption. Finally, other aspects are addressed in **RRM** like power allocation, load balancing or mobility [60].

The **RRM** algorithms are typically implemented as part of network planning and optimization processes, often requiring manual intervention and configuration changes by network engineers. However, with the increased density of small-cell networks and radio access technologies, various **RRM** challenges for future heterogeneous networks have emerged. Thus, these techniques need to be automated while taking advantage of monitoring or data collection needed for the management. For that, **SON** are an emerging

techniques for supporting automated **RRM** actions within the network.

2.5.2 Fault management or troubleshooting

The fault management or troubleshooting is a crucial process that consists of detecting, identifying, and solving faults or problems that may disturb the network. Fault management is essential to maintain the reliability, availability, and performance of the network at appropriate levels [28]. It consists of:

- Fault Detection: continuous monitoring of **BSs**, antennas, transmission links, and network interfaces, to identify any anomalies that may occur on the network. This can be achieved through real-time monitoring, alarms, performance metrics, and fault detection algorithms like **ML** based anomaly detection [93]. A fault can lead to a complete system crash or only degradation. When a fault is detected, logs are triggered in the format of:
 - Alarms: may be notifications from the Simple Network Management Protocol (SNMP) traps or as log files generated by the syslog protocol [28]. These messages contain a precious information about the root cause and the type of fault. Some faults may be partially observable or unobservable like sleeping cells [35]. Log and alarm management comes with various challenges that include: the collection, filtering, and prioritization of alarms to enable efficient fault diagnosis for a rapid response. In fact, these messages are sometimes received quite often by the **NMS** or **OSS**, where some of them are just informative and others contain urgent notifications. For example, a single failure may trigger several messages due to the dependency of devices. False positive alarms can also complicate the management task and delay the fault diagnosis as well as various clock synchronization in distributed systems.
 - Performance metrics: collecting network performance metrics are also another way to detect a faulty behaviour [28]. Network metrics may include: delay, packet loss, throughput or network utilization [45]. These metrics are compared to specific thresholds depending on the **SLA** and the performance requirements of network service to decide if the network is acting normaly or if it has a faulty behaviour. However, since these metrics are continuously collected and compared to an acceptable quality level, the network can be overloaded with additional traffic that create a cost related data transfer or computational

cost [47].

- Fault localization and identification: once a failure state is detected, a fault localization process is launched, usually called fault isolation or Root Cause Analysis (RCA). Various techniques can be used to identify the cause a failure state such as alarm correlation techniques that analyse multiple related alarms to identify the root cause. Causality or dependency graphs can also be used with Petri-nets and ML-based analysis like hierarchical clustering or Hidden Markov Model (HMM) [28]. However, this task can be time consuming which may worsen the state of network. It also raises many challenges because of ambiguity and inconsistency of logs.
- Fault recovery: After identifying and isolating the root cause of a failure, recovery actions can be taken to restore the status of the network to the normal behaviour. Recovery actions can encompass reconfiguration of network parameters, software updates, hardware repairs, protection in case of security breaches or replacement of faulty components. Most telecommunication operations were highly dependant on human intervention. These last years with the virtualization, many automated procedures can take place remotely from the OSS system like self healing functions of the SON.

Sometimes, finding the root cause is not always sufficient to perform recovery actions on time, for that compensation and adaptive mechanisms are chosen instead, such as equipment redundancy, links reservation or fault tolerance measures to mitigate the outage and avoid long time service interruption [28]. With virtualization, network experts are expected to highly rely on adaptive measures with autonomous instantiation of virtual resources especially for critical networks to provide the continuity of services. Finally, reporting of the failure state and its impact is also important, to keep traces of the evolution of the network system [92, 105].

2.5.3 Self Organizing Networks (SON)

SON is a set of automation techniques and algorithms used to optimize and self-manage the 5G RAN. It proposes 3 major automation axes [36]:

- Self-configuration: it includes self-configuration of BSs, radio access parameters and the neighbour cell lists. It is locally performed at BS during deployment or upgrade of the network ecosystem.

- Self-optimization: optimization of network parameters by means of some measurements proposed by the network. It autonomously optimizes the coverage, interference, load balancing and capacity in cellular network as well as caching capabilities.
- Self-healing: it aims at autonomously solving or reducing the faults in the network by deploying recovery actions to limit the service interruption. There are 3 main use cases of SON Self-healing including: (i) Self-recovery of network element software, (ii) Self-Healing of board faults and (iii) Cell outage management that consists of 2 steps: Cell Outage Detection (COD) and Cell Outage Compensation (COC) [57, 22].

SON functions can be integrated into the NMS to benefit from its centralized platform for controlling and managing the underlying network architecture. These features may also employ real-time data analysis and decision-making processes to automate several tasks which allows the interaction with other network entities like DU or CU as well as RIC in an Open RAN environment.

2.5.4 Predictive maintenance

Fault management and self-healing methods are a type of reactive maintenance where they act after failure detection. In contrast, the concept of predictive maintenance has existed for many years. It takes the form of planned maintenance such as updates or equipment replacement to avoid future failures and increase the operators profit. These last years, with the emerging technologies of big data analytics, ML and DL techniques as well as IoT for data acquisition, predictive maintenance gained attention for its capability to perform fault forecasting, fault prognosis, and maintenance plans. The purpose behind is to minimise operator's cost, maximize availability and reliability and perform multi-objective optimizations [81].

Network monitoring and analytics enable the collection of real-time data and performance metrics from the RAN and from multiple IoT sensors. It enables advanced analytics algorithms like regression models, Remaining Useful Life (RUL) prediction based on time series analysis (e.g., using an AutoRegressive Integrated Moving Average (ARIMA) model) or advanced DL to predict the progression of faults in order to provide decision-support using DRL for developing and planing maintenance schedules [24].

2.6 Conclusion

This chapter over-viewed the main technologies concerned by this thesis, namely 5G mobile networks, Open RAN and their related network management techniques. Firstly, we gave an overview of the 5G requirements and challenges as well as the resilience aspects. Then, we overviewed the 5G-RAN detailed architecture with its components and the advanced Open RAN concept and architecture. Besides, we listed the possible disruptive events that may destabilize the RAN and the components responsible for managing network problems. Finally, we tackled different network management techniques used within the 5G-RAN that enhance the resilience of the access network.

Network management and resilience enhancement still involve a number of challenges that we aim to address in this thesis. As a first step towards this, the next chapter highlights the concept of resiliency in details and review the state-of-the-art related to our contribution.

RESILIENCE IN WIRELESS NETWORKS

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3.1 Introduction

IN this chapter, we will start by reviewing the notion of resilience, the history of the term and its related domains such as dependability and robustness. Next, we will develop the concept of the resilience found in the literature. Afterwards, we will highlight our approach of resilience, and how it will be tackled in our thesis. Finally, we will provide an overview of the State of the Art regarding the three axes of research identified in this thesis.

3.2 Resilience Definition and Taxonomy

3.2.1 Definition and General Overview

The term "resilience" was introduced first into the English language in the 17th century and it comes from the Latin verb *resilire*, that means to "rebound" or "recoil" [61]. The initial use of this term was recorded in the early 19th century by Robert Mallet that used it to measure and compare the strength of materials that appeared in the construction of the Royal Navy. He defined - the modulus of resilience - a measure that captures the ability of a material to withstand and recover its shape or form after being subjected to pressure, stress, or deformation. Later on, this concept was adopted in various disciplines, including psychology, ecology, engineering, and social sciences. It gained popularity through the psychology domain since its use in 70's to define the resilience of individuals. This refers to the psychological capacity of individuals to maintain mental and emotional well-being in face of adversity, trauma, or significant stress, and to recover and bounce back from difficult experiences. It's important to note that resilience is not the absence of stress or difficulties but rather the ability to adapt and thrive despite of them [61]. It has been further expanded to include also community resilience and organizational resilience, to examine how groups and systems can adapt and recover in the face of challenges.

This term has evolved to become a significant focus of research and practical application in various fields. Obviously, computer science and networking areas are not an exception to this rule. The term was first used in the early 90's and gained prominence in the field in 21st century, to become a central research for many systems. In line with these previous definitions, network resilience has been defined as follows:

"Network Resiliency is thought of as the ability of a network to maintain its performance and provide an acceptable level of service in the face of disruptive events¹ or threats from users perspective."

Fault-Error-Failure paradigm

The *fault-error-failure* model is central to the understanding and mastering of the various threats that may affect a system [20]. Basically, a *failure* is the observable event that happens when the level of a delivered service is less than its normal or acceptable value. The root causes of a failure are known as *faults* which are ineluctably present for whatever system. A fault may shift the internal system state from normal to erroneous situations, creating an *error*, that may lead to an observable failure by end-users. A fault is active when it causes an error, otherwise it is dormant. The faults can have different classifications into various types. Understanding this classification allows engineers to cope correctly with network challenges faced. We cite some of them as follows [102]:

- **System boundaries:** a fault can be internal or external.
- **Cause:** (i) natural (terrestrial like hurricanes, meteorological like storms, or cosmological like space debris), (ii) human made (political or social like terrorism, fires or cyber-attacks; configuration errors like bad routing tables or bad system updates), (iii) system dependency (interdependent infrastructure like cascading failure or lower level failure, example congestion).
- **Dimension:** hardware, software, traffic or protocols.
- **Domain:** medium (wired, wireless), mobility (fixed, mobile), delay (low delay, predictable delay, unpredictable delay), energy (replaceable battery or energy constrained).
- **Scope:** node, links, area (local, regional, global).
- **Significance:** minor, major, catastrophic.
- **Repetition:** single, multiple, adaptive.
- **Persistence:** permanent or transient faults.

It's important to note that the specific types and causes of failures can vary depending on the infrastructure, technologies used, and the specific environment in which the communication system operates.

1. These disruptive events can be also called challenges or changes.

3.2.2 Dependability and resilience domain

Traditionally, the analysis of networking and computer systems robustness finds its origin in the dependability domain [20]. For many years, researchers developed several methods to enrich the study of networking systems through various measures and functions in the context of dependability.

As developed over the past three decades, dependability is an old concept in computer science that has become the norm for engineers and has always been regulated with its specific terms and taxonomy. The dependability domain defines a set of attributes to measure different assets of communication systems with its related methods to enhance their robustness. The attributes contain:

- **Availability:** readiness for correct service at a specific point in the time.
- **Reliability:** continuity of correct service over a period of time or probability of providing correct service over a period of time.
- **Safety:** absence of catastrophic consequences on the users and the environment.
- **Integrity:** absence of improper system alterations.
- **Maintainability:** ability to undertake modifications and repairs.
- **Confidentiality:** is the absence of unauthorized leak of information. It is used when addressing security jointly with integrity and availability attributes. Trustworthiness term is also used to qualify a reliable system from both security and dependability point of view. A system that can be trusted to deliver services with the needed performance over a period of time [102]. It has to be noted that the terminology in the security world has its own rich history, which is out of the scope of this thesis.

Besides, dependability offers several means of achieving robust systems, including:

- **Fault prevention:** aims to prevent from the occurrence or introduction of faults.
- **Fault tolerance:** aims to avoid service failures in the presence of faults.
- **Fault removal:** is responsible for reducing the number of faults by fixing them.
- **Fault forecasting:** aims to predict the number of faults, their future incidence and consequences.

In the early days of resilience approaches in computer science, engineers have used the term of resilience to refer to fault tolerance and fault removals methods like redundancy, checkpointing, or error detection/correction techniques, to ensure system stability in the

presence of failures. Even though, dependability measures and attributes were the most used to quantify the system functional state. However, these measures and especially reliability and availability metrics, have always seen computer and communication systems from a binary perspective, assessing that either the system is working or is down. Researchers started to propose resiliency metrics to quantify the functional state of a system according to multiple levels or degrees [30]. For example, [87, 30] proposed a resilience metric for graph networks that was expressed as the number of pairs of nodes that can communicate to each other in presence of link or node failures.

Overall, the history of resilience in computer science has evolved alongside technological advancements and emerging challenges. The contemporary multilayer networks, ubiquitous systems and distributed computing has brought complexity to network management. Thus, the traditional dependability measures taken for network deployment have become insufficient to cope with today's challenges. In fact, with virtualisation, SDN and cloud-computing, adaptive measures are required to respond dynamically to the various threats that can be faced by communication systems. Since that, resilience started to get distinguished in the networking community. Resilience was generalised from the fault tolerance perspective to change or challenge tolerance. It has embraced the role of a mean to persist and maintain dependability and reliability in spite of changes and threat evolution [20, 52]. Resilience in this context expands the concept of dependability of systems, emphasizing the need to create systems that are flexible and adaptive.

To summarize what have been said on the relation of dependability with resilience: according to the Oxford dictionary dependability (or the most used term reliability) is “the quality of being trustworthy or of performing consistently well,” whereas resilience is “the capacity to recover quickly from difficulties”. It has to be noted that both dependability (or trustworthiness in general) and resilience (or challenge tolerance) participate in building and providing robust systems [102].

These last years, resilience has taken the path to be a domain on its own pushing researchers to be free to innovate. We will develop the resilience domain taxonomy before deep diving into our thesis contributions.

3.2.3 Resilience domain

Researchers have developed various taxonomies to classify and categorize different aspects and components of the concept of network resilience [102]. In what follows, we derive different axes through which resilience can be developed or understood, including:

- **Resilience dimensions:** resilience can be categorized into different dimensions or layers [101]. For example, resilience can be studied in the physical layer (hardware and infrastructure), logical layer (protocols and routing), or operational layer (management and administration). Each layer can have different aspects of network resilience to be analyzed and managed to address the vulnerabilities at each level.
- **Resilience quantification metrics:** resilience can be analysed and measured using various metrics [68]. It may include metrics related to network availability, reliability, and dependability attributes but also other newly defined metrics to characterize the resilience of a system according to multiple levels [41]. Resilience analysis and quantification is the first and crucial step for effective resilience strategy and network performance evaluation. In the networking jargon, usually it is referred as network performance analysis.
- **Resilience mechanisms:** This term designates the mechanisms and strategies used to enhance network resilience. For example, fault detection and recovery, redundancy, or security measures are one of the techniques used to enhance the network resilience. These mechanisms can be classified into various categories based on specific network requirements. In the networking domain, these mechanisms are widely known as network management techniques highlighted in Chapter 2 in Section 2.5.
- **Resilience strategies:** a strategy is needed to enhance the network resilience according to specific operators need. It helps to undertake different approaches and plan effective strategies based on network requirements and constraints [46]. It may include an end-to-end strategy that starts by analysing and quantifying network resilience and then applying resilience mechanism, or it may include only the resilience enhancement mechanism. These strategies can be applied in different manners:
 - **Reactive resilience:** Traditional resilience strategy follows reactive approaches activated in a post-failure phase, that firstly detect the anomaly occurrence and, secondly, react with the appropriate repairing or healing mechanisms. This strategy can engender high outage time and longer service interruption for the special case of cell outages like Sleeping Cells (SCs). However, this strategy is widely used in the RAN domains nowadays. The State of the Art focus more on adaptive solution based on ML and RL online algorithms.
 - **Proactive resilience:** This strategy includes pre-event activities. It existed before by doing preventive actions like redundancy, or replication, and planned

maintenance to avoid failure occurrence. More recently, adaptive measures like dynamic rerouting or **COC** or self-planing, are means to enable adaptability within the network. Recent proactive resilience focuses more on observing the historical data of system abnormal events before specifying how to handle and plan for, or how to reduce effects of future disturbances. Real-time data analytics with **ML** techniques are the most prominent capabilities to enable adaptive effective risk planing. Adaptive measures can be released after failure has been fully repaired and the stress event has finished. This strategy aims to reduce the outage time and limit service interruption. Figure 3.1 illustrates how resilience can modify current systems.

- **Resilience evaluation:** the strategy of network resilience adopted can be evaluated through simulation, modeling, or experimental approaches [101]. The evaluation methods can be categorized based on multiple factors like network scale, type of failures performance metrics, or evaluation tools used. Resilience evaluation assesses not only the technical aspects of resilience but also the practicality and real-world challenges that may be encountered when implementing resilience strategies and mechanisms.

This taxonomy helps to organize the complex and interconnected aspects of network resilience found in the literature, and broke the misunderstanding between various terminologies such as dependability, fault tolerance, resilience and network management. It will further help us in our thesis to propose a structured framework that analyzes, designs and evaluates the network resilience strategy and solutions.

3.3 Network resilience and network management: thesis goal

The **RAN** resilience is relatively a new axe of research. On the one hand, most **RAN** resilience enhancement techniques are done under the concept of network management (see Chapter 2). Most of these techniques aim to optimize and manage each network function individually, to provide enhanced services. On the other hand, when it comes to quantifying the resilience of a wireless network, **RAN** network performance analysis and reliability quantification are two spread concepts widely used to tackle these disruptive events. In reality, there is a lack of proactive resiliency management that involves quanti-

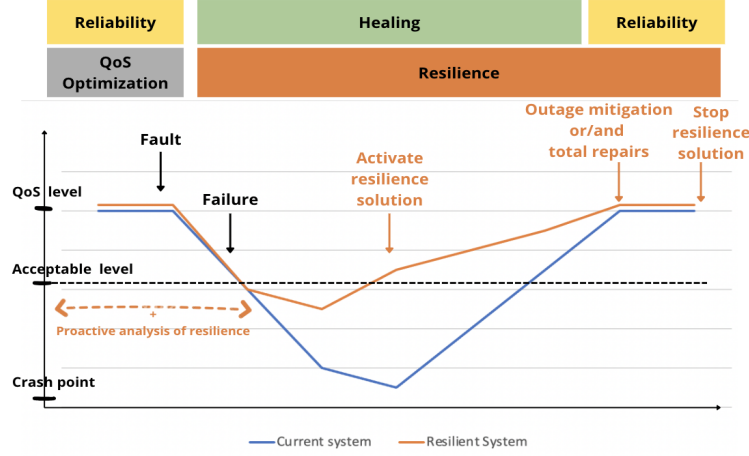


Figure 3.1 – Proposed graph on the resilience impact on current and future systems: Unveiling the context of Resilience, Quality of Service (QoS) Optimization, Healing, and Reliability, inspired from [85].

Explanation: This Figure depicts the impact of integrating resilience into current systems on network performance dynamics. It highlights the relationship between resilience and reliability, healing, and QoS optimization. Optimization primarily enhances QoS in normal network conditions, while reliability focuses on maximizing system uptime and may include preventive measures to prevent failures. Healing addresses system failures by performing total repairs to restore the initial state. Resilience encompasses a broader scope, considering the system's state before, during, and after a failure. It prepares the system to handle failures, aiming to mitigate outages and quickly restore service to an acceptable level after failure events.

fying resilience beforehand and implementing enhancements techniques to improve these quantified resilience measures. In this thesis, we aim to provide an end-to-end resilience strategy within the 5G RAN for the sake of enabling effective management tools. We assume that in the future, service or network providers, or operators, will need to define the network resilience requirements in SLA contracts based on target attributes. This implies a clear vision of 5G network resilience inputs and outputs, and of how to manage it quantitatively [68]. Basically, this work falls into resilience and risk management domains of mobile network infrastructure. We will address the following aspects:

1. Resilience analysis through network performance analysis based on performance indicators and modeling techniques.
2. Resilience enhancement from the viewpoint of network reconfiguration for outage mitigation using DRL techniques.
3. Resilience practicality evaluation in face of real network challenges, particularly ad-

addressing the data scarcity challenge for data-driven solutions in enabling autonomous RAN management.

In what follows, we will highlight the related work of each contribution.

3.4 Research axes: State of the Art

In this section, we will list the State of the Art of each contribution developed in this thesis. We start first by listing various approaches used in resilience analysis, ranging from dependability to modeling, and potentially the ones incorporating the use of performance indicators for resilience quantification. Then, we explore the outage mitigation mechanisms proposed in SON: healing, redundancy and compensation techniques. We finish by going through the main techniques that tackle the scarcity of the data in the telecommunication industry, with a particular emphasis on generative models utilized for generating radio data and their integration in environment sensing applications.

3.4.1 Network performance analysis and resilience quantification

The analysis of mobile networks allows engineers to characterize the system behaviour, and to quantify the resilience using suitable metrics [41]. Frequently, the resilience of systems is analyzed using historical data and providing resilience measurements using quantitative methods. Quantifying system resilience is more complex than what imply simple dependability attributes like reliability [104], but it is always a matter of degree [41], and for sure system resilience is typically not measurable on a single ordinal scale [41]. In fact, an early work in this area [75], defined resilience in terms of disconnection probability in network graphs or in terms of the number of nodes that can communicate. A more recent work in wired networks has focused on collecting system and context information such as alarms or weather information to respond to challenges based on a control loop [101]. In RAN, there is no common and well-defined resilience metrics non analysis methods but there has been works on RAN resiliency quantification. For instance [38], has focused on assessing resilience for site deployment. In this thesis, we extend this concept to manage resilience in RAN with a proactive strategy, during service delivery and based on real time data collection.

Analysing resilience in **RAN** is related to the analysis of services quality over the network. The **QoS** is characterized by multiple **KPIs** like good coverage and capacity, low latency, high throughput, availability, etc [45]. Therefore, to obtain an accurate measurement of global service resilience, it is important to integrate all main **KPIs** in the definition of resilience. To limit complexity and cost of resilience investigation, we adopt a sub-optimal approach that consists of decomposing the initial complex problem into multiple simpler and easier sub-problems. Thus, as a primary approach, we analyze resilience under the scope of coverage and **QoS** metrics, that is, the main network performance indicators. Coverage is an initial prerequisite and one of the main network performance indicators that an operator considers when commercializing cellular communication networks due to its direct impact on service [83]. For **3GPP**, the **QoS** is determined by multiple categories (accessibility, integrity, etc), where each one contains multiple indicators. In [104], the authors proposed a definition of availability, resilience and reliability in the **RAN** domain. Resilience has been expressed as an integral of availability of hardware and radio resources for service, over a period of time. Others propose to extract resilience metrics directly from data and express them in terms of reliability or availability. However, the methods proposed are not flexible and reproducible because they require to store data to recompute the metrics. Furthermore, they quantify resilience only at time t without prediction.

In the literature, modeling is a widely used tool to characterize the behaviour of repairable systems. For instance, **CTMCs** were used in [34], to capture high level status of **BS**, namely optimal, sub-optimal and outage states. Then, they extract reliability metrics from the model. Through a fault prediction framework, they analyse the transient and steady state probability distributions of 3 study cases to predict network status. However, the reported model captures only high-level features of many categories of failure events affecting a **BS**, and neglects the complex cellular network environments. Besides, they don't check in practice, the status with **KPIs**.

Unlike previous work, we propose specifying the modeling of coverage and service states using **CTMCs** instead of considering all types of performance disruptions on **BSs** at once [34]. We consider radio data when modelling the network coverage and service, to reflect as much as possible the reality of the radio environment in the proactive analysis. We then adapt existing measures and define new ones to quantify resilience in terms of coverage and throughput. We use simulation to evaluate our proposed resilience analysis based on **CTMCs**. This analysis method is reproducible because it requires to store only

the model to recompute the metrics, and can be combined with failure mitigation mechanisms (e.g., **COC**) using our proposed framework in Chapter 4. We sum up the following research questions of the first contribution with its added value in Table 3.1, compared to some existing works on resilience analysis in wireless communication.

Research Questions

- How can we analyse quantitatively the resilience of a 5G RAN and beyond based on data collection ?
- How can we manage the resilience automatically within the RAN ?

Reference	Modeling	Resilience Quantification	Radio KPIs	Prediction	Resilience Framework	Evaluation on Simulators
[Suryaprakash and Malanchini, 2016]	✗	✓	✓	✗	✗	✓
[Smith et al., 2011]	✗	✓	✗	✗	✓	✓
[Griffith et al., 2015]	✗	✓	✓	✗	✗	✓
[Sterbenz et al., 2010]	✗	✓	✗	✗	✓	✓
[Farooq et al., 2015]	✓	✗	✗	✓	✓	✗
Our 1st contribution	✓	✓	✓	✓	✓	✓

Table 3.1 – The value added of our first contribution.

3.4.2 Resilience enhancement techniques

Cell outage management is an essential aspect of resilience management that is widely studied in **SON**, in the context of both **COD** and **COC** [16]. An outage can occur due to various reasons such as power failure, disasters, big congestion, and sleeping cell problems. However, detecting the cause of an outage and performing healing mechanisms on it can be a time-consuming task and requires human interventions. For that reason, rapid responses through outage compensation for mitigation in various scenarios are needed to ensure service delivery to users from the user's perspective [57] and enhance the resilience of the network. In the literature, even though significant work has been done in the area of diagnosis and anomaly detection in troubleshooting [92], outage compensation has not been deeply investigated for the **5G-RAN** from an experimental approach due to the complex nature of the **RAN** infrastructure and its associated resource constraints. Technically, in a **RAN**, each **BS** is assigned to serve a specific area, with little or no redundancy [69]. In the literature, one potential approach for cell outage management is deploying multiple Unmanned Aerial Vehicles (**UAVs**) to mitigate outage by covering

coverage and capacity gaps during failures [94]. However, UAV's deployment is usually costly and time-consuming. Another commonly used approach is to adjust antenna neighbouring cell site parameters by activating compensation methods in RAN [57, 58, 22]. For instance, the antenna electrical tilting is a widely adopted technique for enhancing cell coverage and capacity, allowing remote and automatic reconfiguration for network operator engineers [18]. Most of these techniques mainly aim to mitigate the impact of a cell outage by re-configuring the antenna parameters at each neighbour cell area of the outage BS through local coverage and capacity optimization. The issue of optimizing the coverage and capacity in wireless cellular networks has already been addressed in the literature via off-line optimization approaches [98, 33]. Specifically, coverage and capacity are optimized by appropriately tuning the pilot power, antenna tilt and azimuth. While off-line optimization methods may provide valuable insights, it is important to develop methods that adjust involved parameters on-line and in real-time. This is particularly critical with the proliferation of small cell deployments in UDNs, which has increased the complexity of outage management [70]. In addition, various approaches considered single-objective optimization (e.g., coverage), whereas it has been shown that multiple-objectives optimization (e.g., a combination between coverage and service quality or interference reduction) is needed for an efficient performance optimization [32].

With the advancement of ML, data driven solutions have gained interest in wireless networks for its advantages in learning complex patterns from data. Specifically, DRL can autonomously learn optimal decision-making policies, thereby enabling adaptive network management strategies in dynamic and complex environments. Recent studies [69, 118, 74, 100], used DRL for tuning antenna tilt, with either beamforming or transmit power in downlink. However, the majority of the COC methods come with a centralized approach involving an outage at one BS while requesting the reconfiguration of only neighbouring sites. Besides, these methods often use local optimizations to scale to large network deployments. Moreover, these approaches may not address the potential problems of multiple BS outages, especially when outage BSs are geographically co-located. Another reason why the conventional approaches based on local optimization may struggle to achieve optimal outage mitigation is the impact on the neighbouring sites and compensating BSs that is not taken into account in previous works. This impact was studied in [23] by observing degraded metrics on the neighbouring cells without providing effective solutions to reduce it during the compensation.

Given the aforementioned issues, we believe that performing a global optimization

on the entire network zone can overcome these issues. As such, our second contribution addresses the problem of resilience enhancement based on overall network performance objectives in a multi-cell environment. By leveraging the power of **DRL** algorithms, we can efficiently address the global optimization and handle the complexity of emerging wireless networks, thereby dynamically adapting and optimizing network resilience in real-time. Specifically, we propose to train a multi-agent **DRL** across an entire network zone. The algorithm will try to optimize the global network performance in terms of coverage and service indicators from the user's perspective by adjusting both the antenna tilt and the transmitted antenna power in the downlink of all cells operating in the considered network service area. In [26], the multi-agent **DRL** was proposed to optimize coverage and capacity in RAN, however, it was not proposed in the context of outage compensation and resilience optimization. In Chapter 5, we develop our novel solution of multi-agent **DRL** approach for resilience that optimize the total user throughput as well as both the coverage and service availability for enhancing the network resilience. For that, a multi-objective optimization problem is formulated in Chapter 5 and deployed within a distributed setting of small cell **UDNs**, assuming that outage occurs when the network performance is below the resiliency requirements developed in the first contribution of Chapter 4. We validate the effectiveness of our proposed approach on a standardized simulator using propagation formulas and standardized path loss of small cells deployment in **UDNs**. This contribution is developed in the context of enabling an end-to-end resilience management strategy. Specifically, it links the resiliency analysis with its optimization within a network area, it enables the activation of an automated resilience management strategy. This strategy dynamically adapts the network to face various outage scenarios, following the targeted needs of network operators as it is illustrated in Chapter 4 and 5. We sum up the following research questions of the second contribution with its added value in Table 3.2, compared to some existing works on coverage and capacity optimization as well as **COC** methods.

Research Questions

- How to mitigate cell outage in large scale and dense networks ?
- How to link resilience analysis with its optimization within targeted network zones ?
- Is it possible to reduce outage impact of neighbouring cells while ensuring resiliency constraints ?

Reference	Multi-agent DRL or Large Scale Optimization	Outage Mitigation	Tunning Multiple Parameters	Standardized Propagation Environment	Multi Objective Optimization
[Onireti et al., 2016]	X	✓	✓	X	X
[M.Amirijoo et al., 2011]	X	✓	✓	✓	X
[Yang et al., 2019]	X	✓	X	✓	X
[Moysen and Giupponi, 2014]	X	✓	✓	X	X
[Moghaddam and Razavizadeh, 2017]	X	X	✓	X	X
[Iwamoto et al., 2023]	X	✓	X	X	X
[Dreifuerst et al., 2021]	X	X	✓	✓	✓
[Sivaraj et al., 2015]	X	✓	✓	✓	X
[Bouton et al., 2023]	✓	X	✓	✓	X
Our 2nd contribution	✓	✓	✓	✓	✓

Table 3.2 – The value added of our second contribution.

3.4.3 Data-driven solutions in face of real-networks challenges: data scarcity

Data-driven solutions are the center of attention in moving automation for future of cellular networks, especially for **RAN** performance analysis, optimization, as well as troubleshooting and resilience management. To achieve zero-touch automation and ensure efficient network management in future networks, these techniques rely on big amounts of training data. Consequently, the success of data driven solutions is limited by a fundamental challenge faced by cellular network research community: scarcity of training data [80]. In the literature, solutions referred to as Data Augmentation techniques have been investigated to expand limited dataset [59]. The generative model is a well-known method of data augmentation that has the advantage of directly learning the statistical characteristics of source data in an unsupervised way. It ensures the generation of additional data to take advantage of big data capabilities and thus, to improve the accuracy of **ML** models. [96, 88] have recently demonstrated the effectiveness of **GAN** and **VAE** in overcoming the problems associated with limited dataset in many domains such as image analysis, natural language processing or positioning applications. In [86] deep generative models are used for positioning applications in indoor/outdoor situations based on cell ID and Received Signal Strength (RSS) to train **ML** algorithms. [56] proposes an improved **GAN** based on the Wasserstein distance and a gradient penalty to generate fake anomaly samples and improve anomaly detection accuracy. Other **GAN**-based approaches in cellular networks contexts include the use of **GANs** to address the imbalance data issue in cell outage detection [120]. Unlike **GANs**, that operates using implicit density estimation, other generative methods like **VAEs**, belong to the explicit density category. **VAEs** were used in [119] to handle labeled training data scarcity problem for anomaly detection use-

cases in RAN. In the cases of severely imbalanced datasets, traditional ML techniques will struggle to efficiently classify anomalies from normal data. Other solutions exist to tackle the data scarcity issue. We refer the reader to [80], for further information about interpolation, domain-knowledge based solutions, transfer learning, Meta-learning as well as simulators and testbeds. Unlike most of related works that rely on original data to augment the source dataset with synthetic data and increase the accuracy, we are interested in exploring the possibility of training ML models on only synthetic data (generated by generative models) to avoid carrying the original source data but rather the generative model only. This solution will allow the network to overcome the cost issues and heavy constraints of collecting, storing and sharing data by rather transferring the generative model only between network nodes.

In particular, the challenge of data scarcity presents obstacles for tasks in network performance analysis that rely on extensive data collection, such as modeling the network using time series data over an extended period (as the contribution in Chapter 4). In practice, other use cases can be affected by the scarcity of data problem such as anomaly detection and various classification algorithms. Regarding the unavailability of real failure data from operators, and to explore the efficiency of synthetic data generation in classification algorithms, we rely on an alternative use case involving environment sensing. As highlighted in Chapter 1, the user behavior and its environment can impact the network performance. In fact, performing environment detection (i.e., environment sensing) can successfully mirror the network status. For example, the case of user Indoor-Outdoor Detection (IOD) was explored in [50] using data-driven solutions to provide a more accurate user localization within its environment. This new sensing capability inside the network can augment the efficiency of wireless network operations, in terms of better Quality of Experience (QoE) [82] or accurate user localisation detection [62], and slice selection to switch from a slice with more flexible resources to a resilient one [77]. The next generation of positioning systems has to perform well both indoors and outdoors. For that reason, the availability of sufficient data is mandatory for an accurate environment detection. In the literature, [86, 97] propose the usage of data augmentation techniques for positioning applications in environment detection based on indoor/outdoor situations, to train ML algorithms with both real data and augmented data. [97] investigates simple data augmentation techniques (e.g. translation, rotation, etc.) based on electronic fingerprints of access points positions and captured Received Signal Strength Indication (RSSIs) on a target area. In Chapter 6, we will further investigate whether a synthetic training dataset

generated using well-known generative models can yield the same results for environment sensing case as using an original real dataset without compromising the sensing accuracy. Unlike related works that focus mainly on data augmentation to increase accuracy of classification algorithms, we will explore instead, the possibility of replacing the real collected data with synthetic data, to overcome storage and data transfer issues. For that, we will use different generative models to generate two 3GPP radio features and perform IOD on these synthetic data. To ensure an efficient representation of real data, we evaluate the quality of the generated data with various metrics and validate their classification capabilities using real use cases, like IOD. We sum up the following research questions of the third contribution with its added value in Table 3.3, comparing it to some closely related works on data augmentation in wireless communication.

Research Questions

- How can we overcome the data scarcity challenge in radio environments ? - Is it possible to do accurate classification tasks in RAN based on ML/DL algorithms in a context of lack/absence of data sharing ?

Reference	Classification of Synthetic Data Only	Generative DL	Learn 3GPP Data Distribution	Data Generation Framework	Evaluate Data Quality
[Njima et al., 2021]	X	✓	✓	✓	X
[Qureshi et al., 2020]	X	X	✓	✓	X
[Sivakumar et al., 2023]	✓	✓	X	✓	X
[Sinha et al., 2019]	X	X	✓	✓	X
[Njima et al., 2021]	X	✓	X	X	X
[Rizk et al., 2019]	X	✓	✓	✓	X
Our 3rd contribution	✓	✓	✓	✓	✓

Table 3.3 – The value added of our third contribution.

3.5 Conclusion

This chapter provides a detailed taxonomy of the resilience domain, dependability and its relation with network management. It also over-views the State of the Art of the research axes that we identified in this thesis, which are network performance analysis

and resilience quantification, resilience optimization and enhancement techniques within **5G-RAN** based on data-driven solutions and lastly, tackling the practicality evaluation within a real network in face of the challenge of the scarcity of data. It has to be noted that the lack of 5G Standalone deployments is the major drawback for research. This leads to a difficult collection of information, including datasets, and promotes the use of simulators for this purpose. The next chapter will target the first contribution namely, measuring and analysing resilience based on network performance indicators and modeling techniques.

MEASURING AND ANALYSING RESILIENCE BASED ON NETWORK PERFORMANCE INDICATORS AND MODELING TECHNIQUES

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4.1 Introduction

As stated previously, we propose modelling using CTMCs for coverage and service states of a given serving area containing multiple BSs. Markov chains are a powerful tool widely used in repairable systems study. It is based on stochastic processes allowing to predict network status and characterizing system behaviour. It is composed of states and transitions between these states. The models will serve to analyse the network resilience, extract relevant metrics to define new measures of resilience or adapt existing ones to quantify the resilience levels in terms of coverage and service. First, we will present the network analysis use case with the related architecture. Then, we develop and detail our proposed approach. Finally, we discuss the experimental setup based on models' validations and network status prediction with our proposed resilience metrics. For that we relied on the related work highlighted in Section 3.4.1 to develop this contribution. We summarize the main contributions of the resilience analysis based on radio KPIs developed in this chapter as follows:

- Propose a quantification method for resilience analysis based on CTMCs modeling tool and using radio KPIs to model coverage and service status of a 5G-RAN serving area.
- Validate the effectiveness of our proposed approach on a 3GPP standardized simulator, on which the numerical results show that the Markov chains succeed in capturing the overall network characteristics and predict its average behaviour in short or mid-term.
- Propose an automatic framework that analyzes, optimizes and evaluates the resilience management of the access network in virtualized cellular environments.

4.2 5G-RAN system architecture and performance indicator description

4.2.1 5G architecture and Key Performance Indicators (KPIs) for resilience

We consider a 5G network comprising multiple BSs with macro cells and a large number of small cells. Such network deploys an architecture with large small cells and handles

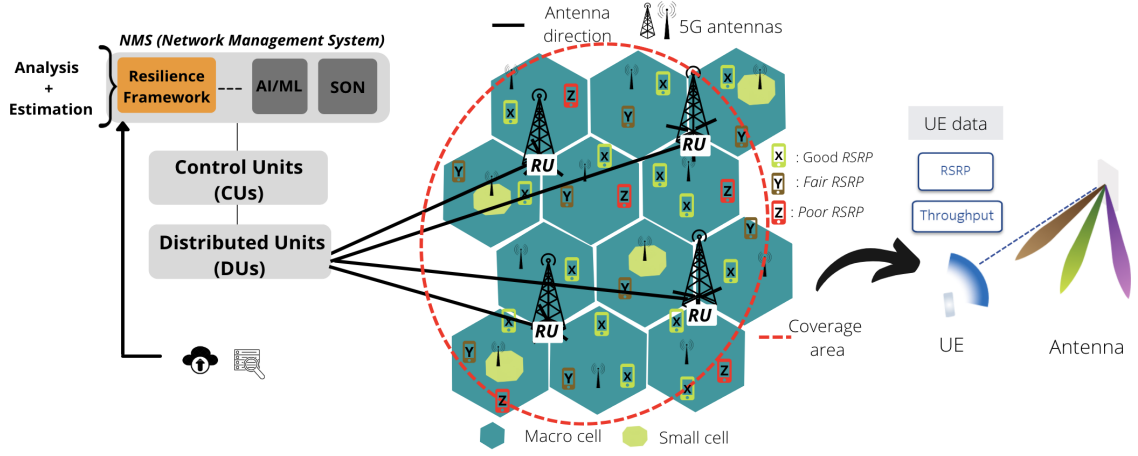


Figure 4.1 – Considered coverage area and architecture of 5G cellular sites.

multiple heterogeneous devices. UEs are connected to RRH or RUs, which send information to the 5G network via the DU and then to the CU (see Figure 4.1). The management plane of the radio system is executed by the NMS. This module can integrate our proposed resilience management framework. Depicted in Figure 4.2, the proposed framework gives an overview of how the proactive resilience can be supported in 5G-RAN or in future cellular network architectures. It can be applied on demand to enhance the resilience of a group of cells, a geographical area or a slice. It comprises two principle modules. A first module responsible for the analysis of resilience. Using network performance indicators, the analysis module allows predicting network state, outages and quantifying their impacts. The second estimator module uses the results of the resilience analysis to perform decision making on what type of adaptive resilience mechanisms to activate. The framework works using data collected from BSs and stores all the relevant information needed for the process into a resilience knowledge base. To allow efficient coordination between all the modules, a resilience manager entity is responsible for controlling the entire process. The framework will be further discussed to demonstrate its usability in enhancing the resilience of network services. The purpose of this contribution is to provide a method for the analysis module while the techniques that can be used in the estimator module is left for the second contribution.

A geographical area is considered as covered when the UE is able to connect to its mobile network, establishing and maintaining a session for a minimum period of time, achieve a specific data transmission speed, and access different services. We consider radio data and performance indicators when modelling the network coverage and service, to reflect as

much as possible the reality of the radio environment in the proactive analysis. On the one hand, the **UE** connection to network requires to receive a signal strength from **BS** above an acceptable threshold. On the other hand, to maintain a good connection and access a service, the **UE** should achieve a specific data transmission speed (i.e., throughput or data rate) over the connection established. In urban areas, the **UE** can be covered simultaneously from multiple **gNBs** to reduce coverage related-failures. But, rural areas have sparse deployments where no or rare overlapping coverage is available so coverage problems are more frequent. In both cases, coverage degradation or loss can still be observed within a geographical area, as a consequence service can be also disturbed.

As a first step towards the global network resilience analysis, we consider analyzing a specific aspects that are coverage and service integrity. Coverage is one of the key factors that an operator considers when commercializing cellular communication networks due to its direct impact on service [83] and service integrity is an important indicator for high data rate services like **eMBB**.

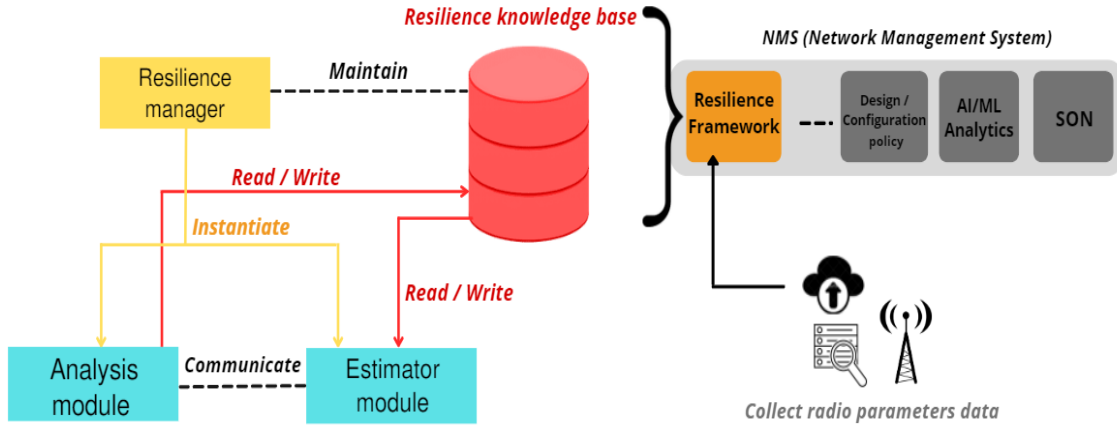


Figure 4.2 – Proposed **RAN** Resilience Framework.

4.2.2 Coverage analysis

For 5G, the Channel State Information (**CSI**) - **RSRP** is a valuable layer 1 measurement to provide information about the signal strength received by users within a service area. It is defined as a linear average over the power contributions (in Watts) of a single Reference Signal (**RS**) resource element (in dBm) [10]. The measures lie between -140 dBm and -44 dBm and give a good idea about the radio coverage experienced by users.

In our work, we assume a coverage area in which a set of phone users are distributed uniformly. The number of users within the area is considered static. In real applications it may correspond to a constant traffic during a fixed period of time where the number of users vary slowly. Under the hypothesis of static traffic and uniform distribution of users, we split users into 3 categories according to their levels of **RSRP**. Figure 4.1 shows in the **5G** cellular architecture the positions of each category users in terms of **RSRP** level that can be observed over a coverage area.

Let us denote by $x = x(t)$, $y = y(t)$ and $z = z(t)$ the percentage of users that has *Good*, *Fair*, *Poor* levels of **RSRP** respectively at specific time t . The traffic is considered static and the sum of all percentages is equal to 100%. We investigate 2 configurations of **RSRP** levels (C1 & C2). Table 4.1 shows the radio RF conditions of **RSRP** values in both cases 1 & 2. The first type corresponds to a network configuration that serves basic services with minimal requirements in terms of coverage, whereas the second one corresponds to a network configuration that serves critical services with higher requirements in terms of coverage, and thus higher **RSRP** value boundaries.

RF Conditions	Classification	(1) RSRP (dBm)	(2) RSRP (dBm)
	Good (or excellent)	-90 to -44	-80 to -44
	Fair (Mid cell)	-126 to -91	-100 to -81
	Poor (Cell Edge)	-140 to -127	-140 to -101

Table 4.1 – Radio Frequency (RF) condition configurations (**RSRP**).

4.2.3 Service analysis

In addition to signal strength for coverage analysis, we consider the received data rate (i.e. user throughput) in modelling network states to assess the service quality as a first step, since it is a crucial indicator to check the integrity of **eMBB** data services [9]. In fact, the service integrity is measured by the throughput and latency metrics that contribute to **QoS**. Since the **CN** induces more latency than the RAN, we consider only the received user throughput for service integrity, for our **5G-RAN** performance analysis, and leave the latency consideration for future work.

Throughput (in Kbps) is a valuable **KPI** to obtain information about **QoS** of the user session. The throughput depends on the transmission channel bandwidth and quality, and the amount of radio Resource Blocks (**RBs**) allocated [9]. Let us denote by D the

requested data rate for a given service, and by Th the throughput achieved per UE. Let $d = d(t)$ be the percentage of users receiving at least the requested data rate.

4.3 Resilience analysis and quantification methodology

In our work, both RSRP and Th data will be investigated in the definition of Markov models, to assess the network states and quantify the network resilience. We summarize the analysis methodology as follows:

- (A) Definition of a Markov model (states and transitions) based on coverage and service performance indicators.
- (B) Prediction of outage occurrence while computing transient and steady state probability distributions.
- (C) Quantification and analysis of system resilience using resiliency metrics to characterize the behaviour of coverage and service status within a service area.

4.3.1 Model developments

We propose two CTMCs models to represent the different network states of L 5G cells in a given geographical area. Let $X_{RSRP}(t)$ and $X_{Th}(t)$ be the CTMCs models that capture radio coverage and service integrity states using RSRP and Th of all users, respectively. Both models have 5 states with full transitions. Due to their similarities, we define the generic CTMCs model $X(t)$ (see Figure 4.3) with finite state space $S = \{G = \text{“Good”}, F = \text{“Fine”}, A = \text{“Acceptable”}, P = \text{“Poor”}, O = \text{“Outage”}\}$. We call G, A and O the “main states” and F and P the “intermediate states”. This classification allows having a fine grained observation for a better anticipation of outages. The states are defined differently for each indicator as follows:

Coverage model

We define each state in terms of the tuple (x, y, z) previously described within the coverage area of a gNB. We set out to 5% the admissible percentage of users, that receive an RSRP below the threshold associated with poor RSRP. The model considers the radio system to be resilient when the majority of users within a service area enjoy a

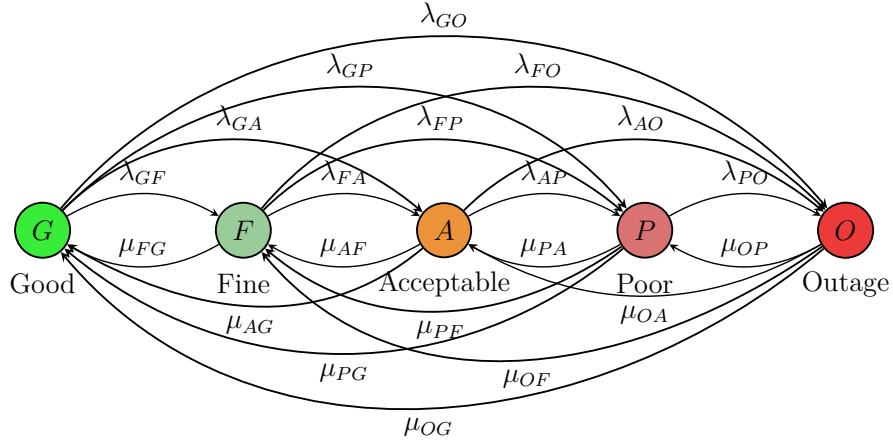


Figure 4.3 – Markov model of coverage and/or service status.

minimum acceptable coverage threshold specified with **RSRP** levels given in Table 4.1. This implies that the operator network should guarantee a minimal radio coverage of 95% to be resilient. This is directly inspired from assumptions of mobile network radio planning [64]. Thus the states definition:

1. $X_{RSRP}(t) = G$ for “Good” if $x > y$, $x \geq z$, $x > y + z$ and if the percentage of users with poor **RSRP** verifies $z < 5\%$.
2. $X_{RSRP}(t) = F$ for “Fine” if $x > y$, $x \geq z$ and the percentage of users with poor **RSRP** verifies $z < 5\%$ but $x \leq y + z$.
3. $X_{RSRP}(t) = A$ for “Acceptable” if $y > x$, $y \geq z$ and the percentage of users with poor **RSRP** verifies $0 \leq z < 4\%$.
4. $X_{RSRP}(t) = P$ for “Poor” if $y > x$, $y \geq z$ and the users percentage with poor **RSRP** verifies $4 \leq z < 5\%$.
5. $X_{RSRP}(t) = O$ for “Outage” if the percentage of users having poor **RSRP** verifies $z \geq 5\%$.

This means that cells carry traffic with best (resp. fine, acceptable) performances in state G (resp. F, A). In P , they carry some traffic, but with poor performance, and in O , the coverage is at least severely degraded, and possibly with no traffic carried. The reader can verify that all states are fulfilled by the tuple (x, y, z) where all percentage sum is 100%, and the coverage status of the service area can only have one state at a time. Depending on which **RSRP** levels will be considered between C1 or C2 as shown in Table 4.1, the user percentages x, y , and z , having *Good*, *Fair*, and *Poor* received

signal strength respectively, will depend on the **RSRP** value boundaries defined. Thus, the network states that will be observed will differ from one type to another.

Service model

We define each state in terms of users' percentage d that receives at least the requested data rate D , namely $Th \geq D$. The states are defined as follows:

1. $X_{Th}(t) = G$ for “Good” if $d \geq 80\%$.
2. $X_{Th}(t) = F$ for “Fair” if $65\% \leq d < 80\%$
3. $X_{Th}(t) = A$ for “Acceptable” if $50\% \leq d < 65\%$.
4. $X_{Th}(t) = P$ for “Poor” if $30\% \leq d < 50\%$.
5. $X_{Th}(t) = O$ for “Outage” if $d < 30\%$.

Models properties: We use the generic model $X(t)$ for describing both $X_{RSRP}(t)$ and $X_{Th}(t)$. In the proposed Markov models, we classify transitions into failure transitions with rates λ_* and recovery transitions with rates μ_* . The former are perturbations that can degrade the status of coverage or service (e.g., interference, sleeping cells, disasters) and the latter restore the coverage or service to optimal states (e.g., coverage enhancement techniques, self-healing, redundancy, compensation or mitigation functions, etc). The infinitesimal generator matrix $\mathbf{Q}$ of $X(t)$ is:

$$\mathbf{Q} = \begin{pmatrix} -\alpha & \lambda_{GF} & \lambda_{GA} & \lambda_{GP} & \lambda_{GO} \\ \mu_{FG} & -\beta & \lambda_{FA} & \lambda_{FP} & \lambda_{FO} \\ \mu_{AG} & \mu_{AF} & -\gamma & \lambda_{AP} & \lambda_{AO} \\ \mu_{PG} & \mu_{PF} & \mu_{PA} & -\delta & \lambda_{PO} \\ \mu_{OG} & \mu_{OF} & \mu_{OA} & \mu_{OP} & -\theta \end{pmatrix} \text{ where } \begin{cases} \alpha = \lambda_{GF} + \lambda_{GA} + \lambda_{GP} + \lambda_{GO}, \\ \beta = \mu_{FG} + \lambda_{FA} + \lambda_{FP} + \lambda_{FO}, \\ \gamma = \mu_{AG} + \mu_{AF} + \lambda_{AP} + \lambda_{AO}, \\ \delta = \mu_{PG} + \mu_{PF} + \mu_{PA} + \lambda_{PO}, \\ \theta = \mu_{OG} + \mu_{OF} + \mu_{OA} + \mu_{OP}. \end{cases} \quad (4.1)$$

In the following, the transient and the steady state distribution equations are deduced from the model in order to compute state probabilities, to predict the network status and to define resilience metrics.

4.3.2 Markov chain analysis

Compute failure and recovery transitions

To compute the transition rates, we retrieve data logs of **RSRP** and Th of all users within a service area from the network (in our work from a simulation run). Using the

data logs and the states definition, we compute a time series of multiple network states history (a model's trajectory) of coverage or service indicators. Then, the transitions λ_* (or μ_*) from state i to another state j are estimated as follows:

$$\lambda_{ij} = \frac{P_{ij}}{T_i} \quad \text{where} \quad P_{ij} = \frac{n_{ij}}{\sum_k n_{ik}}. \quad (4.2)$$

where, T_i is the total time spent in state i and P_{ij} is the probability to switch from a state i to another state j , estimated computing the ratio between the number n_{ij} of transitions that switch from state i to state j , respectively, and the total number of transitions that exit the state i .

Markov model validation

To check if the model reflects the input system behaviour and captures the underlying characteristics of data logs and network states, we compare the distributions and the statistical characteristics of the network states delivered from data logs with the states sequences generated and computed from the CTMCs. The comparison of the distributions is done using the similarity distance measure Kullback-Leibler Divergence (KLD), D_{KL} [25]. It is expressed as an entropy between two probability distributions $p(x)$ and $q(x)$:

$$D_{KL} (p(x) || q(x)) = \sum_{x \in X} p(x) \ln \frac{p(x)}{q(x)}. \quad (4.3)$$

Moreover, we compute the statistical characteristics of the network states sequences using two reliability known metrics: Mean Time To Repair (MTTR) and Mean Time To Failure (MTTF) [34]. The former is expressed as the sum of all downtime (i.e., time spent in outage state) over the total number of failures in Eq. (4.4), and the latter is measured as the sum of all uptime (i.e., time spent in operational states) frames over the total number of uptime periods (see Eq. (4.5)). In practice, these metrics are estimated using a standard confidence interval. We choose a confidence interval of 95%.

$$MTTR = \frac{\sum_{i=1}^n \text{downtime}(i)}{n}. \quad (4.4)$$

$$MTTF = \frac{\sum_{i=1}^n \text{uptime}(i)}{n}. \quad (4.5)$$

Transient and steady state analysis

Transient state analysis: Using the generator matrix $\mathbf{Q}$, the dynamic behaviour of the resilient CTMCs model can be described by the Kolmogorov differential equation $P'(t) = P(t) \cdot \mathbf{Q}$ where $P(t) = (P_G(t), P_F(t), P_A(t), P_P(t), P_O(t))$ (so, $\sum_{i \in S} P_i(t) = 1$). The transient state probability vector $P(t)$ of the resilient model can be obtained by solving the Ordinary Differential Equation (ODE) system $P'(t) = P(t) \times Q$ described as follows:

$$\begin{cases} P'_G(t) = -\alpha P_G(t) + \mu_{FG} P_F(t) + \mu_{AG} P_A(t) + \mu_{PG} P_P(t) + \mu_{OG} P_O(t), \\ P'_F(t) = \lambda_{GF} P_G(t) - \beta P_F(t) + \mu_{AF} P_A(t) + \mu_{PF} P_P(t) + \mu_{OF} P_O(t), \\ P'_A(t) = \lambda_{GA} P_G(t) + \lambda_{FA} P_F(t) - \gamma P_A(t) + \mu_{PA} P_P(t) + \mu_{OA} P_O(t), \\ P'_P(t) = \lambda_{GP} P_G(t) + \lambda_{FP} P_F(t) + \lambda_{AP} P_A(t) - \delta P_P(t) + \mu_{OP} P_O(t), \\ P'_O(t) = \lambda_{GO} P_G(t) + \lambda_{FO} P_F(t) + \lambda_{AO} P_A(t) + \lambda_{PO} P_P(t) - \theta P_O(t). \end{cases} \quad (4.6)$$

Steady state analysis: The steady state distribution reflects the behaviour of the system in the long run. It requires to solve the linear equation system $\pi \cdot \mathbf{Q} = 0$ where $\pi = (\pi_G, \pi_F, \pi_A, \pi_P, \pi_O)$, plus the normalization condition $\sum_{i \in S} \pi_i = 1$. The linear system is:

$$\begin{cases} -\alpha \pi_G(t) + \mu_{FG} \pi_F(t) + \mu_{AG} \pi_A(t) + \mu_{PG} \pi_P(t) + \mu_{OG} \pi_O(t) = 0, \\ \lambda_{GF} \pi_G(t) - \beta \pi_F(t) + \mu_{AF} \pi_A(t) + \mu_{PF} \pi_P(t) + \mu_{OF} \pi_O(t) = 0, \\ \lambda_{GA} \pi_G(t) + \lambda_{FA} \pi_F(t) - \gamma \pi_A(t) + \mu_{PA} \pi_P(t) + \mu_{OA} \pi_O(t) = 0, \\ \lambda_{GP} \pi_G(t) + \lambda_{FP} \pi_F(t) + \lambda_{AP} \pi_A(t) - \delta \pi_P(t) + \mu_{OP} \pi_O(t) = 0, \\ P'_O(t) = \lambda_{GO} \pi_G(t) + \lambda_{FO} \pi_F(t) + \lambda_{AO} \pi_A(t) + \lambda_{PO} \pi_P(t) - \theta \pi_O(t) = 0. \end{cases} \quad (4.7)$$

4.3.3 Resilience quantification

The problem of quantifying system resilience has been elusive [41]. There is a lack of standardization in resilience quantification, especially in the RAN domain, and many researchers are coming up with their own definitions of resilience metrics. System resilience is more complex than what implies simple dependability attributes like reliability. It is not a simple Boolean function, it is always a matter of degree, and, for sure, system resilience is typically not measurable on a single ordinal scale. We think of resilience metrics as an attribute different from the other reliability or survivability metrics. For a proactive resilience analysis, we investigate metrics that enable an estimation of future changes in

the network (see below part (1)). In fact, we propose two stochastic metrics that quantify the resilience level. They allow to measure the distance between the estimated coverage and service status and the targeted minimal requirements. Below in part (2), we propose a metric that assesses how the network can “bounce back” to a normal state via various resilience mechanisms. We refer it as a score of resilience. So, it is a measurement of the improvement in terms of resilience brought by resilience mechanisms.

(1) We propose two different metrics to quantify and estimate the evolution of network resilience within a geographical zone or a service area at the levels of:

- Radio coverage, using the Markov model transient state probabilities $P(t)$ of $X_{RSRP}(t)$
- Service integrity, using the Markov model transient state probabilities $P(t)$ of $X_{Th}(t)$.
- **Radio coverage:** We define the resilience metric *Global Stochastic Mean RSRP* (GSMR), denoted $\mathcal{M}(t)$, as the mean value of RSRP medians at time t [48]:

$$\begin{aligned} \mathcal{M}(t) = & med_{G_{RSRP}}(t) \cdot P_G(t) + med_{F_{RSRP}}(t) \cdot P_F(t) + med_{A_{RSRP}}(t) \cdot P_A(t) \\ & + med_{P_{RSRP}}(t) \cdot P_P(t) + med_{O_{RSRP}}(t) \cdot P_O(t). \end{aligned} \quad (4.8)$$

where, the value of $med_{i_{RSRP}}(t)$, where $i \in S$, is the RSRP median over all UEs distributed between tuple percentage (x, y, z) at each state i , observed between 0 and t . These percentages are associated with RSRP medians of Good, Fair and Poor levels described in Table 4.1. Thus, for each state i , $med_{i_{RSRP}}(t) = med_{Good_{RSRP}}(t) \cdot x + med_{Fair_{RSRP}}(t) \cdot y + med_{Poor_{RSRP}}(t) \cdot z$ and $P_i(t)$ are the state probabilities. In practice, it is preferable to look at lower and upper average bounds of $\mathcal{M}(t)$ where (x, y, z) takes respectively, the lowest and highest percentages at each state configuration. They are extracted directly from the states definition (e.g., at 'G', $\max(x, y, z) = (1, 0, 0)$ and $\min(x, y, z) \approx (0.5, 0.45, 0.05)$).

– **Service integrity:** Based on [104], we propose a resilience metric that measures the network probability of providing at least an acceptable service integrity state over a given period T_c . In other words, where the majority of UEs receives an average throughput greater than the requested data rate D for a given service. It is referred as the *Probability of Achieving the Requested Throughput* (PART) and is expressed as:

$$\mathcal{PR}_{T_c}(t) = \frac{1}{T_c} \int_{t-T_c/2}^{t+T_c/2} \sum_{i \in S_R} \mathbb{P}_i(t) dt, \quad (4.9)$$

where T_c is a sliding period considered to track the requested throughput availability D using Th of all users, and S_R is the set of states $\{G, F, A\}$ where $d \geq 50\%$.

(2) Quantifying the gain that might be brought by a network integrating a resilient mechanism:

- We denote the resilience value by $RM_Res(t)$ when the network integrates resilient mechanisms and by $NRM_Res(t)$ when there is no resilient mechanisms. We define the metric of resilient score as the ratio between the resilience level between RM and NRM cases. The score inspired from a previous work in [41], is given in Eq. (4.10):

$$Res_score(t) = \frac{RM_Res(t)}{NRM_Res(t)}. \quad (4.10)$$

We note that, this metric is general but in this work, $RM_Res(t)$ and $NRM_Res(t)$ will be computed using Eq. (4.8) in Watt scale.

Remark about methodology and resilience metrics

1) Once the transition rates in the model are available, the analyst can answer “what if” questions and evaluate any kind of metric, even those that will be defined “tomorrow”. For instance, consider, as a performance criteria, the time spent at the set of main states $\{G, A\}$. Call τ that random variable, assuming the model starts at G . Standard Markov properties give us the queue of the distribution of τ (a kind of reliability at time t metric), or its average. As an illustration, the expectation $\text{Exp}(\tau)$ is:

$$\text{Exp}(\tau) = \frac{\lambda_{GF} + \lambda_{GP} + \lambda_{GO} + \lambda_{AF} + \lambda_{AP} + \mu_{AO}}{(\lambda_{GF} + \lambda_{GA} + \lambda_{GP} + \lambda_{GO})(\mu_{AG} + \mu_{AF} + \lambda_{AP} + \lambda_{AO}) - \lambda_{GA} \cdot \mu_{AG}}, \quad (4.11)$$

where the λ and μ parameters are the outgoing transition rates of states $\{G, A\}$ defined in matrix $\mathbf{Q}$. The same can be done if we look at the subset of states $\{G, F, A\}$, or if we are interested in other more complex metrics.

2) For sure, other resilience metrics can also be defined to enrich the analysis. Our work fits a first step of the whole resilience vision. In future work, another category of metrics enriched with multiple QoS indicators as interference, mobility or latency will be considered. Their inclusion is more appropriate to ensure an accurate global resilience measurement and to enhance risk management during decision making of resilience mechanisms solutions.

4.4 Resilience management scheme

As stated before in Section 4.2, a resilience management scheme can be deployed to enhance RAN resilience within a control loop via a data-based and an automated

framework located at **NMS** level in **5G** (see Figure 4.2). We provide a snapshot of how the resilience framework can be executed in the case of coverage and service resilience management. The Figure 4.4 shows that the framework starts with:

- The analysis module learning the transient rates (λ, μ) , using statistical analysis from past failure logs to build the Markov models. These estimated rates will be used to analyse the transient and steady state distribution, in order to predict the network status and quantify current and future resilience levels with for example the proposed metrics such as GSMR, PART, **MTTF**, and **MTTR**. This module can also be extended to integrate other forecasting methods such as predictive **ML** methods along with anomaly detection methods for accurate network performance analysis.
- Based on the output of the analysis and the resilience metrics, some scripts containing instructions can be prepared to activate adaptive resilience mechanisms to restore coverage and service in the area, such as modifying dynamically antenna tilt or transmit power of neighboring cells for outage compensation [57] (see Chapter 5). The estimator module is driven by the operators' resilience policy, to take the right decisions on which resilient mechanism to activate and at what time. The estimator can use intelligent decision algorithms like regression or **RL**. Both modules run in background and in real time, and can communicate with each other. The historical data, model, transient rates, policies and scripts are stored into a database (Figure 4.2).
- Finally, the resilience process is evaluated with real-time metrics to validate the accuracy of the estimation process.

Moreover, a resilience manager will serve to instantiate the modules, coordinate their communication and control the process. In this module, we can specify for example the coverage and service thresholds that an operator is targeting to satisfy, as well as all the service requirements specified in the **SLA**. Furthermore, the manager module is responsible for making decisions on the resilience management strategy. For example, it can decide if the strategy can be executed proactively or reactively, on a specific area (e.g., indoor or outdoor), at a specific slice, or at a specific geographical zone. The pipeline is executed within a life cycle. In the **O-RAN** architecture, the **RIC** module can be considered to integrate all the **DL** and intelligent techniques to use all the useful interfaces in the Open **RAN** dedicated for analysis and optimization through data collection.

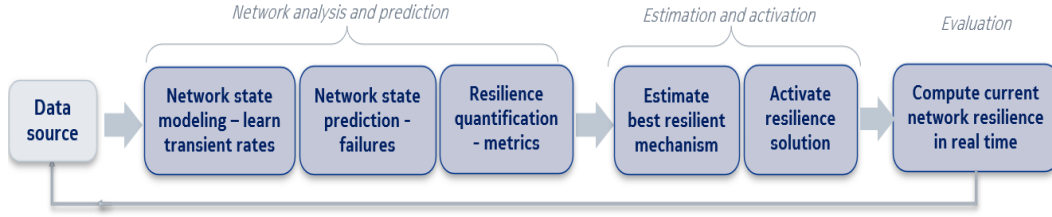


Figure 4.4 – Resilience analysis and estimation steps within the resilience Framework.

4.5 Performance evaluation

In this section, we will evaluate numerically our resilience analysis strategy detailed in Section 4.3 on two realistic simulation scenarios that contain failures. The simulations are done using the SONTTool simulator [110], a Nokia simulator developed and maintained up-to-date on Matlab. The downlink principles of the simulator are presented in [110] and uplink modeling aspects in [109]. We track coverage and service states evolution based on data logs of measured **RSRP** and Th of all users. Tracking is done over a given area covering 21 cells and during 7 days. For each scenario and using the **CTMCs** defined in Section 4.3.1, we compute the transition rates of the coverage and service models over the 6 first days of the data logs using Eq. (4.2). Following the analysis detailed in Section 4.3.2, we solve the ODE system to obtain state probabilities $P(t)$. Then, we validate the Markov models. Finally, we discuss the results about the prediction of the network resilience using the metrics given in Section 4.3.3. To this end, we compare the resilience metric GSMR that estimates the evolution of mean **RSRP** with the mean **RSRP** measured on the 7th day from data logs. In addition, the resilience metric PART will be compared to the *asymptotic availability* of the requested throughput D for users measured on the 7th day of simulation logs, to assess the correctness of the prediction. The PART metric gives insights about the availability of the requested throughput for the majority of users within a service area. Finally, the $Res_score(t)$ metric will be used to quantify the improvement in resilience coverage when integrating a resilience solution to an existent non resilient network, in case of basic or critical network services.

4.5.1 Experimental setup

(A) Layout, scenarios and network states: We consider a regular hexagonal network layout with the configuration described in Table 4.2. A total of 1000 **UEs** are uniformly dropped into the whole area. We track the evolution of measured **RSRP** and

Th for UEs moving in the network during 7 days with SONTTool simulator. We collect their traces with a granularity of a 20s time-step for two scenarios, $S1$ and $S2$. $S1$ corresponds to a network configuration where outage is more likely to occur and persists for hours. $S2$ is more resilient: outage may occur, but the network can recover quickly. Failures are simulated using random tuning of antenna sites transmit power (TxPower, $P0$).

Parameter	Value	Parameter	Value
Network type	Hexagonal	Indoor/Outdoor users number	800 / 200
Number of cells	21	Indoor users speed	3-10 KM/h
Inter site distance	200 m	Outdoor users speed	40 Km/h
Number of users	1000	UEs Requested data rate (D)	512 Kbps

Table 4.2 – Network configuration on simulator.

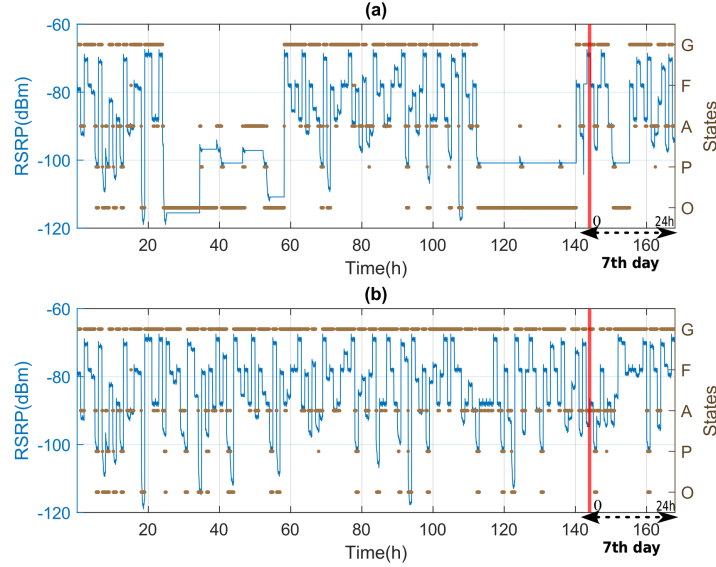
Figure 4.5 – Evolution of average RSRP generated by the simulator and its corresponding radio coverage states sequences: (a) $S1$, (b) $S2$.

Figure 4.5 and Figure 4.6 depict the evolution of average RSRP and Th . In $S1$, the network is subject to two major failures over a longer time period (around 40h and 120h), whereas $S2$ is subject to multiple down-times over shorter periods. In the figures, failure occurrences correspond to poor overall RSRP or Th levels, and their duration includes the time taken to detect, analyse and repair the outage. The RSRP levels used by default in this experimental section are the one defined in classification C1, showed in Table 4.1. Further, we won't denote which classification is used, except for Figure 4.10, where we will explicitly mention C1 & C2, to provide service level comparison discussion. Using the

CTMCs states definition in Section 4.3.1, we compute the sequences of average network states each 5 time steps for both radio coverage and service integrity. They are given in Figure 4.5 and Figure 4.6 for S1 and S2, and we refer to them as the original state sequences. In each scenario, the coverage state can differ a bit from the service state (e.g., in S1, at 50h, RSRP state is 'A' vs. Th state is 'F'). In fact, outages may have different impact on performance indicators. Thus, studying different indicators helps engineers assessing the overall network resilience according to operator policy. Moreover, to visualise what is happening on the network layout, we show in Figure 4.7 some snapshots of coverage maps of multiple radio coverage states based on RSRP values.

4.5.2 Transitions computation and Markov models validation

The network states time series of the 6 first days are used to compute failure and recovery transitions (λ_*, μ_*) of S1 & S2 using Eq. (4.2). Some transitions between two states may not be observed and their rates are set to 0. Then, we obtain the 5 states probabilities $P(t)$ for each of the four Markov models (S1, S2) $\times$ (RSRP, Th), by solving their corresponding ODE systems. For solving the equations, we assume that the network state condition starts at best state 'G'. Before analysing the resilience of the network, we first check if the CTMCs capture accurately the behaviour of the network. To do so, we generate 10 times 6 days of network states sequences evolution using the computed $P(t)$

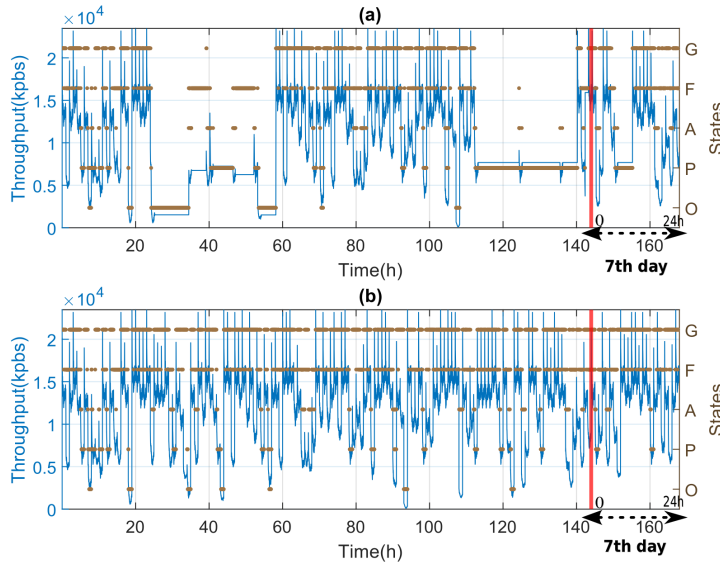


Figure 4.6 – Evolution of average throughput generated by the simulator and its corresponding service integrity states sequences: (a) S1, (b) S2.

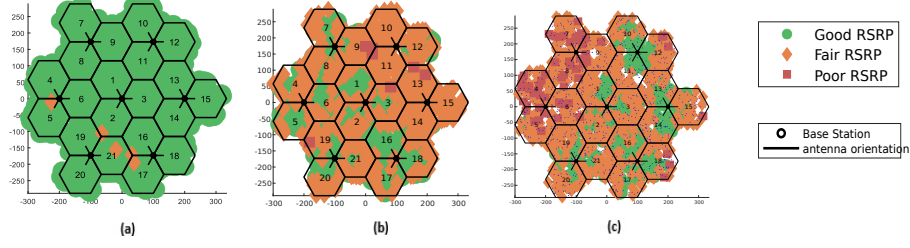


Figure 4.7 – Snapshots of radio Coverage maps based on **UE RSRP** values from left to right: (a) Good, (b) Acceptable, (c) Outage.

and extract their average statistical characteristics. To this end, we compute the **MTTR** and the **MTTF** of Eq. (4.4), on original states delivered from simulations and on the generated states computed from the **CTMCs**. The results are given in Table 4.3 for each metric with a confidence level 95%. The one-to-one comparison of each metric reveals that **MTTR** and **MTTF** are similar between the original and generated states sequences. It also indicates that **MTTR** confirms that S2 is more resilient than S1 (i.e., less than 1h vs. 2h average outage duration, respectively). Besides, we derive in Table 4.3 the **KLD** between the distribution of the original states sequences and the distribution of the generated states sequences, $D_{KL}(original, generated)$ in Eq. (4.3). The low value of this metric indicates high similarity between the distributions. From the comparison of these basic metrics, we illustrate that the **CTMCs** are producing valid output information that corresponds to the behaviour of the network original data input, which is a preliminary validation for the **CTMCs**-based resilience quantification.

Original x 6 days	Scenario 1		Scenario 2	
Metric / Indicators	Coverage	Service	Coverage	Service
MTTF (Hours) $\pm$	3.36 $\pm$ 1.9	2.93 $\pm$ 1.9	4.70 $\pm$ 2.3	5.08 $\pm$ 2.9
MTTR (Hours) $\pm$	2.75 $\pm$ 1.8	2.10 $\pm$ 1.4	0.65 $\pm$ 0.2	0.70 $\pm$ 0.3
Generated 10 x 6 days	Scenario 1		Scenario 2	
	Coverage	Service	Coverage	Service
MTTF (Hours) $\pm$	3.67 $\pm$ 1.9	3.18 $\pm$ 2.2	4.63 $\pm$ 2.1	5.35 $\pm$ 2.7
MTTR (Hours) $\pm$	2.78 $\pm$ 1.3	2.09 $\pm$ 0.8	0.62 $\pm$ 0.4	0.68 $\pm$ 0.4
KLD	0.002	0.005	0.003	0.005

Table 4.3 – Network states characteristics comparison.

4.5.3 Experimental results: prediction of network status

(a) **Quantitative outage estimation:** The states probabilities $P(t)$ allow to quantify the risk of outage at time t and predict the network states. Figure 4.8 shows the evolution of coverage states probabilities for S1 and S2. The curve predicts that S1 has

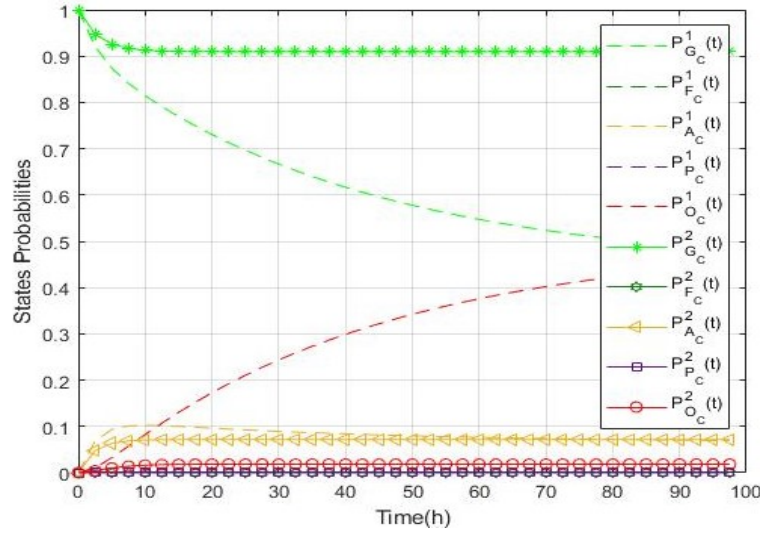


Figure 4.8 – Evolution of radio coverage states probabilities (S1, S2): $P_{i_C}^1$ and $P_{i_C}^2$ stand for probability of state $i \in S$ of coverage indicator in S1 and in S2 scenarios, respectively.

higher outage risk (40-45%) compared to S2 (2-3%) after 3 days. At the same time, S2 has better chances to provide good coverage state than S1 since the probability of good coverage state $P_G(t)$ in S2 drops to $\sim 90\%$, where in S1 $P_G(t)$ drops to $\sim 50\%$ after 3 days. Besides, Figure 4.9 shows coverage vs. service states probabilities evolution for S1. The evolution for coverage and service states probabilities for the same scenario is different. There are more chances to observe the intermediate states 'Fine' $P_F(t)$ and 'Poor' $P_P(t)$ in service states than in coverage states. Besides, the outage risks after 3 days are higher for coverage than for service states. The engineer can conclude that outage on antennas (failure scenario considered in this work), has more impact on coverage **RSRP** than on service integrity Th . The same conclusions are driven for S2. Besides, we note that the service level considered by engineers has an impact of modeling the network states. In fact, we have defined earlier 2 possible classifications of **RSRP** levels detailed in Table 4.1. To illustrate this impact, we consider the data collected in scenario 2 (S2) and plot the evolution of coverage probability states in case of C1 and C2 classification of **RSRP** levels respectively, in Figure 4.10. The Figure shows that network state evolutions are worst in case of C2 than C1. In fact the outage state probability can achieve 40% in case of C2 while in C1 it remains around 1-5%, and the good coverage state probability decreases till 90% in C1, while in C2 it may reach 45%. If we suppose that the data in scenario S2 correspond to critical services being delivered (e.g., Vehicle-to-Vehicle communication), the performances of the network in terms of coverage are no longer satisfied if the operator

considers using **RSRP** classification 2 (C2). In other words, the network performance is degraded in the case of classification 2 despite having the same **RSRP** data. Thus, the operator needs to align his service policy and its critical levels with the correct inputs levels of the resilience analysis to obtain valid outcomes. This offers the flexibility for engineers to modify the Markov model definition and levels on demand along with the evolution of the specific needs of the operator.

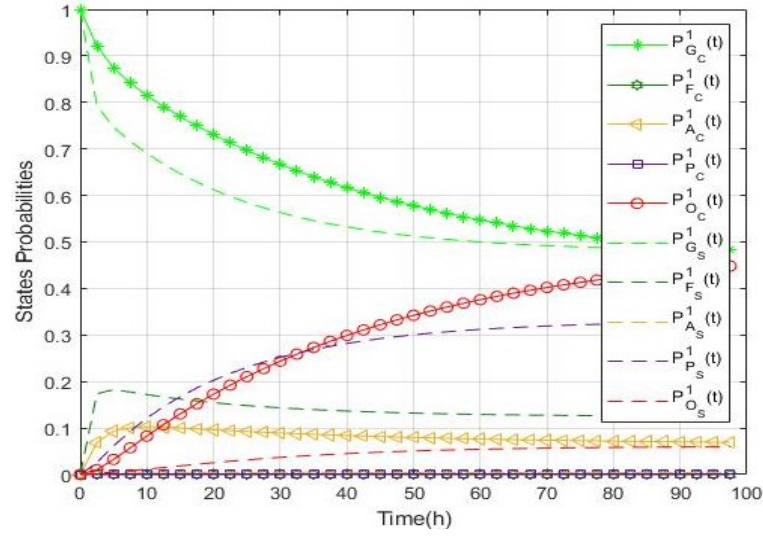


Figure 4.9 – Evolution of coverage vs. service states probabilities (S1): $P_{i_C}^1$ and $P_{i_S}^1$ stand for probability of state $i \in S$ of coverage and service indicators, respectively in S1 scenario.

(b) Network resiliency prediction: To get better insights on the network resilience, engineers can rely on meaningful resilience metrics (expressed in Eq. (4.9) and in Eq. (4.8) instead of states probabilities. In fact, Figure 4.11 shows the evolution of resilience metrics GSMR from Eq. (4.8) (shaded areas) and PART from Eq. (4.9) (lines). The GSMR helps to identify the potential range where the value of mean **RSRP** is likely to evolve. These stochastic average bounds are given as indicators and not as absolute maximum and minimum values. In Figure 4.11, we observe that in S1, the GSMR may drop to -95 dBm 12h later. We compare it to the mean **RSRP** measured at 12h on the 7th day from **RSRP** data logs. Indeed, this measurement is taken at 156h in Figure 4.5.(a), precisely at 12h after the 6 first days. We observe that, at this time and for S1, the mean measured **RSRP** drops to -100 dBm. For S2, the GSMR may drop to -92 dBm after 20 h. Similarly, when looking on the 7th day of simulation scenario and at 20h after the 6 first days, namely at 164h in Figure 4.5.(b), we observe that, at this time, the mean measured **RSRP** drops to -90 dBm. We note that, at 16h after the 6 first days, precisely at 160h in Figure 4.5.(b),

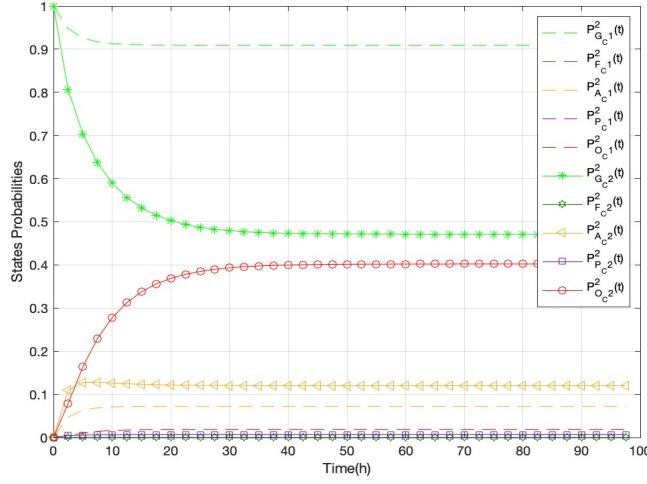


Figure 4.10 – Evolution of coverage states probabilities (S2): $P_{i_{C1}}^2$ and $P_{i_{C2}}^2$ stand for probability of state $i \in S$ of coverage indicator, respectively in the S2 scenario.

the mean measured **RSRP** is equal to -100 dBm, which is slightly lower than the value given by GSMR that predicts -95 dBm at the same time.

The second metric PART gives insights about the availability of the requested data rate D for at least 50% of users during a sliding period of 24h. We take the value of PART metric at $t=24h$, where it drops to 73% for S1 and to 97% for S2. This prediction is compared with

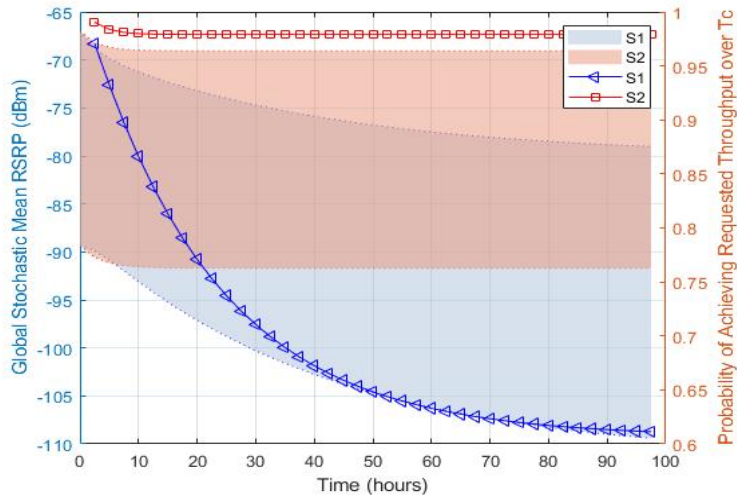


Figure 4.11 – Estimation of GSMR lower and upper bounds (shaded area) and PART metric (line) over a period of 24h in S1 (blue) and S2 (red) scenarios.

the *asymptotic availability* of the requested throughput D , for at least 50% of simulated users measured on the last day. This metric corresponds to the frequency of occurrences of the set of network service states $\{G, F, A\}$. The measured *asymptotic availability* is equal to 73% and 95% for S1 and S2, respectively. Therefore, GSMR and PART metrics help engineers to get a good estimation on the network resilience. Depending on the starting state, the analysis can, of course, output different resilience level values.

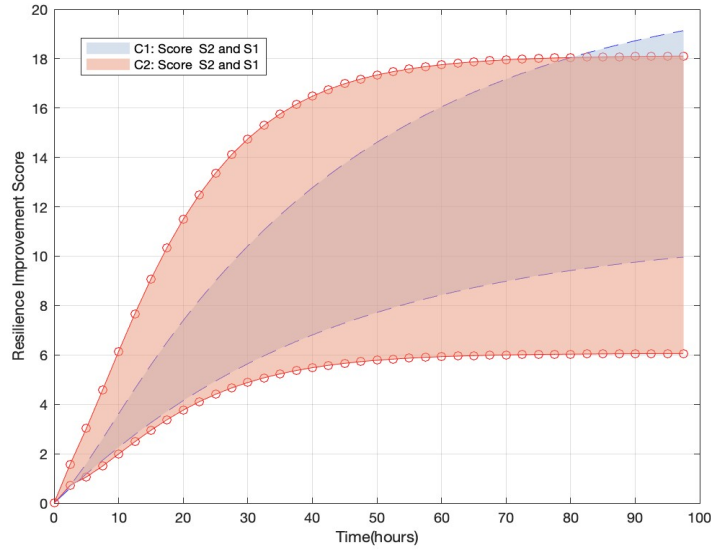


Figure 4.12 – Estimation of resilience improvement score $\text{Res_score}(t)$ in both classification C1 (blue) and C2 (red), when considering integrating the resilience solution of S2 in S1 network.

(c) Resilience improvement score: Considering that scenario S1 represents a network with no resilience solution and that scenario S2 represents a network with a resilience solution, we suppose that an operator would like to implement the solution of resilience deployed in network scenario S2, in the network scenario S1. The intuitive process is to estimate the improvement score that would be brought by this solution. To do that, we rely on the resilience metric $\text{Res_score}(t)$ defined in Eq. (4.10). We compute this score metric based on the *GSMR* metric computed for S1 and S2 previously. In Figure 4.12, we plot the estimated resilience improvement score over time $\text{Res_score}(t)$ in terms of coverage, when considering integrating the resilience solution of S2 in the network of S1 in dB scale. As stated earlier, two network categories C1 & C2 for basic network services classification and critical network services classification respectively from Table 4.1 are considered in

the computation of the resilience improvement score. We observe that the $\text{Res_score}(t)$ metric tends to increase over time and reaches an improvement of 10-20dB for basic services and 6-18dB for critical services. Thus this metric allows engineers deciding on the best decisions to make when evaluating network resilience optimization strategies. It offers a quantitative way to decide automatically on the optimal optimization solutions to be triggered and can help to evaluate and compare different networks resilience.

(d) Outcome discussion: CTMCs are a powerful tool to provide a characterization and prediction of the average network behaviour over short term delay. The operator can compare the estimated resilience metric value with a specific threshold to react on time and mitigate the outages. For instance, if there is a high risk of outage, engineers have to trigger the antenna tilt or increase its power to maintain coverage using the estimator module. More details on the actionable knowledge were provided in [48]. Coupling this approach with methods of anomaly detection or RCA can help in better decision making of the adaptive resilient mechanisms. This method requires to keep track of coverage and service indicators. No additional traffic is required because our CTMCs uses existing 3GPP radio data collected inside RAN. But, it induces to repeat the resilience computation and analysis periodically due to the stationarity property of the Markovian models. The challenge resides in storage of historical data and computational cost.

(e) Reproduce-ability of the analysis regarding KPIs reporting frequency: As previously mentioned, we collect data with a granularity of 20s time steps, each corresponds to 1s of indicators collection (i.e., intermittent collection). This choice is motivated by the limitations of the simulator's capacity and the desire for simplicity in implementation. Otherwise, executing and simulating the entire network second by second or even milliseconds for an entire week would be impractical. With this approach, we assumed that minor fluctuations occurring within seconds may not indicate a persistent issue, leading to an outage and thus focusing on observing the average behaviour of the network. This, explains the motivation for choosing a higher granularity of data collection in the simulation. However, in the context of 5G downlink communication, the 3GPP has standardized the reporting frequency of KPIs collection. The duration of a radio frame can vary depending on the sub-transport used. Typically, for sub-transport based on Orthogonal Frequency-Division Multiple Access (OFDMA), the duration of a radio frame is 10 ms [12]. If we would like to collect data for 1s, then it corresponds to having 100 time frames containing each an indicator value. We note that the analysis requires to track the network performance continuously for long periods of time. To avoid overload-

ing the network with data collection, particularly for resilience functions and network performance analysis tasks that often run in background for extended periods, a strategy involves aggregating resilience-related data over a second in the lower layers and send the aggregated information in the upper layers. This aggregation entails computing the average value of **RSRP** or Th over one second, which corresponds to averaging the values over 100 radio frames of 10 ms each. Alternatively, another approach involves executing the analysis with a 10 ms time frame while considering the constraints of data storage. The data storage limitation is explored in the third contribution of the thesis.

4.6 Conclusion

In this chapter, we presented a proactive quantitative resilience analysis for **5G-RAN** and beyond networks. The analysis uses two Markov processes for modelling network coverage and service using **RSRP** data and Throughput data respectively. Based on the Markov models, we can predict radio coverage and service integrity states, and propose metrics to quantify the level of network resilience. To show the usability of our approach, we conducted a numerical analysis through simulations in different failure scenarios. According to numerical results, the analysis can help to efficiently forecast the average behaviour of mobile network states, at the level of outages and resilience, in short or mid-term duration. Besides, quantifying network resilience with multiple metrics for each performance indicator allows to determine the impact on each indicator separately. A resilience management scheme was discussed in order to apply this approach on **5G** and beyond networks architecture. The next chapter will leverage the possible solutions for resilience optimization and network performance enhancement.

RESILIENCE OPTIMISATION BASED ON DEEP REINFORCEMENT LEARNING (DRL)

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5.1 Introduction

The network normal behaviour can be compromised by network outage events, where one or more BSs suddenly become unavailable. In order to maintain a resilient and reliable network services from user perspective, we tackle the problem of outage mitigation through adaptively reconfiguring the network in scenarios with BS outages in 5G-RAN small-cell deployments. The idea is to adapt the radio parameters of the BSs surrounding the outage area, in order to face these challenges dynamically and mitigate the impact of outages to maintain a resilient and reliable network services from users' perspective. As stated in the related work of Chapter 3 in Section 3.4.2, the majority of the COC methods come with a centralized approach involving an outage at one BS while requesting the reconfiguration of only neighbouring sites. Besides, these methods often use local optimizations to scale to large network deployments. Specifically, this setting can fail to achieve optimal outage mitigation if more than one outage occur at the BSs, and especially if the failed BSs are located close to each other or adjacent in the considered networking zone. In particular, Figure 5.1 illustrates that the local optimization approach in the case of multiple BSs outage may lead to an imbalanced compensation between the different network outage areas. The neighbouring BSs may not be completely successful in coordinating adjustments between outage areas, leading to a sub-optimal resource allocation and lower network-level performance. Another reason why the conventional approaches based on local optimization may struggle to achieve optimal outage mitigation, is the impact on the neighbouring sites and compensating BSs that is not taken into account in previous works. In addition, Figure 5.1 illustrates the case of a single BS outage that the performance of the neighbouring BSs that attempt to cover the users from the outage zone can be degraded due to an increase of cell load.

Given the aforementioned issues, we believe that performing a global optimization on the entire network zone can overcome these issues. On the one hand, it will allow us to involve farther BSs to support the direct compensating BSs (i.e., neighbouring BSs to the outage area) to absorb the impact and achieve better performance under outage. On the other hand, considering the whole network zone as a cohesive entity will automatically balance the optimization during the learning process in case of multiple BSs outages. Moreover, these approaches may not address the potential problems of multiple BS outages, especially when outage BSs are geographically co-located.

In this chapter, we will develop and detail our solution of resilience optimization, that

we summarize its main contributions as follows:

- We consider the multi-cell network area used in Section 4.5.1 and try to dynamically and intelligently optimize its resilience. In particular, we first formulate a multi-objective optimization problem to satisfy the coverage and service availability requirements and at the same time improve the service quality by maximizing the total throughput to reduce the impact of outage compensation on the compensating BSs. This is achieved by requesting the reconfiguration of not only neighbouring BSs of the outage area but also farther BS within the considered network zone to play a role in supporting the compensation (see Figure 5.1).
- Given that the formulated optimization problem is non-convex and Non-deterministic Polynomial-time hard (NP-hard), even when all parameters of the system are known in advance, implementing them in practice is not feasible. Hence, we propose a novel multi-agent DRL for optimizing the resilience of a 5G-RAN and beyond networks area using global optimization to scale to large network deployments. The distributed setting of the proposed DRL method considers the network as a cohesive entity to capture the complexity of the network and relation between cells. Specifically, we consider the joint configuration of both antenna transmit power and antenna downtilt for all the operational BSs in the considered area to ensure an optimal coverage and capacity optimization (see Figure 5.1).
- We take into account different outage scenarios in the training process to allow our proposed multi-agent DRL algorithm to face various outage situations. This addresses one of the key challenges of resilience optimization which is enhancing resilience regardless of the unpredictable nature of threats and uncertainties that networks will encounter.
- We validate the effectiveness of our proposed approach on a 3GPP standardized simulator, on which the numerical results show significant improvements in both coverage and service resilience as well as optimal service quality enhancement compared to conventional approaches. For that, realistic propagation formulas and standardized path loss of small cell deployments in UDNs were used to practically demonstrate the usability of our proposed approach.
- This work is developed in the context of enabling an end-to-end resilience management strategy. More specifically, our proposed approach is an extension to our first contribution on resilience analysis in Chapter 4. It integrates resiliency constraints extracted from the analysis results to the optimization process. By linking

resiliency analysis and its optimization within a network area, it enables the activation of an automated resilience management strategy. This strategy dynamically adapts the network to efficiently deal with various outage scenarios, following the targeted needs of network operators.

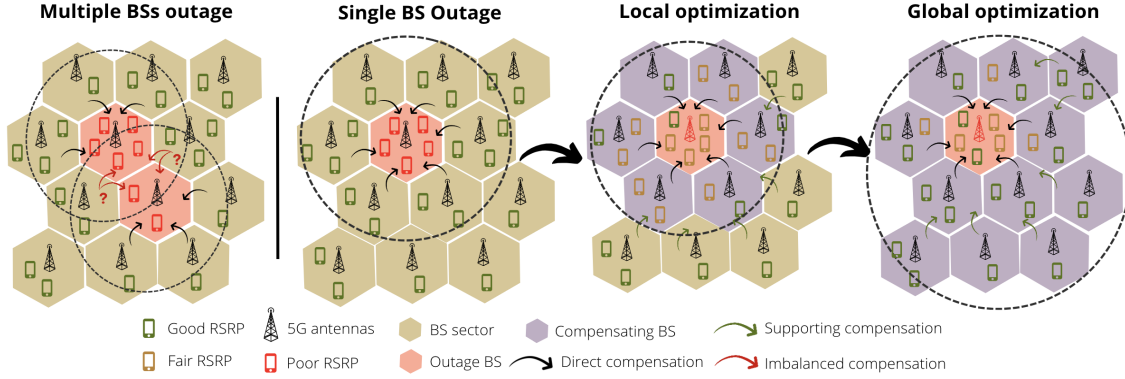


Figure 5.1 – RAN resilience local and global optimization.

5.2 System description

In this section, we present the networking system description that will be used for the resilience optimization. Then, we point out the relation between the resilience analysis and its optimization within the scope of effective management.

5.2.1 Propagation environment

We consider a mobile network service area in an urban environment served by multiple BSs. Let us assume that each BS site is equipped with three antennas, each covering one sector. From a practical perspective, this assumption corresponds to typical mobile network deployments as a BS serves users inside its sector. It is worth noting that, the term cell is used to refer to one sector in this chapter. We assume that each sector can be geometrically approximated as a hexagon, thus the network is multi-cellular and sectorized. In practice, due to inconsistent radio propagation characteristics and environment landscape, the shape of the sector is not a perfect hexagon [65].

Let M denotes the total number of cells in a given geographical area and N denotes the number of UEs in the same network area at specific time t . A UE connects to the network

through its Mobile Station (MS) or User Terminal (UT) and is served by a specific BS in the given service area. We suppose, that the j^{th} BS antenna, such that $j \in \{1, \dots, M\}$ with $M \gg 3$, transmits signal with power P_{t_j} in the network area. The signal is amplified with the gain of the BS antenna, denoted as $G_{tj}(\theta_j)$, where θ_j is the antenna downtilt. The signal propagates through the wireless channel between the j^{th} BS antenna and the i^{th} UE, with $i \in \{1, \dots, N\}$. Radio signals launched by a transmitter experience signal attenuation as they traverse through the propagation channel. This attenuation is a function of the carrier frequency, the heights of the BS and MS, the BS-MS link distance d , as well as the environment type (i.e., dense urban, suburban or rural). Path loss is a large-scale fading parameter, which determines the mean signal attenuation as a function of the BS to MS distance.

Path loss: In contrast to conventional approaches that often rely on the simplified free-space path loss model described by Friis' propagation formula for its simplicity [106], this study adopts a more realistic approach by considering a real-world network deployment scenario. Specifically, we focus on an urban environment and leverage the standardized 3GPP path loss model tailored for small cell deployments known as the Urban Micro (UMi) path loss model, as defined in the 3GPP specification TR 38.901 [3]. By utilizing this path loss, we aim to better capture the complexity of signal propagation in urban environments. This approach allows us to account for factors such as building density, street layouts, and other urban features that significantly influence signal propagation characteristics. It will provide a more accurate representation of the propagation environment, leading to more reliable and informative results for network planning and optimization.

Assuming that both the BS and MS are separated by a distance d_{2D} and d_{3D} in meters (m) in both 2D and 3D planes, respectively. A BS with height h_{BS} transmits a signal with frequency f (corresponding to wavelength λ), to the UT with a height of $1.5m \leq h_{UT} \leq 22.5m$. The correspondent Line Of Sight (LOS) path loss equations in dB scale described in [3] as follows:

$$PL_{UMi-LOS} = \begin{cases} PL1 & \text{if } 10m \leq d_{2D} \leq d'_{Bp}, \\ PL2 & \text{if } d'_{Bp} \leq d_{2D} \leq 5km, \end{cases} \quad (5.1)$$

where,

$$\begin{aligned} PL1 &= 32.4 + 21 \log_{10}(d_{3D}) + 20 \log_{10}(fc), \\ PL2 &= 32.4 + 40 \log_{10}(d_{3D}) + 20 \log_{10}(fc) \\ &\quad - 9.5 \log_{10}((d'_{Bp})^2 + (h_{BS} - h_{UT})^2). \end{aligned}$$

Here, the number d'_{Bp} is the Breakpoint (Bp) distance $d'_{Bp} = 4h'_{BS}h'_{UT}fc/c$, with the effective BS antenna and UT antenna heights are computed respectively as follows: $h'_{BS} = h_{BS} - h_e$ and $h'_{UT} = h_{UT} - h_e$. In the case of UMi environment, the effective environment height is $h_e = 1m$. Besides, fc is the carrier frequency of the transmitted signal in Hz, and the light speed $c = 3 \times 10^8 m/s$. For the sake of simplicity the non line of sight path loss equation is not showed here, but it is described in 3GPP standard [3].

Received signal: When the j^{th} BS antenna transmits a power P_{tj} , it is first amplified by the gain of the BS antenna before it faces attentions in the air interface characterized by the path loss equations PL_{UMi} , where Eq. (5.1) describes the LOS path loss formula. The received user signal strength P_r is defined as:

$$P_r = P_{tj} + G_{tj}(\theta_j) + G_r - PL_{UMi}, \quad (5.2)$$

where $G_{tj}(\theta_j)$ is the j^{th} transmit BS antenna gain expressed in dBi and θ_j is the antenna downtilt. The formula of the BS antenna gain is further described in Eq. (5.7). Besides, G_r denotes the received user antenna gain in dBi. It is usually set as 0 dB for an omnidirectional antenna like broadband patch antennas used in mobile phones since they radiate equally in all directions like an isotropic antenna (i.e., 0 dBi equivalent to 0 dB since the reference gain in 5G that is added to the antenna gain is 0 dBi to obtain the gain in dB scale). Finally PL_{UMi} is the path loss described in Eq. (5.1). A user is capable to connect to a BS cell if he receives a signal strength above the minimal threshold Pr_ϵ . This threshold is related to the antenna receiver sensitivity, and is defined in this chapter around -127 dBm as shown in Table 4.1.

Antenna radiation Pattern: In 5G BSs deployment, a 3D antenna pattern is usually used in combination with cell sectorization to exploit frequency reuse, reduce interference among users, and increase cell capacity (see Figure 5.2). In this method, each sector is served by an array of $(S \times P)$ cross polarized antennas as shown in Figure 5.3. The BS antenna is modelled by a uniform rectangular panel arrays spaced in the horizontal direction with a spacing of d_h and in the vertical direction with a spacing of d_v [3]. For the sake of simplicity, we assume having a 1 dimensional antenna vertical array panel ($P = 1$) at each cell sector. The 3D antenna pattern is typically given by a horizontal (azimuth)

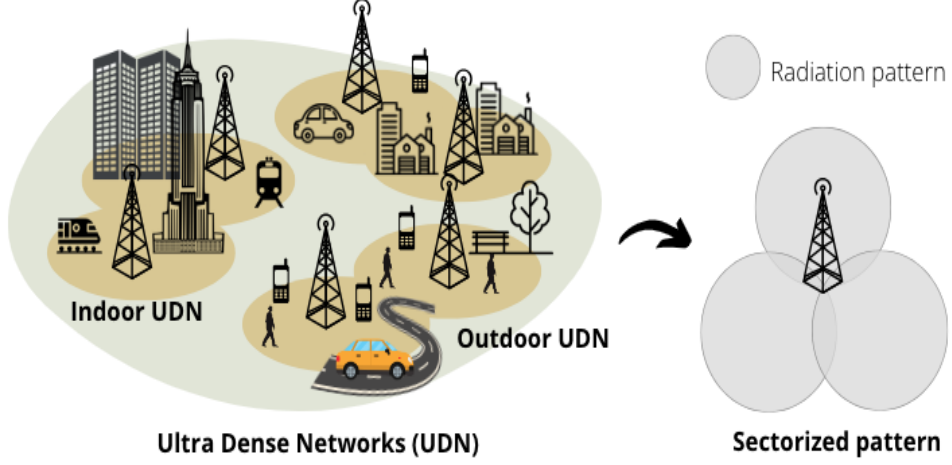


Figure 5.2 – Ultra Dense Networks (UDNs) and antenna radiation pattern.

and a vertical (elevation) cuts as shown in Figure 5.4. This extrapolation is typically used by 3GPP to approximate the real 3D pattern. We assume that user u having a height h_{UE} from the ground, is served by cell j with a height h_{BS} . Every user is connected to exactly a single BS and is served by its correspondent antenna serving cell c . The angles formed by the transmitted beam from the BS are extrapolated in Figure 5.4 in both vertical (elevation) and horizontal (azimuth) planes. Having an omnidirectional UE's antenna pattern, the angles of arrivals θ and ϕ between the BS antenna main lobe and the UT are defined by the following equations:

$$\theta = \tanh^{-1} \frac{h_{BS} - h_{UE}}{d_{2D}}, \quad (5.3)$$

$$\phi = \tanh^{-1} \phi_{user} - \phi_{BS}, \quad (5.4)$$

where d_{2D} is the distance between the BS antenna and the UT in 2D and Φ_{BS} is the azimuth orientation of the BS antenna. Typically a single BS serves three cells which has the azimuth orientations $\Phi_{BS} = \{0^\circ, 120^\circ, -120^\circ\}$ [110].

We assume having a sectorized antenna radiation pattern in the azimuth A_v and elevation A_h planes as defined in [1]. We follow the extrapolation approach in [65, 110] that sum up the two patterns to get the 3D pattern $G(\theta, \phi)$ as follows:

$$A_v(\theta) = -\min[12 \left(\frac{\theta - \theta_{tilt}}{\theta_{3dB}} \right)^2, SLL_v], \quad (5.5)$$

$$A_h(\phi) = -\min[12 \left(\frac{\phi}{\phi_{3dB}}\right)^2, SLL_h], \quad (5.6)$$

$$G(\theta, \phi) = G_{max} - [A_v(\theta) + A_h(\phi)], \quad (5.7)$$

where θ and ϕ are the angles of arrival between the BS antenna main lobe and the mobile user receiver defined in Eq. (5.3) and Eq. (5.4) in the Cartesian referential. θ_{tilt} designates the antenna downtilt angle with $\theta_{tilt} = \theta_{mtilt} + \theta_{etilt}$. The mechanical tilt is usually fixed and can be modified manually by human intervention, whereas the electrical tilt can be modified remotely by tuning the transmit signals phases [19]. When $\theta_{tilt} = 0$ the antenna points to the horizon. G_{max} is the maximum antenna element gain that is usually specified between 7-15dBi by the manufacturer. Moreover, θ_{3db} and ϕ_{3db} represent the 3dB beam-width in the elevation and azimuth planes. Finally, SLL_v and SLL_h are the azimuth and elevation side lobe levels respectively, that provide a minimum power which is leaked to the sectors other than the desired one and which have a typical value of 15 to 30 dB.

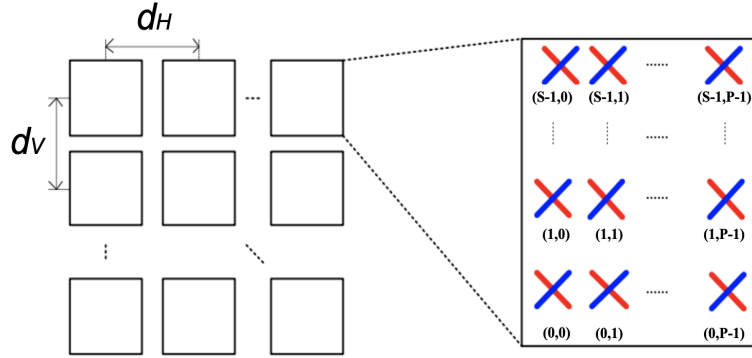


Figure 5.3 – Cross-polarized antenna panel [4].

Throughput Calculation: The data rate (i.e., user Th) with which the UE is served by a cell antenna can be expressed using the Shannon–Hartley theorem formula based on the number of Physical Resource Blocks (PRBs) allocated to the user in bits per second as follows:

$$Th = B_{PRB} \cdot \eta \cdot \log_2\left(1 + \frac{Pr}{I + n_0}\right), \quad (5.8)$$

where B_{PRB} represents the bandwidth of each PRB and η is the number of PRBs allocated to the user which is computed using the power unit of the UT device and the available number of PRBs at the BS antenna. The throughput is also computed using the

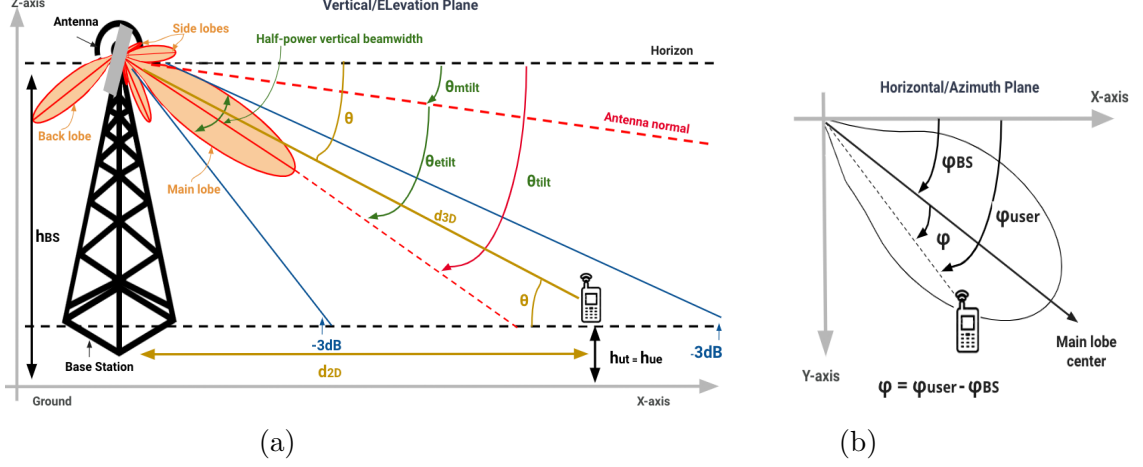


Figure 5.4 – Transmission pattern parameters: (a) Elevation plane and (b) Azimuth plane.

Shannon spectral efficiency $\log_2(1 + \frac{Pr}{I+n_0})$ where the fraction $\frac{Pr}{I+n_0}$ represents the signal-to-noise-and-interference ratio. The ratio is expressed as the factor between the received signal Pr and the thermal noise n_0 with the interference power I . The thermal noise is usually considered as the Additive White Gaussian Noise (AWGN) with $n_0 \sim N(0, \sigma^2)$ representing a Gaussian random variable with zero mean and variance σ^2 . Besides, I represents the total power of interfering signals received at the user and transmitted by the non serving cells, except the power signal received by the serving cell c , such that $I = \sum_{j \in M, j \neq c} Pr_j$ in watt scale. A condition is established on the throughput, affirming that if a user can not be covered by a BS then the user is unable to access data services. This means that when $Pr < Pr_\epsilon$ then $Th = 0$, emphasizing the role of coverage in enabling service accessibility. We summarize the parameters used in this chapter in Table 5.1.

5.2.2 Resilience analysis role in the optimization

The analysis of resilience developed in Chapter 4, has provided a quantitative way to assess the resilience level of RAN based on coverage and service performance. Using Markov chains, we were able to model the network into multiple states allowing us to represent the network status in terms of levels (i.e., from "Good", ..., "Outage" state) for both coverage and service performance (see section 4.3). Based on the Markov models, various metrics can be derived to quantify network resilience. As stated before in the

Parameter	Value
θ, ϕ	Angles of Arrivals (AoA) between BS antenna main lobe beam and the UT
θ_{tilt}	antenna downtilt in elevation pattern
$\theta_{mtilt}, \theta_{etilt}$	antenna mechanical and electrical downtilt in elevation pattern
SSL_v, SSL_h	Side Lobe levels of vertical and horizontal patterns respectively
ϕ_{BS}	Boresight angle of the antenna BS
A_v, A_h	Antenna radiation patterns in vertical (elevation) and horizontal (azimuth) planes respectively
θ_{3db}, ϕ_{3db}	Half power beamwidth of the elevation and azimuth patterns, respectively
G_{max}	Maximum gain of the BS antenna
$G(\theta, \phi)$	3D BS antenna gain
H_{BS}, H_{UT}	Heights of BS and UT from the ground
G_r	Received antenna gain of UE
PL	Path loss function
P_t	Transmit antenna signal strength in dBm scale
d_{2D}, d_{3D}	distance between antenna BS and UT in 2D and 3D respectively
d_{ij}	Distance between j^{th} antenna BS and i^{th} UT
L	Number of outage BSs
UE_i, BS_j	i^{th} UT and j^{th} antenna BS
Pr_ϵ	Minimal threshold of the received signal required to cover the user
D_ϵ	Minimal requested throughput by the user

Table 5.1 – List of all parameters throughout this chapter.

State of the Art, researchers have defined resilience metrics as the availability of network services over a given time period [49, 104]. These metrics aim to characterize the network's resilience, which is defined as the ability of a network to maintain its services and operational functionalities under failures (see Chapter 3). However, most online optimization approaches focus on enhancing the resilience at specific time instances, thereby indirectly improving resilience over the long term (i.e., over a period of time). Consequently, the conditions used to define each resilience level in X_{RSRP} and X_{Th} can serve as constraints in the optimization objective function.

We define $\hat{P}_{coverage}$ and $\hat{P}_{service}$ as coverage and service level thresholds respectively, needed for the network system to deliver a resilient behaviour at time t . Based on the states definition and the minimal coverage condition, we set $\hat{P}_{coverage} = 0.95$. This implies that the network operator should guarantee a minimal radio coverage for 95% of users to be resilient from coverage perspective. It is directly inspired from assumptions of mobile network radio planning. Following the resilience analysis in Chapter 4, we consider that the radio system is resilient from coverage perspective at time t if $X_{RSRP} = G, F, A$, or P . The coverage level threshold $\hat{P}_{coverage}$ can vary depending on the operators needs, and the definition of network states can also be customized. Besides, using the states definition and the minimal service condition, we set $\hat{P}_{service} = 0.5$. We define network resilience from service perspective as the ability of the network to fulfill the minimal throughput requirements for 50% of users. Thus, we consider that the radio system is resilient from service perspective at time t if $X_{Th} = G, F$, or A . The service level threshold $\hat{P}_{service}$ can vary depending on the operators needs, as well as the definition of network states in Chapter 4 can be customized.

By ensuring the coverage and service availability above the thresholds through optimization, we claim that the iterative process of resilience optimization at time t , contributes positively to long-term network performance, thereby improving metrics of network resilience over time period. Besides, it ensures that the optimization process takes into account the desired coverage and QoS levels under different circumstances, following a tailored and multi-objective optimization. Moreover, it offers a clear way for evaluating the resilience optimization and how the network performance of both coverage and service quality evolves under various conditions and scenarios. Therefore, aligning the resilience analysis with the resilience optimization goals, will provide an end-to-end resilience strategy. In the next section, we develop our approach on resilience optimization through multi-agent DRL.

5.3 Resilience optimization with multi-agent Deep Q-Network (DQN)

In this section, we detail our solution by giving the problem formulation of the multi-objective optimization of resilience and model it using Markov Decision Process (MDP). Then, we present the multi-agent DRL algorithm for the resilience optimization.

5.3.1 Problem formulation

We consider a service area with M BSs and N test user points defined by their coordinates, such that $UE_i \in \{(x_1, y_1), \dots, (x_N, y_N)\}$ and $BS_j \in \{(a_1, b_1), \dots, (a_M, b_M)\}$ respectively. The distance between the i^{th} user and the j^{th} BS antenna in 3D is given by $d_{ij} = \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2 + (h_{BS} - h_{UE})^2}$.

Let us assume that a subset of L BSs are in an outage state due to various reasons not considered in this study, such that $BS_O = \{BS_{o_1}, \dots, BS_{o_L}\}$ where $L < M$. We are interested in a scenario where a certain number of BSs are off, making some users to lose the connection and degrade their service. Thus, the status of the network reflects a problem within users KPIs. We tune both antenna electrical downtilt θ_{etilt} and transmit power P_t , to optimize the user KPIs that are the user throughput Th and received signal Pr in addition to coverage and service availability defined in Chapter 4 at time t such that the resilience of the network measured over a period of time is also improved.

Let $\theta_{etilt_j} \in [0^\circ, 14^\circ]$ be the set of possible tilt values of functional BSs and $P_{t_j} \in [0dBm, 40dBm]$ the set of possible values of the transmit antenna power of these same BSs. Unlike related studies that tune only neighbouring antennas sites radio parameters, we attempt to tune both tilt and transmit power of all BSs belonging to the set $\{BS\} \setminus \{BS_O\}$ within the network area. The goal is to ensure, in the one hand, that coverage and service are consistently available across the service area, and, in the other hand, that the network is mitigating compensation impact in the area by delivering higher data rates and better QoS, resulting in solving a multi-objective function. To define coverage and service availability metrics we define two variables as follows:

$$\alpha_i = \begin{cases} 1, & \text{if } Pr_i \geq Pr_\epsilon, \\ 0, & \text{otherwise,} \end{cases} \quad (5.9)$$

$$\beta_i = \begin{cases} 1, & \text{if } Th_i \geq D_\epsilon, \\ 0, & \text{otherwise,} \end{cases} \quad (5.10)$$

where Pr_ϵ is the threshold of the received signal in dBm (i.e., **RSRP**) required to connect a user to a serving **BS**, and D_ϵ is the minimal requested data rate by a user i defined in Chapter 4. Consequently, we define the availability of a resilient coverage as the percentage of the users α_i that receive the minimal signal threshold Pr_ϵ , and the availability of a resilient service as the percentage of the users β_i that receive the minimal requested data rate D_ϵ as follows:

$$P_{coverage} = \frac{\sum_i^N \alpha_i}{N}, \quad P_{service} = \frac{\sum_i^N \beta_i}{N}. \quad (5.11)$$

Following the analysis of resilience and constraints levels defined in Chapter 4, we consider that the system is resilient at time t if $P_{coverage} \geq \hat{P}_{coverage}$ and $P_{service} \geq \hat{P}_{service}$. For that, we define a binary variable that verifies either the network is satisfying the coverage and service constraints or not as follows:

$$z = \begin{cases} 1, & \text{if } P_{coverage} \geq \hat{P}_{coverage} \text{ and } P_{service} \geq \hat{P}_{service}, \\ 0, & \text{otherwise.} \end{cases} \quad (5.12)$$

Under the hypothesis of fixed traffic, we formalise the optimization problem in Eq. (5.13) that represents a linear combination between maximizing network throughput Th (see Eq. (5.8)), and ensuring network coverage and service availability. The optimization problem in Eq. (5.13) ensures the continual improvement in quality of service when the resilience thresholds are met, leading to a reduction in the impact of outage on compensating **BSs**. In the case where the resilience constraints fall under the desired thresholds, the second part of the optimization function is formulated to persist in maximizing coverage and service availability. This is intended to mitigate outages and accommodate the maximum number of users across the service area. Consequently, this optimization problem is designed to balance between maximizing throughput and ensuring coverage and service availability, thereby enhancing overall network performance and resilience. We formalise our problem as follows:

$$\begin{aligned}
 \max \quad & z \sum_{i=1}^N Th_i + (1 - z)P_{coverage} \times P_{service} \\
 \text{subject to} \quad & C1 : \text{if } P_{coverage} \geq \hat{P}_{coverage} \\
 & \quad \text{and } P_{service} \geq \hat{P}_{service} \implies z = 1, \\
 & C2 : Th_i \geq D_\epsilon \implies \beta_i = 1, \\
 & C3 : 0 \leq i \leq N, \\
 & C4 : z \in \{0, 1\}.
 \end{aligned} \tag{5.13}$$

We can rewrite in details the optimization problem of Eq. (5.13) in Eq. (5.14) based on all the previous propagation formulas:

$$\begin{aligned}
 \max_{Pr_i, \alpha_i, \beta_i, \theta_{etilt_j}} \quad & z \sum_{i=1, j=c}^N \left(B_{PRB} \cdot N_b \cdot \sigma_i \cdot \log_2 \left(1 + \frac{Pr_{ij}}{n_0} \right) \right) \\
 & + \frac{1-z}{N^2} \sum_{i=1}^N \alpha_i \cdot \sum_{i=1}^N \beta_i \\
 \text{subject to} \quad & C1 : \text{if } P_{coverage} \geq \hat{P}_{coverage} \\
 & \quad \text{and } P_{service} \geq \hat{P}_{service} \implies z = 1, \\
 & C3 : 0 \leq i \leq N, \\
 & C4 : 0 \leq j \leq M, \\
 & C5 : z \in \{0, 1\}. \\
 & C6 : Pr_i > Pr_\epsilon \implies \alpha_i = 1, \\
 & C7 : 0 \text{ dBm} < P_{t_j} \leq 40 \text{ dBm}, \\
 & C8 : 0^\circ \leq \theta_{etilt_j} \leq 14^\circ, \\
 & C9 : j \in \{\text{BS}\} \setminus \{\text{BS}_O\},
 \end{aligned} \tag{5.14}$$

where each constraint ensures a specific condition that is detailed in Table 5.2. Besides $Pr_{ij} = P_{t_j} + G_{tj}(\theta_{ij}, \theta_{etilt_j}, \phi_{ij})$ represents the received signal by the i^{th} user from the j^{th} BS described in Eq. (5.2). The parameters used to define the problem are listed in Table 5.1.

This problem falls into the category of NP-hard problems as described in [65]. Given the big space search and the number of radio parameters that should be tuned to find the optimal solution, traditional algorithms may struggle to provide satisfactory results as they will take a reasonable amount of time. However, RL is a promising solution to address the challenges posed by such NP-hard problems. By leveraging the power of neural networks and RL frameworks, we can learn complex decision-making policies from data

Constraint	Meaning
C1	If availability of coverage is higher or equal than the the coverage threshold $\hat{P}_{coverage}$ and availability of service throughput is higher or equal than the service threshold $\hat{P}_{service}$ then the binary variable $z = 1$.
C2	Received throughput of i^{th} user should be higher than its requested throughput D_ϵ and if so the binary variable $\beta = 1$.
C3	Range of i^{th} users indexes.
C4	Range of j^{th} BS indexes.
C5	Possible values of the binary variable z .
C6	Received signal power of i^{th} user should be higher than threshold Pr_ϵ and if so the binary variable $\alpha = 1$.
C7	Range of transmit signal power.
C8	Range of electrical antenna downtilt.
C9	Range of possible values for the index j includes those that belong to the set of functioning j^{th} BSs that are tuned, except the indexes of BSs that are experiencing an outage state $\{BS_O\}$.

Table 5.2 – List of constraints.

and experience, enabling the network to adapt and improve users KPIs over time and thus the network resilience.

5.3.2 Markov Decision Process (MDP)

This problem of resilience optimization can be formulated as an MDP for the RL based solution. Formally, it is described by the tuple (S, A, T, R, γ) , where S is a finite state space, A is a finite action space, T is the transition model, $R : S \times A \rightarrow R$ is a global reward function, and $\gamma \in [0, 1]$ is a discount factor. A DQN algorithm can be used to solve this type of discrete optimization problem where:

- **State:** represents the current network configuration of all M antennas, which includes the tilt angle of each antenna and the transmit power level for each antenna. The state can be modeled by a matrix of $(M \times 2)$ size where each line corresponds to one cell antenna configuration for both transmit power and antenna tilt.
- **Action:** The action space consists of 9 actions per cell (M cells) for adjusting the tilt angle and the transmit power of each antenna simultaneously. There are 3 actions for changing the tilt angle with $\{-1^\circ, 0^\circ, \text{ or } +1^\circ\}$ degrees, whereas there are 3 actions for changing the transmit power with $\{-5\text{dBm}, 0\text{dBm}, \text{ or } +5\text{dBm}\}$,

resulting in a total of $9 = 3 \times 3$ possible actions per cell. For a three-sectored BS the action space is increased to 9^3 , and for the entire serving area of M cells, the action space is 9^M . Besides, the action status is represented by a matrix of $(M \times 2)$ size where each line correspond to one cell antenna action for both transmit power and antenna tilt. We highlight the large size of the action space over the entire serving area amounting to 9^M . Subsequently, we describe further an approach that involves solving the MDP on each BS while addressing this problem through a distributed setting, thereby, reducing the action space to 9^3 at each BS. This approach necessitates the deployment of multiple cooperative learners agents in the entire networking area.

- **Next state:** is obtained by adding both state s matrix and action matrix to obtain the new antennas configuration matrix s' .
- **Immediate reward:** we choose the immediate reward as a function that reflects the performance we want to optimize. For that, $R(s)$ is the reward of being in or entering a state s . It corresponds to the first part of the optimization function in Eq. (5.13) when coverage and service thresholds are satisfied, and to the second part of the optimization function when the coverage and service constraints fall below the thresholds. In other words, the state reward in Eq. (5.15) corresponds to the total Th when $\hat{P}_{coverage}$ and $\hat{P}_{service}$ are satisfied, otherwise, the state reward corresponds to the product of $P_{coverage}$ and $P_{service}$ if the constraints fall below the thresholds. Besides, the immediate reward $R(s, a, s')$ for taking an action a at state s and resulting in state s' can be expressed as the difference between the reward terms between the state s and the state s' (see Eq. (5.16)).

$$R(s) = \begin{cases} \sum_{i=1, j \in BS_s}^N Th_{ij} & \text{if } P_{coverage} \geq \hat{P}_{coverage} \text{ and } P_{service} \geq \hat{P}_{service}, \\ P_{coverage} \times P_{service} & \text{otherwise,} \end{cases} \quad (5.15)$$

$$R(s, a, s') = R(s') - R(s). \quad (5.16)$$

We note that in Eq. 5.15, the value of the first term of the sum of throughput is way too large compared to the second term of the product of coverage and service availability in the reward function. In fact, the term $P_{coverage} \times P_{service}$ is playing the role of a penalty in the learning process, forcing the optimization to satisfy the coverage and service constraints. Having a dynamic penalty term, instead of a static value like a zero penalty, will provide a gradient of the feedback rather than a binary or static response. This allows the

learning algorithm to understand the severity of constraint violations in a more nuanced way, leading to encourage improvements or outage mitigation rather than just meeting a minimum threshold. For solving this **MDP**, the multi-agent **DQN** algorithm is considered in the following section.

5.3.3 Q-learning for solving the Markov Decision Process (MDP)

Q-learning is a model-free **RL** algorithm. It provides agents with the capability of learning to act optimally in Markovian domains by experiencing the consequences of actions, without requiring them to build maps of the domains. It describes the problem exclusively in terms of three components: state s , action a and reward R . The action (a) that an agent takes at every time step is a function of both the reward and the state (s), which is a description of the environment the agent is in. The mapping from environment states to actions is called policy π . The policy basically defines the agent's way of behaving at a certain time, given a certain situation (state, s). In addition, a value function V is defined to be the measure of how good each interaction is. This is different from the reward in that, the reward signal indicates what is good in the immediate sense, while the value function is more indicative of how good the interaction is in the long run. Our value function can be split into 2 terms:

- **State-value function V** : it measures how good is a state. It is the expected cumulative reward from being in a state s and following a policy π . This is calculated by looking at the summation of the reward at each future time step (see Eq. (5.17)).

$$V^\pi(s) = \mathbb{E}[\sum_{t \geq 0} \gamma^t R_t | s_0 = s, \pi], \quad (5.17)$$

where, γ refers to a constant discount factor, which means that the reward at time step $t+1$ is weighted a little less than the reward at time step t .

- **Action-value function Q (Q-value function)**: measures how good is to perform action a in state s . It is the expected cumulative reward from taking an action a in state s and then following a policy π (see Eq. (5.18)).

$$Q^\pi(s, a) = \mathbb{E}[\sum_{t \geq 0} \gamma^t R_t | s_0 = s, a_0 = a, \pi]. \quad (5.18)$$

The goal of the Q-learning is to find the optimal policy π^* that maximizes the cumulative discounted (or not discounted) reward (see Eq. (5.19)).

$$\pi^* = \arg \max_{\pi} \mathbb{E}[\sum_{t \geq 0} \gamma^t R_t | \pi], \text{ with } s_0 \sim p(s_0). \quad (5.19)$$

If the environment is represented by an **DQN**, it is sufficient to solve it in order to find the optimal policy π^* . However, Q-learning is a model free algorithm, so the information given by the **DQN** is not available. Instead, it applies policy iteration. It consists of going directly from the experience/episode/interaction of the agents and the environment to the value function V and the policy π . The idea is that the Q-learning takes some initial policy π and it evaluates the action-state function Q-value for that policy (when given a **DQN**, the state value is used directly). It does this is throw the bellman expectation in Eq. (5.20).

$$Q^*(s, a) = \mathbb{E}_{s' \sim \epsilon}[r + \gamma \max_{a'} Q^*(s', a') | s, a]. \quad (5.20)$$

This equation basically says that our Q-value function, given that we're following policy π , can be decomposed into expected cumulative reward of the immediate reward R and the Q-value function of the next state S_{t+1} . This equation is the first step of the policy iteration which is called policy evaluation. In order to get a better policy, the second step will perform policy improvement where it simply acts greedily with respect to the Q-value function. In other words, the agent takes the action that maximizes the Q-value in the future steps. In order, to get the optimal policy, the policy evaluation and improvement is repeated over time, until convergence to the optimal policy π^* . The Q-learning updates are obtained following the value iteration function that is proven to converge to Q^* as $i \rightarrow \infty$:

$$Q_{i+1}(s, a) = \mathbb{E}_{s' \sim \epsilon}[r + \gamma \max_{a'} Q_i^*(s', a') | s, a]. \quad (5.21)$$

In real world **RL** problems, this basic approach is totally impractical because the action-value function is estimated separately for each sequence. In other words, it is needed to compute the $Q(s, a)$ for all (s, a) pairs. Hence, when the state/action spaces increase, this approach becomes unscalable. Instead, it is common to use a function approximator to estimate the action-value function, $Q(s, a; \theta) \approx Q^*(s, a)$, such that we don't have to store a completely separate value function for every possible combination and is able to generalize to unknown states. In the **RL** community this is typically a non-linear function approximator that is used instead, such as a neural network in the **DQN** algorithm.

5.3.4 Resilience optimization with multi-agent Deep Q-Network (DQN) experience replay

We refer to a neural network function approximator with parameters (weights and biases) θ as a **DQN**. The **DQN** maintains two separate Q-networks $Q(s, a; \theta)$ and $Q(s, a; \theta^-)$ with current parameters θ and old parameters θ^- respectively. The algorithm for training the **DQN** is detailed in Algorithm 1. The **DQN** agent starts by exploring randomly all possible actions and states with some unknown reward distributions. It uses experience replay by storing the last n experience tuples $e_t = (s_t, a_t, R_t, s_{t+1})$ into a replay memory $D = \{e_1, \dots, e_n\}$, and samples uniformly at random from D when performing updates. During the interaction, the agent selects and executes an action according to an ϵ -greedy policy using the current network updated many times per time-step, and copies the old parameters θ^- after n iterations. The states and actions will serve to construct the input vector known as features, while the rewards will be considered as the target outcomes of the Q-network. During the inner loop of the algorithm, the current parameters π are updated at every iteration i , so as to minimise the mean-squared Bellman error with respect to old parameters θ^- , by optimizing the following loss function (i.e., **DQN** loss). As far as the interaction goes on, the agent needs to exploit the best action found so-far from exploration by taking sequential decisions that maximizes the cumulative reward. Having the right balance between exploration and exploitation guarantees the convergence towards the Bellman target. To resume, the **DQN** algorithm learns the optimal Q-value function that is derived from the optimal policy π^* . The neural network will approximate the estimated Q-value function to the optimal one by minimizing the mean-squared error with consecutive updates.

In order to address our resilience optimization problem formulated in Section 5.3.1 and solve its correspondent **DQN** from section 5.3.2, the centralized version using only one **DQN** agent is unfeasible due to the the complexity brought by the large action space.

The multi-agent framework involves training multiple agents simultaneously, with each agent representing a **BS** within the network that serves 3 cells. This approach is particularly well-suited to our problem domain, as the action space associated with optimizing the operation of each individual **BS** is vast and complex. Unlike a centralized approach with a single agent, that may struggle to handle the M cells with an action space of 9^M , the multi-agent **DQN** enables each **BS** to autonomously learn and adapt its behavior based on local observations over 9^3 action space.

In each training episode, the environment randomly selects BS outages, assigning corresponding agents to those that are inactive while enabling operational BSs and their associated active agents to adapt their strategies based on rewards. The reward for each agent is calculated using observations and propagation effects across the entire area, rather than solely on the local BS. It accounts for load balancing and maximal signal strength for an efficient cell selection for each user. Thus, this reward structure facilitates indirect communication between agents, fostering cooperative learning. This decentralized approach facilitates efficient exploration and exploitation of network dynamics, enhancing performance and resilience in the face of varying network conditions. The full pseudo algorithm is described in Algorithm 2. In the next section, we apply our resilience optimization technique on a deployment of 5G small cells network serving area, to assess experimentally its capability and enhancement efficiency.

Algorithm 1 Deep Q-Network (DQN) algorithm with experience replay

```

Initialize Replay memory  $D$  to capacity  $N$ 
Initialize action-value function  $Q$  with random weights  $\theta$ 
Initialize target action-value function  $\hat{Q}$  with weights  $\theta^- = \theta$ 
for episode = 1, N_episode do
    Initialize sequence  $s_t = x_t$  and pre-processed sequence  $\phi_1 = \phi(s_1)$ 
    for episode = 1, T do
        With probability  $\epsilon$  select a random action  $a_t$ 
        otherwise select  $a_t = \operatorname{argmax}_a Q(\phi(s_t), a; \theta)$ 
        Execute action  $a_t$  in and observe reward  $r_t$  and image  $x_{t+1}$ 
        Set  $S_{t+1} = s_t, a_t, x_{t+1}$  and preprocessed sequence  $\phi_{t+1} = \phi(s_{t+1})$ 
        Store transition  $(\phi_t, a_t, r_t, \phi_{t+1})$ 
        Sample random minibatch of transitions  $(\phi_j, a_j, r_j, \phi_{j+1})$  from  $D$ 
        Set  $y_j = \begin{cases} r_j & \text{if episode terminates at state } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$ 
        Perform a gradient descent step on  $(y_j - Q(\phi_j, a_j; \theta))^2$  with respect to the network parameters  $\theta$ 
        Every C steps reset  $\hat{Q} = Q$ 
    end for
end for

```

Algorithm 2 Multi-agent Deep Q-Network (DQN) Algorithm

```

for Agent = 1, N_agents do
    Initialize Replay memory  $D$  to capacity  $N$ 
    Initialize action-value function  $Q$  with random weights  $\theta$ 
    Initialize target action-value function  $\hat{Q}$  with weights  $\theta^- = \theta$ 
end for
for episode = 1, N_episode do
    Set random number of BS outage N_BS_off
    Set random index of BS outages BS_off_idx
    for Agent = 1, N_agents do
        if Agent not in BS_off_idx then
            Initialize sequence  $s_t$  and preprocessed sequence  $\phi_1$ 
            for episode = 1, T do
                With probability  $\epsilon$  select a random action  $a_t$ 
                otherwise select  $a_t = \operatorname{argmax}_a Q(\phi(s_t), a; \theta)$ 
                Execute action  $a_t$ 
                for user  $i = 1, N$  do
                    for cell  $j = 1, M$  do
                        if cell is working then
                            Compute  $Pr_{ij}$ 
                        end if
                    end for
                end for
                Sort all  $Pr_{ij}$  for each user
                Apply load balancing and apply cell selection
                Compute immediate reward  $r_t$  and observe image  $x_{t+1}$ 
                Set  $S_{t+1} = s_t, a_t, x_{t+1}$ 
                preprocess sequence  $\phi_{t+1} = \phi(s_{t+1})$ 
                Store transition  $(\phi_t, a_t, r_t, \phi_{t+1})$ 
                Sample random minibatch of transitions  $(\phi_j, a_j, r_j, \phi_{j+1})$  from  $D$ 
                Set  $y_j = \begin{cases} r_j & \text{if } S_{t+1} \text{ terminal} \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$ 
                Perform a gradient descent step on  $(y_j - Q(\phi_j, a_j; \theta))^2$  with
                respect to the network parameters  $\theta$ 
                Every C steps reset  $\hat{Q} = Q$  for each agent
            end for
        end if
    end for

```

5.4 Simulation and results

In this section, we start by presenting the system configuration parameters and setups. We will first show and discuss the training performance of the proposed multi-agent **DRL**. Then, we show the evaluation of the resilience solution on the simulated environment on both coverage and **QoS** optimization achieved by the proposed multi-agent **DRL** method.

5.4.1 Simulation setup

To simulate the **5G-RAN** network based on **3GPP** specifications, we employ a full dynamic system tool. We set up a baseline reference scenario that consists of 21 gNBs (i.e., **BSs**) having an inter-site distance of 300m. This layout derives the presence of 7 **BSs**, each deploying a single **DQN** agent, resulting in a total of seven distributed **RL** agents. To evaluate the resilience solution on the simulator, we consider 2,500 testing points uniformly distributed across the service area, each representing a connected user in the network. The detailed network configuration parameters are listed in Table 5.3.

To simulate a hardware failure in the network, at some point in the simulation, the antenna gain of the selected **BSs** is attenuated to -100dBi that leads to a cell outage in a network. We extract path loss measurements from the simulator to obtain accurate attenuation estimates at each testing user point and utilize them in the propagation formula. For the training, we deliberately vary the degrees of stress and failure scenarios, by randomly selecting up to five **BSs** for outage simulation. The number and the index of **BSs** are randomly selected during the training. We vary the number of **BS** outage L from 1 to 5. The case of all **BSs** outage except one (i.e., 6 **BSs** off) is not considered since we assume that one **BS** alone is incapable of recovering all the users of the network area. Besides, the case of all **BS** outage (i.e., 7 **BS** off) is also not considered because no **BS** is left for the outage mitigation. By considering these different situations during training, this enables the **DRL** models to learn adverse events on the underlying network environment and evaluate the overall performance and resilience throughout this study.

The evaluation focuses on tracking the number of covered users and the satisfaction level of users with their service. Additionally, we monitor the evolution of average **RSRP** and Th metrics under multiple network conditions. First, we discuss the loss and total reward evolution for one **DQN** agent as an example (see Figure 5.5), and perform multiple inferences with the proposed multi-agent **DQN** varying the number of **BS** outages from 1 to 5. We present the performance estimation evolution on all cases in Figure 5.7, and

Parameter	Value
Network type	Hexagonal
Cellular layout	21 small cell sites
Inter-site distance	300m
Sectors	3 sectors per cell
Number of BSs	7 BSs
Number of outage BS	$L \in \{1, 2, 3, 4, 5\}$
User distribution	Uniform random distribution
Path loss	'TR38901_UMiv2'
Number of users	2500 users
Users speed	3-10 KM/h
UT height h_{UE}	1.5 meters
BS height h_{UE}	10 meters
Frequency Band	28GHz
Mechanical downtilt	$\theta_{mtilt} = 0^\circ$
Electrical downtilt	$\theta_{etilt} \in [0^\circ, 14^\circ]$
Transmit antenna signal	$P_{t_j} \in [0\text{dBm}, 40\text{dBm}]$
UEs Requested data rate (D_e)	3 Mbps
Number of PRB	100
ϕ_{BS} antenna boresight	$\{0^\circ, 120^\circ, -120^\circ\}$
Antenna max gain G_{max}	8dBi
Elevation Half power beamwidth	$\theta_{3dB} = 65^\circ$
Azimuth Half power beamwidth	$\phi_{3dB} = 65^\circ$
Noise per PRB	-99 dBm
SSL_v	30 dB
SSL_h	30 dB
User antenna gain G_r	0dBi
User antenna type	Omnidirectionnal
PRB Bandwidth	10 MHz
$\hat{P}_{coverage}$	0.95
$\hat{P}_{service}$	0.5

Table 5.3 – Network configuration on simulator.

illustrate the network behaviour in 3 cases of BS outages on Figure 5.6. Then, we evaluate the proposed multi-agent DQN solution in a dynamic scenario simulated using the SONTTool Nokia simulator [110], developed and maintained up-to-date on Matlab. The downlink principles of the simulator are presented in [110] and uplink modeling aspects in [109]. Subsequently, we deploy our proposed resilience solution based multi-agent DQN on the simulator to trigger it dynamically when an outage state is detected, and track the network performance on a realistic environment propagation conditions. This standardized simulator will closely mirror reality and capture essential aspects of network behavior while reflecting the performance of our resilience strategy. We evaluate the resilience solution in scenarios where the number of BSs varies between two distinct sets: $L \in \{1, 2, 3\}$ and $L \in \{4, 5\}$. Also, we assess the benefit of our resilience solution in the case of 1 BS off. We compare our solution based on the multi-agent DQN with a benchmark solution that consist in changing only neighbouring BSs (i.e., local optimization and centralized compensation such as in Figure 5.1), as well as with no resilience solution settings. The list of terminology that will be used throughout this experimental section is listed in Table 5.4. We note that other experiments have been conducted using multi-agent proximal policy optimization algorithm, which yielded similar results, emphasizing the effectiveness of the distributed solution. However, we show only the results with multi-agent DQN for the sake of simplicity.

This comprehensive analysis and discussion will allow us to gauge the effectiveness of the resilience solution across different BS configurations and provide valuable insights into its impact on network performance and user experience.

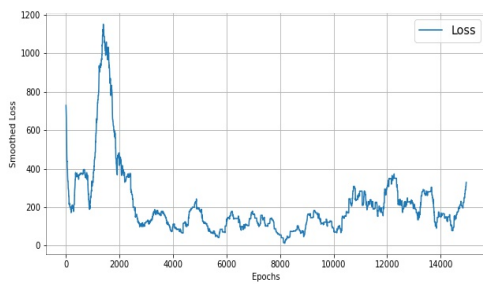
5.4.2 Training results

- *Single agent DQN training performance:* We train each DQN model for 1,000 episodes, at each episode, a 500 time steps are taken by the agent for learning a single path of the Q-value. In our investigation of the DQN training process, we closely monitored the evolution of loss and total reward over successive training iterations. We plot one agent loss and total reward evolution over the total number of episodes in Figure 5.5. As the DQN model begins its training journey, we observed a rapid decline in loss accompanied by a notable increase in total reward. This initial phase of training demonstrated the network's ability to swiftly learn and adapt to the environment, effectively optimizing its policy to maximize cumulative reward. However, throughout the training, we noticed an instability in the evolution of total reward which reflects the known behaviour of the DQN. Despite

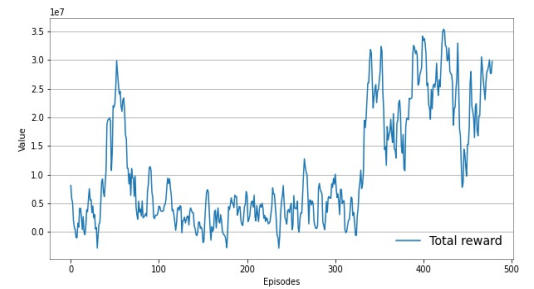
Term	Meaning
Covered users	Users that receive the minimal signal strength threshold $Pr_i > -127$ dBm (see Table 4.1)
Satisfied users	Users that receive the minimal requested data rate where their $Th_i \geq D_\epsilon$
Good RSRP users	Users that receive at least a signal strength of -90 dBm (see Table 4.1)
Fair RSRP users	Users that receive a signal strength of between -126 dBm and -90 dBm (see Table 4.1)
Poor RSRP users	Users that receive a signal strength of below -127 dBm (see Table 4.1)
BS off	A BS that is experiencing an outage and is off from transmitting any signal
Coverage Availability	Percentage of covered users in the network area
Service Availability	Percentage of satisfied users in the network area
Resilient Network	Coverage availability greater than $\hat{P}_{coverage} = 95\%$ and Service availability greater than $\hat{P}_{service} = 50\%$

Table 5.4 – List of terminology for the experimental section.

this, the DQN continued to exhibit a steady improvement in loss roughly approaching convergence. These observations indicate that our DQN model successfully learn to face the underlying network problems to improve the overall performance.



(a)



(b)

Figure 5.5 – (a) Single agent evolution of its smoothed loss over time - window size = 500 steps; (b) Single agent evolution of its total reward over time.

- *Multi-agent DQN inference performance:* To analyse the performance and resilience enhancement of our model, we conduct multiple inferences with 10 actions with one action per step of the multi-agent DQN under scenarios involving 1 to 5 outages. In Figure 5.6, we plot in the one hand the coverage enhancement indicators: coverage availability evolution (i.e., covered users percentage) and the percentage of good, fair, and poor RSRP users. In the other hand we plot the data-rate service indicators: service availability evolution (i.e., satisfied users percentage) as well as the average throughput Th . As an example we focus on scenarios when number of BS outage $L \in \{2, 3, 4\}$ outages. Since the case of 1 BS outage is highly similar to 2 BSs outage and the case of 5 BSs outage is similar to 4 BSs outage. Further in Figure 5.7, we provide a summary of coverage and service availability performance enhancement (average and standard deviation) in all outage cases.

- *Multi-agent DQN inference examples:* We notice in Figure 5.6 that in all cases, our solution succeeds to improve the overall network performance, which implies improving coverage and service availability and by extension reduce network downtime and optimize the network resilience. For example, in Figure 5.6a, Figure 5.6c and Figure 5.6e the percentage of covered users is improved by up to 99.7% for 2 BSs outage, 91% for 3 BSs outage and by up to 80% in case of 4 BSs outage. The last case is not sufficient to pull out the network status from the outage state as the percentage of uncovered users is still greater than 5%. However, the operator can involve other surrounding cells which are not showed in the studied zone to help obtaining a better enhancement. In addition to these observations, the percentage of satisfied users is improved by up to 50% for 2 BSs outage, 30% for 3 BSs outage and by up to 20% in case of 4 BSs outage. These lower percentages can be attributed to an insufficient received user signal strength (i.e., RSRP), resulting in lower service quality expected during severe coverage issues. Besides, in all cases the average Th is successfully improved, as learnt by the DQN models. As for coverage through RSRP users percentage indicators in Figure 5.6b, Figure 5.6d and Figure 5.6f, we notice that at the early stages of actions steps, the poor users percentage starts to decrease while the fair users percentage starts to increase. Later on, the fair users percentage decreases while the good users percentage increases and the poor users remains at its lowest value. This aligns with the objective of our multi-objective optimization algorithm, which aims to enhance not only availability but also to optimize the average performance and service quality during outages.

- *Multi-agent DQN inference results summary:* The summary of both coverage and service enhancement estimation statistics (median and standard deviation) are provided

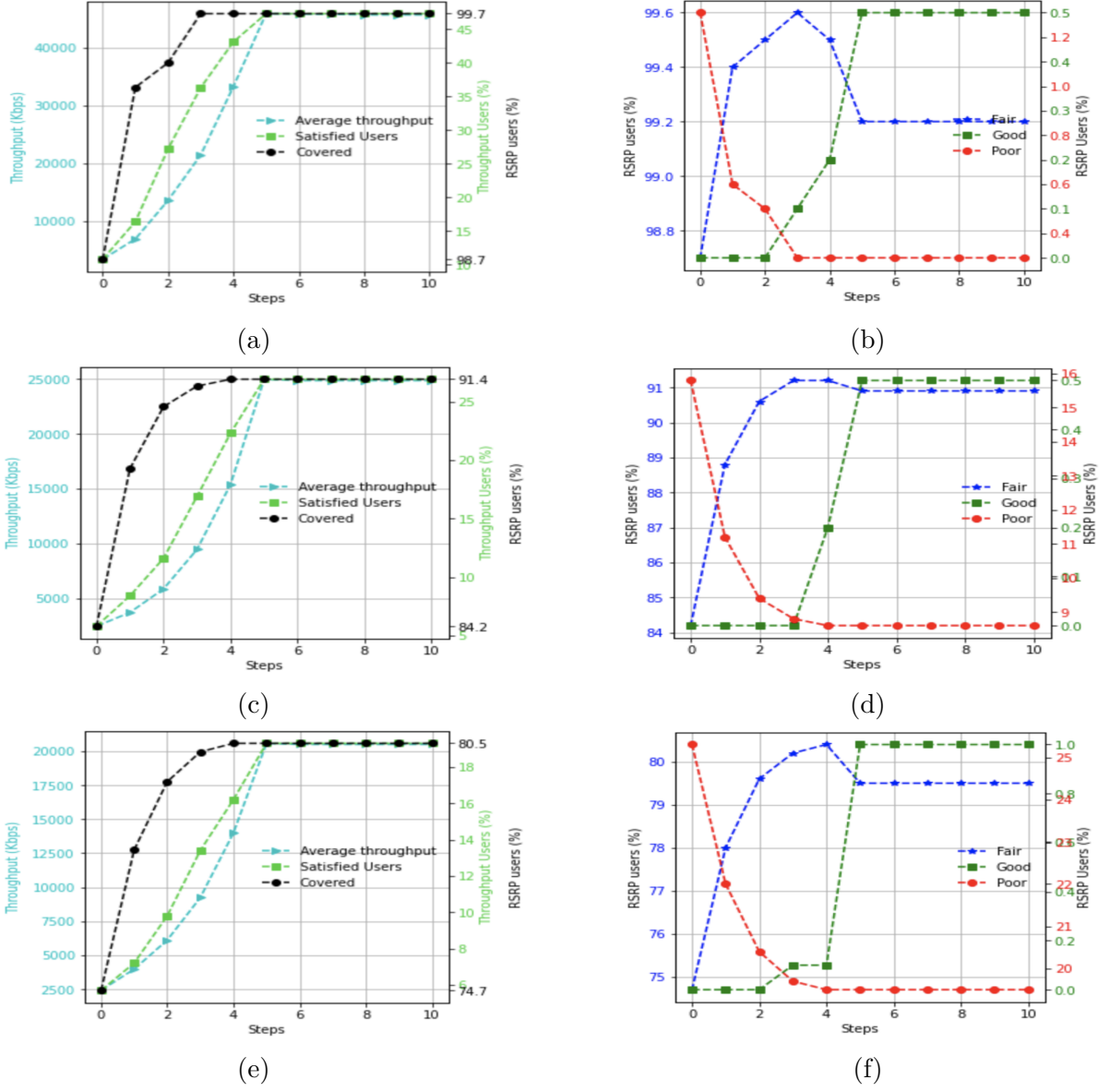


Figure 5.6 – Inference of multi-agent **DQN** when (a,b) 2 **BS** outage, (c,d) 3 **BS** outage and (e,f) 4 **BS** outage. The estimation of: (a,c,e) Percentage of satisfied and covered users service with the average throughput evolution, and (b,d,f) The percentage of **RSRP** Good, Fair, Poor users evolution.

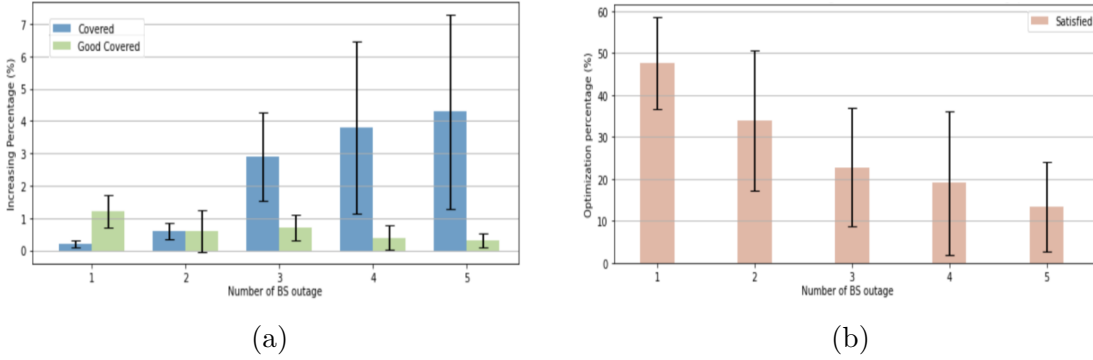


Figure 5.7 – Estimation of average performance increase over multiple inferences for: (a) Coverage availability through the percentage of covered and good **RSRP** users increase (b) Service availability through the percentage of satisfied users receiving the requested throughput.

in Figure 5.7. We perform over 20 inferences with 10 actions with one action per step in each **BS**s outage case. We compute the increase percentage difference obtained within each inference for both covered and satisfied users, as well as for good **RSRP** users percentage increase. We derive the median and standard deviation for each outage case. Specifically, we notice that in cases of 1, 2 and 3 **BS**s outage the coverage is increased with 1-4% only while it achieves 5-7% in cases of 4 and 5 **BS**s outage. However, the estimated increase of good **RSRP** users percentage does not exceed 2% improvement in all cases. In fact, the percentage of covered users' improvement increases with the number of **BS** outages, while the improvement of good **RSRP** users decreases as the number of **BS**s outage increases. This phenomenon is explained by the fact that with more **BS**s outage, there are more uncovered users, and in cases of severe degradation (4 and 5 **BS**s outage), our algorithm gives priority to recovering more users than improving the service quality for some users. This observation is consistent with the goal of our multi-objective optimization algorithm and underscores the adaptability of our proposed solution. As for the satisfied users improvement, we reach up to 40-60% of **QoS** improvement in best cases (1, 2, 3 **BS**s outage) and reach up to 20-30% in worst cases (4 and 5 **BS**s outage). This percentage decreases as the number of **BS** outages increases. In fact, under severe degradations, more uncovered users can hardly be recovered with a good **RSRP** as the solicited compensating **BS**s are quite far, and subsequently, achieving requested Th becomes more challenging to ensure good service quality, which explains this trend. In these cases, our algorithm prioritizes the availability of minimal conditions for the majority of users.

These estimation of performance and resilience enhancement reflect the success of our proposed solution in improving the network resilience. It also underscores the fact that the algorithm based on **DRL** is well suited for seeking both availability (i.e., resilience) and **QoS** improvement under abnormal network conditions. Nevertheless, these discussed statics are only estimations obtained with propagation formula and model inference, we aim to evaluate our proposed solution in a real-like and dynamic network to asses the effectiveness of the solution and its impact on network resiliency. The next section is dedicated for the evaluation on the standardized dynamic simulator.

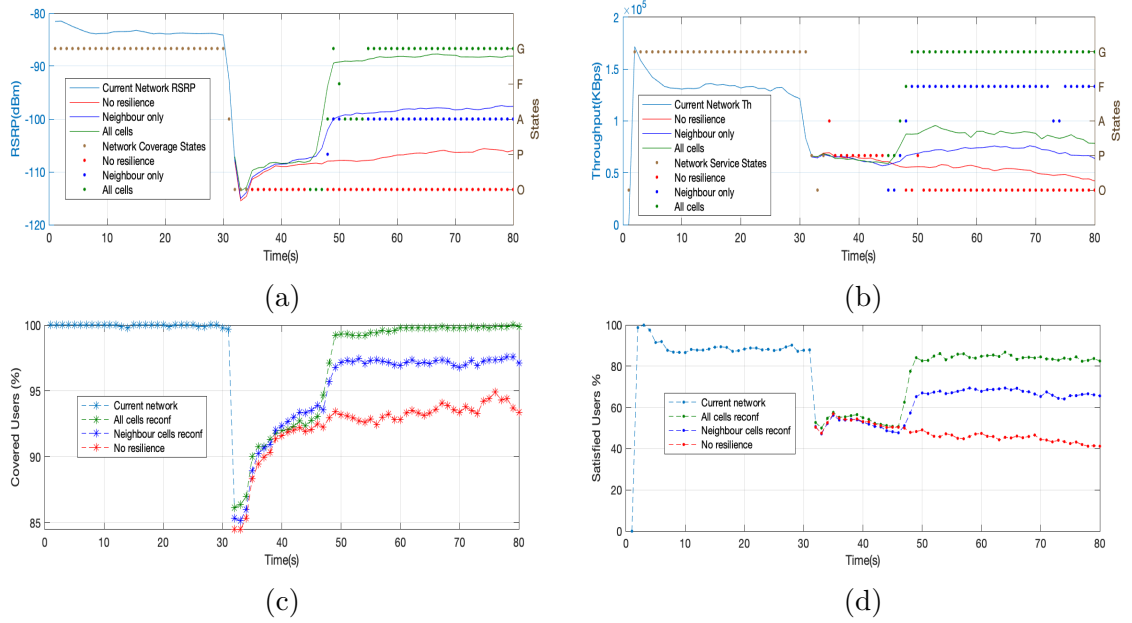


Figure 5.8 – Network performance evolution of the current network in case of 1 Base Station (BS) outage with: no resilience, neighboring reconfiguration only, and multi-agent Deep Q-Network (DQN)-based full cell reconfiguration for: (a) Average received user signal (RSRP) (b) Average throughput (c) Percentage of covered users (d) Percentage of satisfied users.

5.4.3 Evaluation results on simulator

At the simulator, we set a network with the configuration listed in Table 5.3. We conduct different outage conditions by up to 5 BSs outages and track the current network behaviour in terms of average users **RSRP** and users *Th*, as well as the percentage of covered and satisfied users. We simulate the network for 80 seconds long and stress the network at the second 30-th. We trigger dynamically the optimization solution 5 seconds

after detecting an outage state. We make up to 5 actions reconfiguration on the cell sites antennas, by sending signaling information to the operational BSs to modify the electrical tilt and the transmit signal dynamically. During the simulation, we collect RSRP and user Th at each user for a granularity of 1s. In Figure 5.8, we start by studying the scenario of 1 BS outage. We respectively compare the following three cases: when no resilience solution is triggered, when a conventional solution that consists of reconfiguring only neighbouring BSs as usually assumed in the literature is triggered (i.e., local optimization), and when our proposed multi-agent DRL solution is triggered to reconfigure the entire network zone. Then, we evaluate the performance of the multi-agent DRL on the cases of 2, 3, 4 and 5 BSs outage in Figure 5.9.

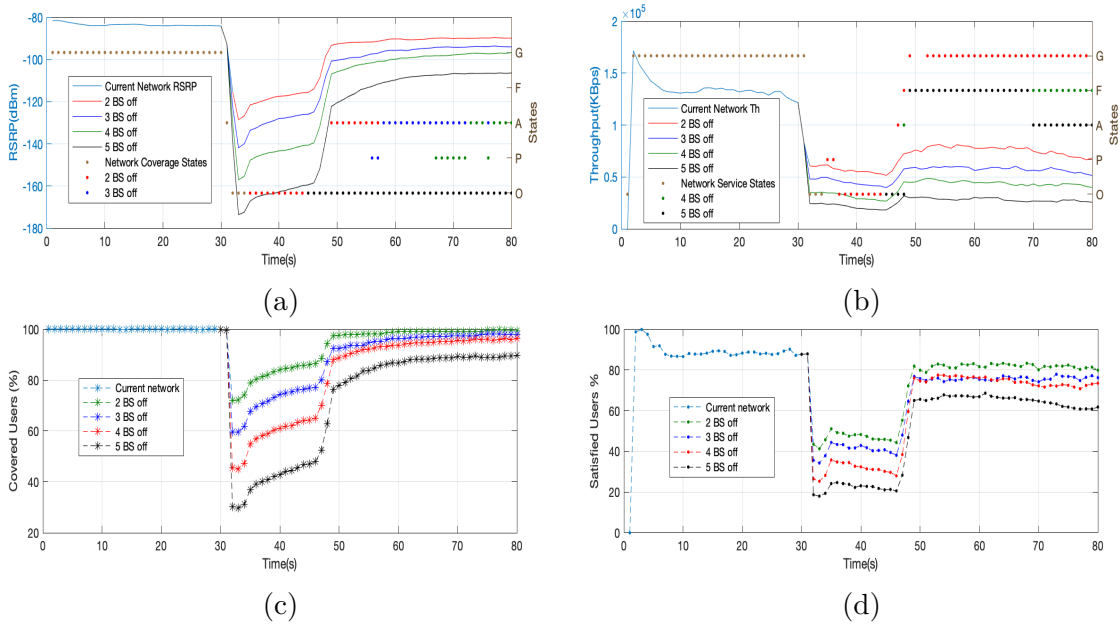


Figure 5.9 – Network performance evolution of the current network in case of 2 to 5 BS outages with the Multi-Agent Deep Q-Network (DQN)-based full cell reconfiguration for: (a) Average Received User Signal (RSRP) (b) Average Throughput (c) Percentage of covered users (d) Percentage of satisfied users.

The dynamic behaviour of the network shown in Figure 5.8 reveals that our method (in green) succeeds in restoring the initial average RSRP (Figure 5.8a) and recovering back most of the users in the outage area (Figure 5.8c) at the same level of before outage occurrence (Good coverage and service states in green points). Unlike, the conventional methods of only neighbouring cells reconfiguration (in blue) that restore back the network state to only acceptable level for coverage and fair state for service (blue points).

However, the average Th is not increased at the same level as before outage, because the simulator takes into consideration different interference levels and attenuation parameters not taken into account in our propagation formulas during the **DQN** training. Despite this observation, the service availability is successfully restored at the requested level. In fact, some users may experience some attenuation in service quality but they still access the service with the requested levels and hence the resilience of network in terms of service is still achieved. Finally, the Figure 5.9 depicts the comparison of performance and resilience enhancement using our proposed multi-agent **DQN** approach in cases of 2, 3, 4 and 5 **BS**s outage. As noted before in the discussion of Figure 5.7, despite the success of the proposed approach in improving network overall performance along with satisfying coverage and service availability, the mitigation technique of outages through cell reconfiguration is limited with the degree of severeness of the outage. Hence, for extreme cases or disasters, a special branch of resilience disaster study exists for deploying redundant networking equipment and **BS**s, especially for critical networks. In the next section, we will provide small insights of what can be done in theses situations, and leave it for future perspectives.

To sum up, our method based on multi-agent **DQN** for cells reconfiguration of an entire network zone succeeds in learning and improving the average user received signal strength **RSRP** and its correspondent user Th under various network outage scenarios. It also helps to increase the percentage of covered and satisfied users, which means it enhances the coverage and service availability, resulting in improving the network resilience. This method outperforms conventional methods of only direct neighbouring cells reconfiguration and local optimization. In a broader context, the method leads to a reduction of outage down-time and increase system up-time. Therefore, improving the availability at time t will improve the resilience of a network over a period of time. This global optimization of resilience will allow operators targeting specific network zones that experience outage such as indoor or outdoor areas (see Figure 5.2), leading to a more efficient resource allocation and network management. This approach could involve deploying adaptive resilience strategies across various network environments, each tailored to meet specific demands. This method have shown it's limitation in case of severe degradation and with optimal **QoS** optimization in specific cases, since increasing the signal transmit power may add more interference complexity management in real world, especially in dense networks. Finally, by performing the resilience analysis developed in the Chapter 4 in a loop with the optimization, it will allow to evaluate the network performance in real-time and manage

the network using an end-to-end strategy.

5.5 Disaster planning: BSs redundancy and cell planning optimization

In scenarios where all BSs in our considered area are in an outage state (or all except one BS), the network faces an extreme situation necessitating immediate intervention. In such cases, relying solely on neighboring BSs to adapt their tilt and power transmit signals may prove ineffective due to the vast coverage gap created by the outage zone. To address this challenge, the introduction of redundant BSs, acting as a pivot BSs, becomes inevitable. In this case, the optimization focus shifts towards determining the optimal placement of the pivotal BSs. Although this approach may be costly, it enables us to mitigate the impact of extreme outage scenarios and maintain network resilience and performance under adverse conditions. For that, we formulate an illustrative optimization problem to address this problem and leave the investigation of possible solutions for future work.

Let M denotes the total number of cells in a given geographical area and N denotes the number of test user points in the same network area at specific time t . We assume that each BS has got a fixed configuration of location coordinates, tilt angle and transmit antenna power $P_{t_j} \in \{P_{t_1}, \dots, P_{t_M}\}$ and $\theta_{tilt_j} \in \{\theta_{tilt_1}, \dots, \theta_{tilt_M}\}$. Let a UE be a user served by a specific BS in a given service area through its serving cell c . We suppose, that the j^{th} BS antenna, with $j \in \{1, \dots, M\}$ and $M \gg 3$, transmits signal with power P_{t_j} in the network area. The signal propagates through the wireless channel between the j^{th} BS antenna and the i^{th} UE, $i \in \{1, \dots, N\}$. The received signal is described by Eq. (5.2) and the received data rate in Eq. (5.8).

We assume that a subset L BSs can experience an outage state, such that $BS_O = \{BS_{o_1}, \dots, BS_{o_L}\}$ where $L \leq M$, making some users to loss the connection and degrade their service. One possible idea is to add an additional BS to recover the uncovered user regardless of the state of outage BSs in terms of their number and location. In other words, we can perform a cell planing optimization task by defining an optimization problem that aim to find the best coordinates for the additional BS (a_{ABS}, b_{ABS}) with its tilt angle θ_{ABS} and transmit power $P_{t_{ABS}}$ such that, the total throughput and received signal strength with the resilience score are maximized. For that we define, a variable ξ such that:

$$\xi_i = \begin{cases} 1, & \text{if user } i \text{ is served by the additional BS} \\ 0, & \text{otherwise} \end{cases} \quad (5.22)$$

Based on the previous section formulas, we formalise the described problem as follows:

$$\begin{aligned} \max_{Pr_i, \alpha_i, \beta_i} \quad & \sum_{i=1}^N (1 - \xi_i) \cdot Th_{ij} + \sum_{i=1}^N \xi_i \cdot Th_{iABS} \\ \text{s.t.} \quad & C1 : P_{coverage} \geq \hat{P}_{coverage}, \\ & C2 : P_{service} \geq \hat{P}_{service}, \\ & C3 : Th_{ij} \geq D_\epsilon \text{ or } Th_{iABS} \geq D_\epsilon \implies \beta_i = 1, \\ & C4 : \xi_i \in \{0, 1\}, \\ & C5 : 0 \leq i \leq N \text{ and } 0 \leq j \leq M, \\ & C6 : j \in \{BS\} \setminus \{BS_O\}. \end{aligned} \quad (5.23)$$

We maximise the total throughput received by users such that the coverage and service availability constraints are satisfied (i.e., constraints 1 and 2 respectively). For that the received throughput by the i^{th} user from either the additional BS or from any other existing functional j^{th} BSs, is maximised such that it aims to satisfy the requested throughput and if so, the binary variable $\beta = 1$ (i.e., constraint 3). The variable ξ_i is defined in Eq. (5.22) and can take either 0 or 1 values (i.e., constraint 4). The constraints C5 and C6 ensure that the indexes i and j take the correct values.

This problem can also be written using a DQN, where the state represents the configuration of the additional BS (e.g, horizontal and vertical coordinates, transmit power and tilt angle). Besides, a possible action space can include some discrete actions such as: (i) changing the horizontal and vertical coordinates with $\{-1m, 0m, +1m\}$ meters, (ii) changing the transmit power with $\{-5dBm, 0dBm, +1dBm\}$ similar to problem in Eq. (5.13), and (iii) changing the tilt angle with $\{-1^\circ, 0^\circ, +1^\circ\}$. Thus, the resulting action space is 3^4 , which is relatively small compared to our previous problem in Eq. (5.13). This problem can be solved using Q-learning, dynamic programming or even a simple DQN model. Clustering can also be considered such as in [29] for adding one or more than one BS depending on the operator budget. This problem falls into both cell planing optimization and proactive maintenance studies [107]. Even if this problem in Eq. (5.23) can look easier to solve compared to our previous problem in Eq. (5.13), however it brings an additional cost to network operators by deploying more radio equipments. Thus, solving

this issue is left for future work.

5.6 Conclusion

In this chapter, we presented an adaptive and reactive resilience optimisation solution based on multi-agent **DQN** algorithm in a scenario where one or multiple **BSs** can face outages. To optimize resilience, we defined a multi-objective reward based on maximizing average throughput while simultaneously considering enhancements in coverage and service availability. The models were trained on a distributed setting, enabling cooperative learning among the agents through propagation formulas and cell load balancing. To assess the effectiveness of our proposed solution, we conducted extensive simulations, running the algorithm multiple times under varying conditions of **BS** outages. The results demonstrated that the proposed solution succeeds in improving the network overall performance under disruptive events, and by extension the resilience of the network. We deploy the resilience optimization solution into a real-world simulator, enabling us to draw meaningful insights and conclusions regarding its applicability and potential real-world impact. The next chapter is dedicated for addressing the real world implementation challenges of data-driven solutions within the **RAN** management. A special focus will be given for the data scarcity in case of network performance analysis.

REAL-WORLD IMPLEMENTATION

CHALLENGES: DATA SCARCITY

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6.1 Introduction

Data-driven solutions stand out as the primary choice for enabling automated management of future networks, their performance optimization as well as their resilience management. In this context, the network will become a center of collection and processing of situational radio data. The radio signals or data are gathered by devices and BSs and processed inside the network. Due to the ever-growing proliferation of mobile communicating devices connected to next generation networks, data collection can become an extremely expensive process when an accurate view of what is happening in the field covered by BSs is desired. As stated in the related work in Chapter 3 in Section 3.4.3, gathering a large number of various situations is required to get an accurate estimation of environmental situations. So, the challenge for mobile infrastructure with constrained bandwidth, computational costs and storage ability is to accommodate such data volumes without significantly increasing capital and operational expenses (CAPEX/OPEX).

A standard solution called Minimization of Drive Test (MDT) was proposed in 3GPP Release 10 [11] in last generations of mobile communications for automating and minimizing the amount of collected data while preserving the accuracy of information contained in the data. MDT is a feature (i.e., an automated mechanism) that enables operators to utilize test UEs to collect radio measurements of some KPIs and associated information in a cost efficient manner. However a solution to reduce the volume of data gathered with MDT, is to collect only very few measurements per KPI over limited number of clusters of cells. However, when the data collected is scarce, it particularly poses a problem for automation solutions that leverage MDT) [80]. This scarcity also impacts various tasks of network performance analysis or optimization, such as the use case developed in Chapter 4, which models the network based on a continuous collection of radio data (i.e., time series or sequence data). Besides, the issue of storing large amounts of data at CU and DU is crucial in this context. Despite the scarcity of the data, MDT and other types of data can accumulate rapidly, especially in large-scale networks.

To tackle this challenge, synthetic data generation is a solution for enabling data-driven solution to perform efficient network analysis. To do so, synthetic data should mirror real-world data accurately. This implicates the use of robust techniques of data generation. For that, we conduct a comparative study of four well known generative models to produce on-demand synthetic radio data. These are GANs, WGAN, VAEs and GMMs. Experiments are conducted following the paradigm of Training on Synthetic data and Testing

on Real Data (TSTR). Relying on density based and performance metrics we evaluate the data quality in terms of distribution similarity and variability respectively. We assess the detection capability of the generated data within the context of environment sensing in the **RAN**, which represents a use case for network performance analysis. Specifically, we evaluate synthetic data's ability in distinguishing between indoor and outdoor users. This task falls into network performance analysis aspect and is frequently employed to identify the effects of the environment on different network zones. This scenario is important because it highlights the importance of data in identifying and offering comprehensive insights on environmental conditions that may effect the network performance. Thereby, it can play a role in allowing focused optimization tailored to distinct environments, such as indoor or outdoor. For that, we track F1-score on 4 Indoor-Outdoor Detection (**IOD**) clustering algorithms: K-means, **GMM**s for clustering, **BIRCH** and **DEC** algorithms.

We will be able to (i) show that synthetic data can be used and supported to train **ML** based solutions for user environment sensing. (ii) Propose an automatic framework that learns, generates and evaluates the quality of synthetic radio data, (iii) Provide a comparative study of four distinct generative models and four unsupervised **IOD** models. In what follows, we will explain the motivation behind the environment sensing and its utility for anomaly detection and indirectly resiliency analysis. Then we will provide the background of generative models, and provide the details of the methodology of user environment sensing based on synthetic data through **IOD** use case. The framework is also presented and the problem is formulated. Finally, experiments and results are discussed and a conclusion is given.

In this chapter, we will develop and detail our solution of synthetic radio data generation for data-driven solutions, that we summarize its main contributions as follows:

- Show that synthetic data can be used and supported to train data-driven solutions for network performance analysis, taking as a use case for the study **ML** based solutions for user environment sensing.
- Propose an automatic framework that learns, generates and evaluates the quality of synthetic radio data using density similarity and variability metrics. Experimentally show that they are good indicators of the expected **IOD** performance.
- Provide a comparative study of four distinct generative models and four unsupervised **IOD** models, and show the impact of limiting the training dataset size on the quality of generated data.

6.1.1 Environment sensing in the scope of network performance analysis

The mobile users are considered as the end nodes connected to the **RAN**. Those nodes/users are constantly moving in their environment resulting in affecting the network load distribution and impacting the wireless network performance. The network infrastructure acts itself as a sensor to gather situational information related to user's location (e.g. indoor or outdoor location) [67]. This data can be processed by the network higher layers to deliver better performances in multiple operations in **RAN** such as:

- **QoS** Optimization: environmental detection can help in tailoring network parameters to the user's context to optimize **QoS**. For example, if a user is detected to be in a moving vehicle, the network can prioritize low-latency communication to support applications like autonomous driving or video streaming without interruptions.
- Adaptive Resource Allocation: by detecting the user's environment, the network operators can adapt resource allocation strategies accordingly to the observations. For instance, in crowded outdoor environments, where there might be a higher number of devices and potential interference, the network can dynamically allocate resources to ensure consistent service quality and minimize the impact of congestion. Besides, detecting high concentrations of indoor users in specific locations, such as shopping malls or stadiums, can help optimize resource allocation by dynamically adjusting network capacity to accommodate increased demand and prevent congestion-related outages.
- Outage Detection: concentrated user activity in specific areas can result in localized congestion or capacity issues. For example, identifying indoor users experiencing connectivity issues can indicate potential infrastructure failures within buildings, such as fiber optic cable damage or equipment malfunctions. Besides, detecting a sudden switch of traffic patterns of many users from indoor to outdoor can be the sign of an underlying network outage. By pinpointing regions network operators can prioritize restoration efforts and allocate resources effectively to restore connectivity and resilience.
- Resilience Management: detecting indoor users during a power outage can help prioritize the restoration of critical services in densely populated indoor environments, such as office buildings or residential complexes, to minimize disruption and ensure continuity of essential communications. Furthermore, recognizing outdoor users in

areas affected by natural disasters, such as earthquakes or floods or/and weather-related problems, can prompt proactive measures such as rerouting network traffic, reinforcing outdoor infrastructure, or deploying backup power sources to maintain service availability and resilience in outdoor areas.

- Security Threat Identification: environment detection can help performing indoor security monitoring. For example, detecting indoor users experiencing network security breaches, such as unauthorized access attempts or malware infections, can trigger security alerts for potential threats within closed environments. Besides, it helps providing outdoor surveillance by recognizing outdoor users engaged in suspicious activities, such as unauthorized network access or cyber-attacks.

As highlighted in Chapter 2, network management and troubleshooting encompass multiples aspects from reliability, energy efficiency, till sustainability and security, all fall under the scope of resiliency. The case of IOD is a classification task that helps in identifying traffic pattern that will serve to analyse the performance of the network. The User Environment Detection (UED) is one aspect of network performance analysis that allow obtaining insights for a variety of services installed across the network. When the data become scarce to perform data-driven solutions properly and solve various analysis tasks, overcoming this challenge become important to unlock automation for future networks.

6.2 Background on generative models

Generative models are unsupervised learning methods for estimating density function. They received a lot of attention in the last ten years, with the creation of GANs and VAEs [37, 51]. Since then, improved versions were proposed such as WGANs or Bayesian GANs to get rid of training problems [39, 89]. Besides, lesser complex ML algorithms like GMMs succeeded in learning multi-modal distributions [84]. Unlike basic data augmentation techniques (e.g translation, rotation, flipping), generative models are known for their effectiveness in learning directly the density distribution of input data and produce unlimited amounts of samples from it.

6.2.1 Generative Adversarial Networks (GANs)

GAN is based on an adversarial training of two neural networks referred as generator g and discriminator d with weights and biases parameters denoted as ω and θ respectively.

The generator function $g(z, \omega)$ samples data from a random latent distribution $P(z)$ represented by a noise input vector z , and attempts to approximate to original distribution P_{data} of input real data x . The discriminator function $d(x, \theta)$ estimates if a sample is coming from original dataset rather than from g by outputting a binary value, either 0 for fake or 1 for real. The loss of g and d is a minmax game:

$$\min_g \max_d \mathbb{E}_{x \sim P_{data}} [\log d(x; \theta)] + \mathbb{E}_{z \sim P_g} [\log (1 - d(g(z; \omega); \theta))] \quad (6.1)$$

where P_g is the generated data distribution. d maximizes the probability of assigning the correct label to input data while g is trained to minimize $\log(1 - d(g(z)))$.

6.2.2 Wasserstein Generative Adversarial Networks (WGANs)

WGAN is a derivative of original **GAN** that uses the Wasserstein distance metric expressed in Eq. (6.9) ($\rho = 1$). The metric measures the distance between P_{data} and P_g . The discriminator function referred to as f is called a 'critic'. As in **GAN**, f and g play the following minmax game:

$$\min_g \max_{\|f\|_{L \leq 1}} \mathbb{E}_{x \sim P_{data}} [f(x; \theta)] - \mathbb{E}_{z \sim P_g} [f(g(z; \theta))]. \quad (6.2)$$

The original **WGAN** improves training stability and prevents mode collapse compared with **GAN**. It sometimes still generates poor samples or fails to converge. Hence we use **WGAN**-GP that adds a Gradient Penalty (GP) to the loss to meet the Lipschitz constraint ($\|f\|_{L \leq 1}$) and to improve the model stability.

$$\mathcal{L} = \mathbb{E}_{\tilde{x} \sim \mathbb{P}_g} [f(\tilde{x})] - \mathbb{E}_{x \sim \mathbb{P}_{data}} [f(x)] + \lambda \mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}} [(\|\nabla_{\hat{x}} f(\hat{x})\|_2 - 1)^2], \quad (6.3)$$

where $\hat{x} = t\tilde{x} + (1 - t)x$ with $t \in [0, 1]$.

6.2.3 Variational Auto Encoders

VAE is based on an auto encoder method that uses dimension reduction capacity to encode the input data distribution and to learn explicitly its density parameters: the mean μ and the co-variance matrix σ . Those parameters are used in the decoder as parameters of a Gaussian distribution, from which we sample the latent space z to learn the input distribution.

$$\mathcal{L} = \|x - d(z)\|^2 + D_{KL}[N(\mu_x, \sigma_x), N(0, I)], \quad (6.4)$$

where $d(z)$ is the output of the decoding scheme to be minimised, and D_{KL} is the **KLD** (see Eq. (6.7)), measured between the generated distribution (compressed version of the encoding scheme) N and a standard Gaussian distribution with mean 0 and variance 1.

6.2.4 Gaussian Mixture Models

GMM is an unsupervised **ML** algorithm that can be used for multiple purposes like clustering, classification and generation, starting with the postulate that the data distribution is composed of a combination of multiple Gaussians with unknown parameters. It is based on a weighted sum of N gaussian components densities as follows:

$$P(x|\lambda) = \sum_{i=1}^N w_i \cdot g(x, \mu_i | \sigma_i), \quad (6.5)$$

where x are the observations, w_i are the mixture weights, where $i = \{1, \dots, N\}$ and $\sum_{i=1}^N w_i = 1$. The $\Sigma_i g(x, \mu_i)$ are the component Gaussian densities. λ are the **GMM** parameters (w_i, μ_i, σ_i) to be estimated and that maximize the likelihood of **GMM** given the training data. λ are estimated using the iterative expectation-maximization algorithm.

6.3 Synthetic Data for User Environment Sensing

In this section we present our methodology of environment sensing aided with synthetic data.

6.3.1 Problem formulation and proposed framework

The environment represents one of the main contextual components of user behavior. Different user behaviors would result in a significant difference in traffic generation and service usage, which directly influence the **BS** performance. Thus, analyzing the user behavior is widely considered [67] to improve **5G** and beyond networks services and network performances. One of the applications consists in detecting the user environment with the **IOD** when the **UE** is connected to the network, whether the user is indoor (buildings, home, office, mall, etc) or outdoor (transport, pedestrian, etc).

To perform **IOD** using synthetic data, we propose an automatic framework depicted in Figure 6.1 that (I) learns data distribution with generative models and evaluates syn-

thetic data quality to select the best generator model at a node A. Afterwards, using the transferred generative model to another node B to (II) produce synthetic data and then to perform real-life environment sensing. To investigate the accuracy of the generative process executed by the framework, we conduct a comparative study of four different generative models. For this purpose, we evaluate generated data quality in terms of distribution similarity and variability using generic metrics. Finally, generated data is fed into different classification models of **IOD** to validate the detection capability of synthetic data. So, the framework is executed so as to maximise the performance of the **IOD** classifier trained on generated data regarding the one trained on original data such that the performance is less or equal than a certain threshold ϵ . We formulate the problem as:

$$\begin{aligned}
 & Perf(\{f_{\omega_G^*}(x_v)\}, \{y_v\}) - Perf(\{f_{\omega_O^*}(x_v)\}, \{y_v\}) \leq \epsilon \\
 & \text{such that } f_{\omega_G^*} = f(x_{tG}, \omega^*) \text{ where } x_{tG} \in \{g(\theta^*, z)\} \\
 & f_{\omega_O^*} = f(x_t, \omega^*) \text{ where } x_t \sim P_{data} \\
 & (x_v, y_v) \in V \text{ where } x_v \sim P_{data}
 \end{aligned} \tag{6.6}$$

where $Perf(\{f_{\omega_G^*}(x_v)\}, \{y_v\})$ is the performance of the best **IOD** model on the validation dataset denoted as V . The set is fed with testing data from original dataset. The **IOD** classifier function with parameters ω_G^* , denoted as $f_{\omega_G^*}$, is trained on synthetic data x_{tG} sampled from P_g . They are generated by the best generator function $g(\theta^*, z)$ with θ^* and the latent vector z . Besides, $Perf(\{f_{\omega_O^*}(x_v)\}, \{y_v\})$ is the performance of the best **IOD** model on V with parameters ω_O^* trained on original data x_t sampled from P_{data} . $y_v \in \{0, 1\}$ that represents the label for indoor and outdoor environments.

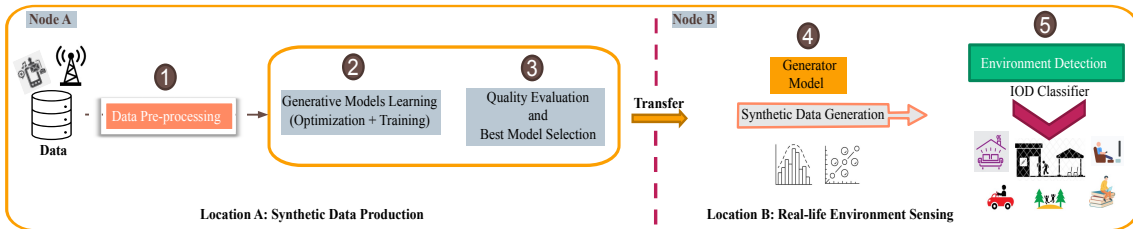


Figure 6.1 – Synthetic Data Generation Framework: Synthetic Data Production and Real-life environment sensing.

6.3.2 Synthetic Data Production

This section details the first part of the framework (Figure 6.1). We start by describing data features used for the training, formulate the generative learning problem and define the metrics for evaluating data quality .

Radio Data Features

For environment detection, many physical layer measurements may be used like GPS coordinates, the cellular signals, the magnetic intensity, or measurements from inertial sensors. In this work, we focus on two 3GPP standard radio features already employed in [62], namely the signal strength - **RSRP** and the signal quality - **RSRQ**. These performance indicators are commonly used in mobile networks context for reflecting the behavior of users. The radio features are as follows:

- **RSRP**: average received power of a single Reference Signal (RS) resource element.
- **RSRQ**: ratio between **RSRP** and the total power of received signal (RSSI).

Data cleaning and verification methods as described in [67], are applied to correct erroneous environment labels as much as possible. Thus, our whole data-set is composed of a vector of two features (**RSRP**, **RSRQ**) described in Figure 6.2.

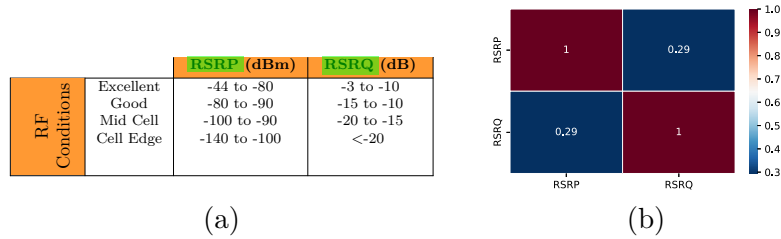


Figure 6.2 – (a) Radio Frequency conditions - (b) Pearson correlation.

Generative models learning

The entry of generative models denoted as $x_t = (x_1, x_2)$ represents a pair of two samples from two radio measurements (**RSRP**, **RSRQ**). x_t is a multivariate variable with a joint probability distribution denoted as P_{data} . The training dataset is made of N training samples $\{x_{tn}\}_{1 \leq n \leq N}$. We start from the assumption that the training data samples contain a good approximation of the true distribution so that an empirical estimation can be made

with no explicit representation of P_{data} . The input data is first cleaned and pre-processed, then an optimization of the model hyper-parameters is performed to effectively train afterwards the generative models. We investigate four generative algorithms that are **GAN**, **VAE**, **WGAN** and **GMM**.

Data quality evaluation

The generator model G has to produce radio data with the best quality. To evaluate the quality of the generated data, the visual inspection of the samples is not a reliable practical guide for automated systems. Consequently, (1) density similarity and (2) variability and variance metrics suitable for evaluating quality of generated data are used by the system in the framework.

(1) Density distribution based metrics that measure the distance between original and generated distribution.

- **JSD**: is a distance measure based on the **KLD**. It measures how much information is lost when the distribution P_g is approximated to original data distribution P_{data} . **KLD** is written as:

$$D_{KL}(P_{data} \| P_g) = \mathbb{E}_{P_{data}} \left[\log\left(\frac{P_{data}}{P_g}\right) \right] = \sum_{i=1}^N P_{data} \cdot \log \frac{P_{data}}{P_g}. \quad (6.7)$$

Unlike **KLD**, **JSD** is a symmetric metric that outputs smooth values. It is relevant when comparing two distributions that are not overlapping.

$$\mathbf{JSD}(P_{data} \| P_g) = \frac{1}{2} D_{KL}(P_{data} \| M) + \frac{1}{2} D_{KL}(P_g \| M), \quad (6.8)$$

where $M = \frac{1}{2}(P_{data} + P_g)$.

- **Wasserstein Distance**: is a similarity distance measure between probability distributions on a given metric space M [42]. It is also referred as Kantorovich–Rubinstein metric or earth mover’s distance. It measures an optimal transport plan with least cost between two probability distributions μ and ν with a ρ – *moment* as follows:

$$W_\rho(\mu, \nu) := \left(\inf_{\gamma \in \Gamma(\mu, \nu)} \int_{M \times M} d(x, y)^\rho d\gamma(x, y) \right)^{1/\rho}, \quad (6.9)$$

where $\Gamma(\mu, \nu)$ is the collection of all measures on M .

(2) Data variance and variability evaluation based on quality metrics that measure quality or/and quantity of data points sampled from the distribution. The data variability reflects the importance of "extreme" data or outlier data present in end tails of the distribution. To have a numerical estimation of data variability, we implement the Precision and Recall for Distribution (PRD) and extract the medians and standard deviations.

- **PRD Area Under the Curve (PRD-AUC)**: gives the Area Under the Curve (AUC) of all the Precision and Recall [90]. Precision measures how much of distribution Q can be generated by a part of reference distribution P while Recall measures how much of P can be generated by a part of Q . They are expressed by:

$$Precision(P_g|P_{data}) = \frac{unique(P_{data}) \cap unique(P_g)}{unique(P_g)}, \quad (6.10)$$

$$Recall(P_g|P_{data}) = \frac{unique(P_{data}) \cap unique(P_g)}{unique(P_{data})}, \quad (6.11)$$

where the function $unique(P)$ returns the unique and distinct elements in the distribution P , removing any duplicates. This ensures that the precision and recall metrics measure the coverage of unique elements rather than their frequency.

- **Medians, means and Standard Deviation (STD)**

6.3.3 Real-Life Environment Sensing

Having the best generator, the second framework part of Figure 6.1 consists in learning the IOD models using synthetic data then applying it to detect real life user environment using real data. We formulate the unsupervised classification learning problem then, we discuss its performance evaluation. The original dataset is split into a training dataset of length p and a testing/validation dataset of length m (with $p + m = N$). The synthetic dataset serves as training data.

IOD ML algorithm training: Given a set of training data denoted as $T = \{\mathbf{x}_{t_1}, \dots, \mathbf{x}_{t_p}\}$ where $\mathbf{x}_{t_i} \in \mathbb{R}^l$ is the i -th data vector of length l with $i \leq p$. Our IOD model contains $l = 2$ features and its training is done over T . When the IOD model is trained with original or generated data, $\mathbf{x}_{t_i}$ is filled respectively with original or generated training samples of (RSRP,RSRQ). Since the generated data is not annotated, we use unsupervised/clustering algorithms to check the detection capability of synthetic data compared with original ones. We investigate four clustering algorithms for our binary unsupervised classification indoor/outdoor that are K-means, GMM for clustering, BIRCH, and DEC.

IOD ML algorithm evaluation: Given a set of validation or testing data denoted as V , such that $V = \{[\mathbf{x}_{v_1} \ y_{v_1}], \dots, (\mathbf{x}_{v_m} \ y_{v_m})\}$, where $\mathbf{x}_{v_i} \in \mathbb{R}^l$ is the i -th data vector of length l with $i \leq m$. $y_{v_i} \in \{0, 1\}$ represents the label for indoor and outdoor environments. For the experiments, we perform a benchmark training over original dataset and a training over synthetic dataset. Then, the IOD classification performance is evaluated over V that contains labeled real data collected from real-life environment context. This allows to evaluate the detection capability of synthetic samples.

6.4 Experimental results

In this section, we experimentally evaluate the effectiveness of the proposed framework to generate high quality synthetic data of RSRP and RSRQ for unsupervised IOD algorithms. Starting from an original dataset collected in Paris region mainly, precisely in both indoor and outdoor environments, we describe the experiments setup and follow the steps of the framework depicted in Figure 6.1. We collect 233K samples with various situations.

(A) Synthetic Data Production: performs data pre-processing, hyperparameter optimization and training of the four generative models. Then, the quality of synthetic data is evaluated using density similarity based metrics (JSD and Wasserstein distance) and variability based metrics (PRD, median and STD). Finally, the best generator is selected.

(B) Real-Life environment sensing: receives the best generator, trains the IOD clustering algorithms using either original or synthetic data. Then, their detection capability is validated based on $F1 - score$ computed using the validation set V . The dataset collected is split into 80% (187K) for the training dataset and 20% (46K) for the testing/validation dataset. The original joint distribution P_{data} is shown in Figure 6.3.

6.4.1 Experimental setup

We are also interested in studying the impact of reducing the training dataset size on the quality of the data produced and on the IOD classification performance. So, the training is done considering multiple sizes of training dataset, $\{100\%, 50\%, 20\%, 10\%, 5\%, 0.45\%\}$.

First, we discuss the training performance of joint synthetic probability P_g comparing to original P_{data} , and the analysis of the training time is performed. Then, we compare

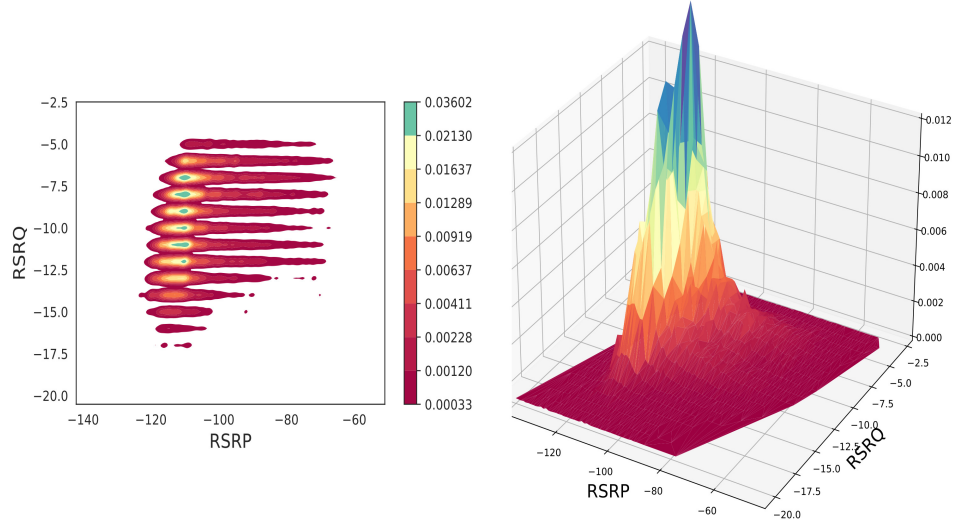


Figure 6.3 – Joint probability distributions of original **RSRP** and **RSRQ**: 2D (left) and 3D (right).

(1) Parameter/Algorithm		GAN	WGAN	VAE		
Number of layers		1	3	1		
Optimizer		Adam	Adam	Adam		
Loss		Binary cross entropy	Wasserstein distance + GP	KLD + Reconstruction loss		
Epochs		10000	100	100		
Batch size		128	128	128		
Training time (s) on 100%		2900	600	700		

(2) Algorithm /Parameter	Number of components	Covariance type	Initial params	Tolerance	Training time (s) on 100%	
GMM	10	Full	K-means	1e-3	4	

(3) Training dataset size	100%	50%	20%	10%	5%	0.45%
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Table 6.1 – Training configuration of generative models.

density similarity and variability metrics for the four algorithms to assess data quality. The impact of reducing the size of the training datasets on the **JSD** is also studied. In the second part, we evaluate the $F1 - score$ of the four **IOD** algorithms trained on original data. We then compare them to the $F1 - score$ obtained when classifying synthetic data. The study goal is to investigate the reproducibility of classification using only synthetic data instead of the original data. We investigate the best generator and clustering algorithm in the context of high size $\{100\%, 50\%, 20\%\}$ or low size $\{10\%, 5\%, 0.45\%\}$ of training datasets. Optimizations and experiments, including training and evaluations, are performed on a Linux machine equipped with Intel Core i7-5930 CPU and GPU, Nvidia GTX Titan X graphic card and 64 GB of RAM.

6.4.2 Synthetic data production

(1) **Data pre-processing:** As a first step, we clean and re-scale data using standardization because this technique provides a more stable and accurate training for our experiments.

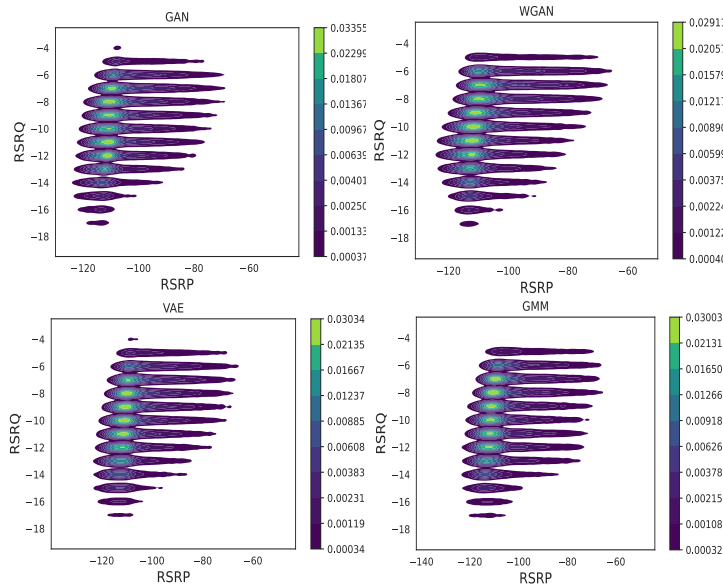


Figure 6.4 – Joint probability distributions of synthetic **RSRP** and **RSRQ** in 2D with: **GAN**, **WGAN**, **VAE** and **GMM**.

(2) **Generative models learning (hyper-parameter optimization and training):** We train the four generative models to learn P_{data} using the optimal hyper-parameters given in Table 6.1. The hyper-parameters (e.g., activation functions or learning rate) are

optimized for deep generative models (**GAN**, **VAE** and **WGAN**). For this purpose, we use the Tree-structured Parzen Estimator (TPE) optimization algorithm which is a Bayesian optimization approach. It looks for the best choices of neural network configuration among a plurality of possibilities in order to optimize its learning performance. Figure 6.4 represents the joint 2D probability distribution obtained with the four generative models. They all look like the original drawn in Figure 6.3. But it is difficult to visually observe the small differences.

(3) Data quality evaluation and best model selection: during the training, we track the evolution of the density, variability and variance of the similarity metrics over 5 distinct trainings and over a significant number of iterations. For accurate analysis, the metrics are averaged every 10 iterations over 5 generated data sequences. The Table 6.2 shows the minimum average values of **JSD**, Wasserstein distance, **PRD**, median and STD. These are quantified for each generative model studied. The Table also details the training execution time for each case.

We observe that **GMM** learning takes less time to converge compared to deep generative model learning and overall achieves better results. The convergence rapidity can be explained by the fact that we are trying to generate a two-dimensional joint probability distribution that seems visually easier to model with a mixture of Gaussians. In addition, we note that the **GAN** training requires more epochs to converge, which was expected from the State of the Art since we train the generator and the discriminator simultaneously. However, using the Wasserstein distance results in a noticeable decrease in the convergence speed of the **GAN**, as expected. **VAE** has a similar runtime as **WGAN**.

	JSD	Wasserstein distance	PRD	Median $\pm$ STD Origin.: -36.5 $\pm$ 48.88	Time (s)
WGAN	0.019	0.795	0.991	-31.79 $\pm$ 48.92	600
GAN	0.015	0.621	0.992	-31.5 $\pm$ 48.97	2900
VAE	0.014	0.608	0.993	-34.25 $\pm$ 48.93	700
GMM	0.012	0.182	0.996	-32.6 $\pm$ 48,89	4

Table 6.2 – Performance comparison on density similarity, variability and variance metrics and training time.

When the density similarity metrics show low values, they reveal high similarity between the distributions of the generated data and the original data. Therefore, they reflect the success of the generative model learning. On the other hand, when they show a high **PRD**, the generative model is able to better generate the "extreme" data present in the

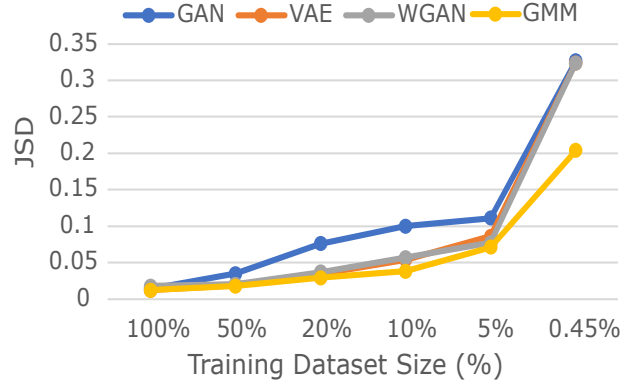


Figure 6.5 – JSD versus training dataset size - GAN, WGAN, VAE and GMM.

distribution tails. The generation of endline data is increased, which improves the variability of the data and thus, the range of observed data that covers more space. According to the metrics (JSD, Wasserstein distance and PRD), GMM and VAE are the best models for learning P_{data} . These good results can be explained by the small range of possible data for the radio indicators and the fact that the joint probability has a bell shape typical of Gaussians. Both models are based on the Gaussian assumption. To deeply analyze the impact of training data volume on the quality of the generated data, Figure 6.5 plots the JSD metric as a function of the size of the training data set. We notice that the curve increases with the percentage of the training data size. The JSD remains roughly stable until 10% and then starts to increase significantly. This is because with generative models, a minimal volume of training data is required to accurately learn the joint probability and produce high quality data. The threshold at which the JSD degrades is between 5% and 10%. Nonetheless, in the context of a small data set size, generative models can continue to reproduce the data. The results empirically show that GMM is the best at generating high quality data in all cases according to JSD.

The following subsection compares IOD models in the case of environment sensing. To select the best generator to transfer to the remote node, we focus on using density similarity metrics. Indeed, outlier data (measured with PRD) have a very small impact on the performance of the IOD task. Specifically, we chose to focus on JSD rather than Wasserstein distance because it is less complex and faster to compute. The framework selects then the best model weights and biases that matches the minimum average JSD and transfers them to node B.

6.4.3 Real-life environment sensing

(4 and 5) Environment detection with IOD classifier: After selecting the best model weights and biases at node A and forwarding them, the generative model is extracted at the remote node B. Synthetic data is then produced to train the unsupervised ML clustering algorithms. Then, their performance is evaluated on V for each best generative model and compared with the performance of IOD models that are trained with original data. Figures 6.6 show the average $F1 - score$ as a function of the training dataset size for both cases of training data (original and synthetic). We notice that the $F1 - score$ decreases with the size of the training dataset in the majority of cases. The evolution of $F1 - score$ is correlated with the evolution of JSD presented in Figure 6.5. Indeed, with fewer training data samples, the joint distribution is less well learned by the generative models, which has a negative impact on the classification results. However, we observe that the GMM increases slightly to 0.45% in Figure 6.6a due to overfitting.

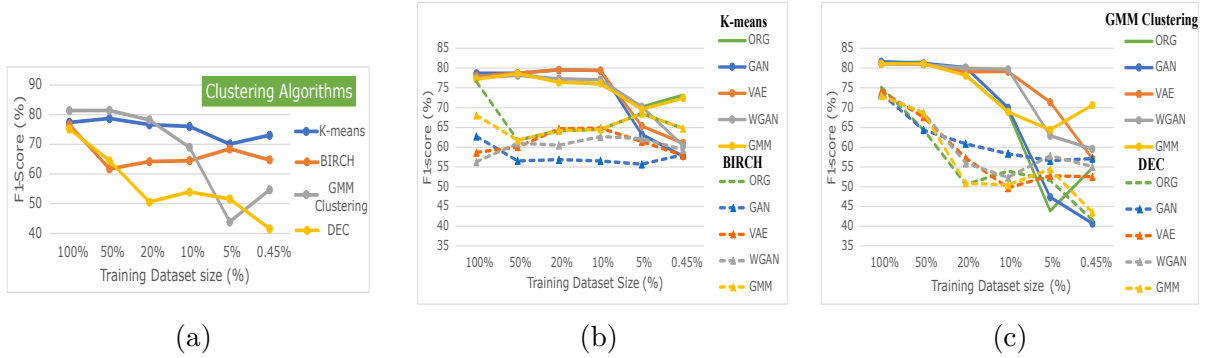


Figure 6.6 – Mean $F1 - score$ versus training dataset size: (a) Clustering algorithms trained with original data - (b) K-means and BIRCH trained with synthetic data - (c) GMM Clustering and DEC trained with synthetic data.

The comparative study in fig 6.6a between the four IOD algorithms trained on original data reveals that GMM for clustering and K-means are the best in high dataset size context, where the $F1 - score = 80\%$. K-means and BIRCH are the best in low dataset size context ($F1 - score = 70\%$). So, the simple ML clustering techniques (K-means, BIRCH, GMM clustering) are enough accurate for IOD case. Besides, their training time is relatively small (less than a minute) with K-means, BIRCH or GMM clustering compared to DEC (10 minutes). DEC is the worst one in terms of classification and time performance because it is a DL technique. Note that in case of low dataset size context, the GMM clustering suffers from the insufficient amount of data. However, when training IOD on

synthetic data only, we observe in Figure 6.6b and Figure 6.6c that in the majority of cases, the $F1 - score$ is similar to the ones obtained with the original data. In a high size context, K-means and GMM Clustering learned on synthetic or original data give similar $F1 - scores$. GMM Clustering with VAE and WGAN performs better in classification for a $F1 - score$ of 81%. BIRCH and DEC trained on synthetic data perform less well, as mentioned above, but achieve the same performance as with the original data. In a small context, all IOD models still provide $F1 - scores$ similar and low $F1 - scores$ except for GMM clustering and DEC. In these cases, IOD models trained on synthetic data perform better than IOD models trained on the original data.

Outcome discussion: Based on the similarity of the $F1 - scores$ observed in the studied cases, we can conclude that the generated data of high quality can achieve similar performance as the original data. These results validate the good detection ability of the generated data, which can be as good as the original data. In practice, engineers can choose the most appropriate quality metric or combination of quality metrics to use in selecting and transmitting the best generator for the use cases being studied. In the context of massive data, transmitting generative models over the network instead of the source data would help overcoming storage costs or data transport issues over the network. When the cost of data transfer is not high but data transfer cannot be performed for other reasons like privacy issues, generative models can then overcome the challenge of data privacy or augmentation. Thus, this work presents a first application to enable environment detection as well as other network performance analysis based on synthetic data. Nevertheless, other challenges remain. Indeed, to ensure data saving at the lowest cost, the use of an accurate and low complexity generative model is a prerequisite. In addition, models must deliver data with labels and account for spatial and temporal dependencies of input features. Their use should be extended to other use cases and other data features with more complex probability distributions.

6.5 Generative Artificial Intelligence (AI) usage for storage optimization in 3GPP architecture

This work of synthetic radio data generation has been extended for an integration into a 3GPP standardized architecture, resulting in a publication within a Nokia patent [66]. The innovation of the patent stipulates that the 5G NetWork Data Analytics Function (NWDAF) can exchange generative models instead of the entire data to reduce the cost

related to data sharing.

The NWDAF is part of the architecture specified in 3GPP TS 23.501 [7] and uses the mechanisms and interfaces specified for 5G Core in 3GPP TS 23.501 and OAM functions. It has got two analytical functions: one for training ML models and the other one for performing inferences and deriving analytical information. This function can consume and produce data on demand. It communicates with the Analytics Data Repository Function (ADRF) that is responsible for storage and retrieval of information. The 5G system architecture allows ADRF to store and retrieve the collected data that comes from various data sources (consumers) such as other 5GC network functions, OAM functions and analytical functions. It may also perform analytics and Data collection using the Data Collection Coordination Function (DCCF). The ADRF can be requested by the NWDAF or indirectly by DCCF to retrieve historical data multiple times by exchanging signaling messages back and through. The NWDAF can also produce data and ask the ADRF for storing it. However, this can rapidly overload the network and add a cost related to the volume of data sharing. Traditionally, this problem is tackled by techniques that focus on reducing the volume of data to be stored like compression, or deploying better storage hardware that consumes less energy.

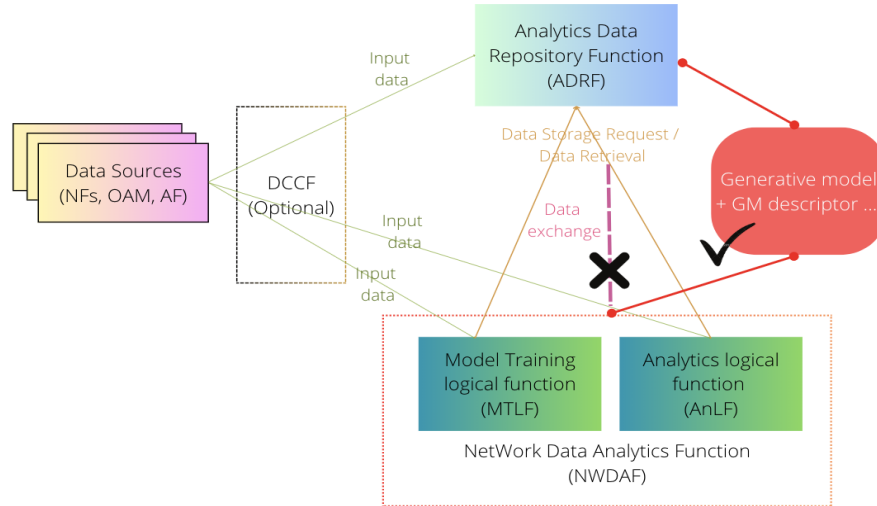


Figure 6.7 – Architecture of connection between the NWDAF and the ADRF with the generator module integration.

To solve the problem, our invention provides a solution for historical data storage management between the NWDAF and the ADRF. By appropriately training generative models such as GANs on data, it is possible to obtain a generator module that can sample

synthetic data on demand with the same quality as the source data. This generator can be used by the NWDAF to produce input data for inference and/or training, and possibly learn a generative model and include it in the services exposed by ADRF, to reduce the volume of transferred and stored data within the ADRF. A brief description of NWDAF architecture is shown in Figure 6.7.

The application of this invention implies adding some signaling messages between the NWDAF and the ADRF. It can be achieved by adding some informative fields in the request messages like: an indicator related to a generative module that informs if the NWDAF is able to execute a generative module instance, or adding a descriptor that describe how to use the generative module to generate synthetic data [5]. Other fields like a description of the data and many more will allow this approach to be executed successfully by the 5G network functions.

6.6 Conclusion

In this chapter, we illustrated a potential approach for tackling the scarcity of the training data challenge for data-driven solution in the context of network performance analysis. We explored the possibility of using only synthetic radio data for ML training algorithms in a context of absence of data sharing. By using generative models, we provided a way to produce high quality synthetic radio 3GPP data. We conducted a comparative study of four popular generative models on large-scale experiments with real data. Using metrics based on density similarity and variability, we highlight the importance of automatic quality assessment of synthetic data. Finally, the detection capability of synthetic data was validated on four different IOD classification algorithms. We experimentally demonstrate that these metrics are good indicators of expected performance. We also show that generating high quality synthetic data can achieve similar performance to the original data. The next chapter will summarize the main contributions of this thesis and their relation, the perspectives and future works, and will list the related publications of this work.

CONCLUSION AND FUTURE WORK

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7.1 Conclusion

RESILIENCE is an emerging concept that has been well recognized among researchers and practitioners, for studying the ability of various systems to adapt to abnormal and stressful events. As our reliance on wireless technology continues to grow, ensuring the resilience of future cellular networks like 5G and beyond, becomes increasingly important in maintaining uninterrupted connectivity and meeting the demands in Quality of Service (QoS). These advanced networks are expected to support a wide range of applications, from Ultra-Reliable Low-Latency Communications (URLLC), and enhanced Mobile BroadBand (eMBB), to massive Machine-Type Communications (mMTC), across diverse environments and encompassing various service needs ranging from basic to critical.

In the literature, efforts have been devoted to develop preventive measures to avoid failures and to optimize network functions such as in domains of Self Organizing Networks (SON), dependability and reliability, as well as in network management systems. However, the unpredictable nature of the wireless environment, the explosion in data traffic and the sheer number of connected devices make it essential to avoid breakdowns and limit downtime for repairs. These difficulties are likely to increase with the proliferation of devices in an increasingly connected world. The situation emphasizes the need for an efficient resilience strategy capable of meeting the evolving needs of users. Such a strategy should provide adaptability and customized optimization tailored to specific resilience requirements, while incorporating targeted metrics for evaluation. Essentially, we believe that enabling such a strategy should involve conducting a thorough analysis of resilience, utilizing appropriate metrics that accurately reflect the performance of the network. Then, based on this information, the network can perform targeted optimization to enhance its resilience. This should be enabled thanks to an automated resilience service that runs on demand for specific network and service areas, based on various data-driven solutions. Creating such an automated framework should not only address resilience management, but overcome its potential implementation challenges to effectively assess its practicability in real-world networks. This thesis falls into the risk management of the 5G Radio Access Network (RAN) and beyond. We primarily presented a detailed overview of the main concepts we used, such as the architecture of 5G-RAN, the requirements and the challenges, the Open RAN (O-RAN), the SON and the network management system. Then, we provided a taxonomy of the resilience concept, considering relatively its novelty in the fields of engineering and networking. In this scope, we identified the research axes

and alleviate the problem raised in this thesis into three main contributions.

Our first contribution was focused on measuring the resilience utilizing modeling and quantification approaches. We used Markov Chains to analyse the network coverage using two Key Performance Indicators (KPIs) that respectively represent the radio coverage and the service integrity. These two KPIs are measured using two radio signals that are the Reference Signal Received Power (RSRP) and the received user throughput, respectively. Based on two independent Markov models, we predicted the states of the radio coverage and the service integrity. We proposed metrics to quantify the resilience level of the network. To showcase the usefulness of our approach, we carried out a numerical analysis using simulations in different failure scenarios. According to numerical results, this approach can help to efficiently forecast the average behaviour of mobile networks in terms of outages and resilience, in short or mid-term duration. This approach allows to proactively analyse basic and critical networks in terms of QoS levels, thereby facilitating their enhancement through a comprehensive evaluation. Besides, quantifying the network resilience with multiple metrics for each KPI allows to determine the impact on each indicator separately. This can allow engineers to gain insights about the effects on each indicator and to activate appropriate resilience mechanisms and implement targeted optimizations to enhance network performance. A framework of resilience management is also discussed in order to apply this approach on virtualized architectures of 5G-RAN and beyond networks.

As a second contribution, we have addressed the problem of resilience optimization using adaptive solutions. We proposed the use of multi-agent Deep Q-learning Network (DQN) algorithm in a scenario where one or multiple Base Stations (BSs) can face outages. To optimize resilience, we formulated a multi-objective reward based on maximizing total throughput while simultaneously considering enhancements in coverage and service availability. For that, we used as constraints in the optimization, the coverage and service availability thresholds that were extracted from the resilience analysis models of the first contribution. To assess the effectiveness of our proposed solution, we conducted extensive simulations, running the algorithm multiple times under varying conditions of BS outage. The results show that the proposed solution improves the overall network performance and, consequently, its resilience. Considering the network area as a cohesive entity during the optimization phase can outperform traditional mitigation techniques that usually involve reconfiguring only local cell sites adjacent to the faulty area unlike our proposed approach.

Our third and final contribution addressed a potential challenge encountered in implementing data-driven solutions for network performance analysis and optimization in real network architectures, which is the scarcity of the collected data. The data scarcity is a well known issue in the telecommunication industry due to the cost, for operators, related to data collection, transport, and storage. However, achieving full automation in future networks for network management including resilience management, requires to guarantee the availability of the data for data-driven solutions, in order to ensure their optimal performance. The main objective of this contribution was to explore the possibility of using only synthetic radio data for machine learning training algorithms in a context of absence of data sharing. We proposed to use generative models to provide high quality synthetic data. For this purpose, we conducted a comparative study of four popular generative models on large-scale experiments with real data. Using metrics based on density similarity and variability, we highlighted the importance of automatically assessing the quality of the produced data. Finally, the detection capability of synthetic data has been tested on an environmental detection use case which is a network performance analysis task. Specifically, we evaluated synthetic data's ability in distinguishing between indoor and outdoor users, a critical aspect of network performance analysis. This task is usually used to enable the identification of environmental influences in specific network areas. This underscores the significance of data in detecting and providing detailed insights into the network status, facilitating targeted optimization efforts tailored to specific areas like indoor or outdoor environments. Thus, four different Indoor-Outdoor Detection (IOD) classification algorithms were considered for the validation phase. We experimentally demonstrated that the metrics used are good indicators of expected performance. We also showed that generating high quality synthetic data can achieve similar performance than with the original data. This work was extended for an implementation within a standardized 3GPP 5G architecture, intended for working across multiple use cases.

We wrap up the relation between the three contributions into the pipeline illustrated in Figure 7.1.

7.2 Future work

In this thesis, we addressed resilience quantification and optimization for both coverage and service in a 5G-RAN and beyond networks architecture as well as the challenge of

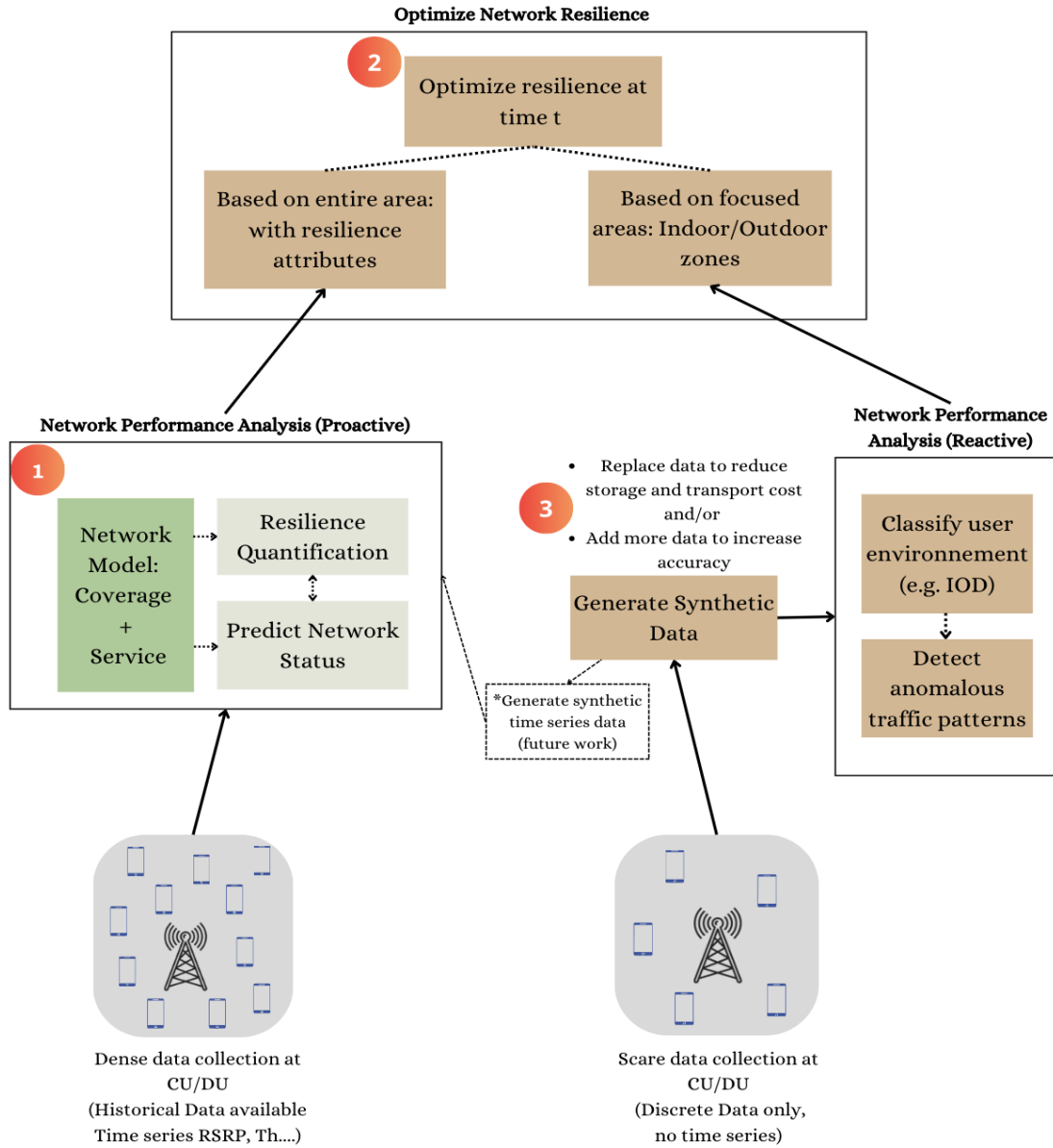


Figure 7.1 – Thesis contributions.

the data scarcity for data-driven solutions. However, there is still work to be done and our contributions can open up further research directions.

In Chapter 4, we addressed the problem of resilience quantification in a proactive strategy by utilizing Markov chains. Historical data on signal strength and throughput were used to define the coverage status and the service status, respectively. However, for a complete analysis of resilience, other performance indicators should also be taken into account. The proposed predictive model can be extended to support other User Equipment (UE) signals like Signal to Interference and Noise Ratio (SINR), Reference Signal Received Quality (RSRQ) or to include latency indicators for Ultra-Reliable Low Latency Communications (URLLC) services where the core network can be involved since it creates higher latency than the RAN.

In Chapter 5, we addressed the optimization of resilience for a network area and from an outage mitigation perspective. By leveraging the power of Deep Reinforcement Learning (DRL), we learned the dynamics of automatic tilt and transmit power reconfiguration to improve the total throughput, as well as coverage and service availability, and, by extension, the resilience. Future work can include the integration of other radio parameters into the optimization, such as improving cell load and reducing latency. Additionally, an extension for a wider network area could be envisaged, with a dynamic accommodation of the number of users and the number of reconfiguration steps can also be considered for tuning. Additionally, a study could be conducted to apply the optimization to specific network areas, such as indoor or outdoor environments. Finally, an application with beamforming can also be explored and a heterogeneous network resilience optimization between both macro cells and small cells can be investigated.

Finally, we tackled in Chapter 6 the data scarcity challenge for data-driven solutions in the telecommunication industry, by using generative models to produce synthetic radio data on demand, thus overcoming the cost of data sharing and data storage. As a first perspective, we propose to test these methods on other data distributions like Mobility Indicator (MI) or Timing Advanced (TA). Besides, we can consider generating data with labels using for example Conditional Generative Adversarial Networks (CGANs) or generating time series RSRP data using discrete-variant GANs or continuous-variant GANs, to allow using the proactive resilience analysis developed in Chapter 4 when time series data is missing. Finally, an extension to any other practicality challenge, such as domain adaptation, can be considered. Since most anomaly detection studies are performed on simulated data to avoid stressing the real network, there is a need to adapt analysis and

optimization models learned on simulated data for their application to real data.

7.3 Publications

This section lists our published papers within this thesis.

Conferences:

1. **S. KAADA**, M. L. Alberi Morel, S. Jelassi and G. Rubino. "Resilience analysis and quantification method for 5G-Radio Access Networks". In 2022 IEEE Network of Future Conference (NoF), pages 1–9, Oct 2022.
2. **S. KAADA**, M. L. Alberi Morel, G. Rubino and S. Jelassi. "Measuring 5G-RAN resilience using coverage and quality of service indicators". In 2023 IEEE/IFIP Network Operations and Management Symposium (NOMS), pages 1–7, 2023.
3. **S. KAADA**, S. A. Hamideche, C. Daems and M. L. Alberi Morel. "Classification with Synthetic Radio Data for Real-life Environment Sensing". In VTC 2023 IEEE Vehicular Technology Conference (VTC), pages 1–7, 2023.

Patent:

1. M. L. Alberi Morel, A. Conte, F. Giust and **S. KAADA**. "Optimized data storage in mobile network scenarios". Nokia Paris Saclay Patent, Aug. 2022.

Journal:

1. **S. KAADA**, D. H. Tran, N. V. Huynh, M. L. Alberi Morel, S. Jelassi and G. Rubino. "Multi-Agent reinforcement Learning for resilience optimization". 2024, (Submitted to IEEE transactions on mobile computing).

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Titre : La résilience en tant que service à la demande des réseaux 5G dirigée par le Machine Learning

Mot clés : 5G RAN, network resilience, coverage, QoS, multi-agent DRL, generative models.

Résumé : Les réseaux 5G et au-delà doivent offrir une connectivité rapide et fiable. Cependant, la nature du réseau d'accès le rend sujet à des défaillances malgré les mécanismes de fiabilité proposés par les concepteurs systèmes. Dans ce contexte, assurer la résilience des réseaux devient cruciale pour les opérateurs, en particulier pour les applications critiques. La résilience se définit par le caractère d'un système qui, face aux défaillances, est capable de maintenir un service fonctionnel. Plutôt que des solutions coûteuses et statiques comme la redondance, l'objectif de cette thèse consiste à proposer une solution de résilience adaptative basée sur les méthodes d'apprentissage automatique pour les futurs réseaux virtuels de la 5G et au-delà, tout en prenant en compte les éventuels challenges rencontrés lors des implémentations dans des réseaux réels. La première contri-

bution analyse la résilience d'une zone de réseau d'accès 5G, en utilisant des chaînes de Markov et des données radio pour prédire l'état de la couverture et de la qualité de service. La deuxième contribution optimise la résilience d'un réseau multi-cellulaire dense pour assurer les contraintes de résilience à l'aide d'un algorithme Deep Q-Network multi-agents. Enfin, dans la dernière contribution nous abordons le défi de la rareté des données collectées afin de faciliter l'automatisation de la gestion des réseaux, notamment la gestion de la résilience. En l'absence de partage des données, on utilise des modèles génératifs pour montrer que la génération de données synthétiques 3GPP de haute qualité, validée par des algorithmes de classification, offre des performances similaires aux données réelles.

Title: Resilience-as-a-Service for 5G RAN driven by Machine Learning methods

Keywords: 5G RAN, network resilience, coverage, QoS, multi-agent DRL, generative models.

Abstract: 5G and beyond networks must provide fast and reliable connectivity. However, the nature of the access network makes it prone to failures despite the reliability mechanisms proposed by system designers. In this context, ensuring network resilience becomes crucial for operators, especially for critical applications. Resilience is defined as the ability of a system to maintain functional service despite failures. Instead of costly and static solutions like redundancy, this thesis aims to propose an adaptive resilience solution based on machine learning methods for future virtual 5G networks and beyond, while considering potential challenges encountered during implementation in real networks. The first contribu-

tion analyzes the resilience of a 5G access network area using Markov chains and radio data to predict network coverage and quality of service status. The second contribution optimizes the resilience of a dense multi-cellular network to satisfy the resilience constraints using a multi-agent Deep Q-Network algorithm. Finally, the last contribution addresses the challenge of scarce collected data to facilitate network management operations, particularly the resilience management. In the absence of data sharing, generative models are used to generate high-quality 3GPP synthetic data. The data is validated by classification algorithms and show that it offers similar performance compared to real data.