User Mobility Prediction and Management using Machine Learning

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Abstract

The next generation mobile networks (NGMNs) are envisioned to overcome current user mobility limitations while improving the network performance. Some of the limitations envisioned for mobility management in the future mobile networks are: addressing the massive traffic growth bottlenecks; providing better quality and experience to end users; supporting ultra high data rates; ensuring ultra low latency, seamless handover (HOs) from one base station (BS) to another, etc. Thus, in order for future networks to manage users mobility through all of the stringent limitations mentioned, artificial intelligence (AI) is deemed to play a key role automating end-to-end process through machine learning (ML).

The objectives of this thesis are to explore user mobility predictions and management use-cases using ML. First, background and literature review is presented which covers, current mobile networks overview, and ML-driven applications to enable user's mobility and management. Followed by the use-cases of mobility prediction in dense mobile networks are analysed and optimised with the use of ML algorithms. The overall framework test accuracy of 91.17% was obtained in comparison to all other mobility prediction algorithms through artificial neural network (ANN). Furthermore, a concept of mobility prediction-based energy consumption is discussed to automate and classify user's mobility and reduce carbon emissions under smart city transportation achieving 98.82% with k-nearest neighbour (KNN) classifier as an optimal result along with 31.83% energy savings gain. Finally, context-aware handover (HO) skipping scenario is analysed in order to improve over all quality of service (QoS) as a framework of mobility management in next generation networks (NGNs). The framework relies on passenger mobility, trains trajectory, travelling time and frequency, network load and signal ratio data in cardinal directions i.e, North, East, West, and South (NEWS) achieving optimum result of 94.51% through support vector machine (SVM) classifier. These results were fed into HO skipping techniques to analyse, coverage probability, throughput, and HO cost. This work is extended by blockchain-enabled privacy preservation mechanism to provide end-to-end secure platform throughout train passengers mobility.

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Statement of Originality

Name: Syed Muhammad Asad

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List of Publications

Journals

1. **Asad, S.**; Ahmad, J.; Hussain, S.; Zoha, A.; Abbasi, Q.; Imran, M. Mobility Prediction-Based Optimisation and Encryption of Passenger Traffic-Flows Using Machine Learning. Special Issue: Application of Sensors in Transportation in the Context of Logistics 4.0 and Industry 4.0, 20.

2. **Asad, S.**; Ansari, S; Ozturk, M; Dashtipour, K.; Rais, R.N.B.; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Mobility Management-Based Autonomous Energy-Aware Framework Using Machine Learning Approach in Dense Mobile Networks. MDPI Signals, 2020.

3. **Asad, S.**; Ansari, S.; Rais, R.N.B.; Abubakar, A.I.; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Edge Intelligence in Private Mobile Networks for Next Generation Railway Systems. Frontiers in Communications and Networks, section IoT and Sensor Networks.

4. **Asad, S.**; Klaine, P.V.; Rais, R.N.B; Dashtipour, K.; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Context-Aware Handover Skipping for Train Passengers in Next Generation Wireless Networks. IEEE Journal of Communications and Networks. Under Review.

5. **Asad, S.**; Zhang, X.; Rais, R.N.B; Sun, Y.; Klaine, P.V.; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Blockchain-empowered Secure Spectrum Sharing for Next Generation Train Networks. IEEE Magazine. In progress.

6. Abubakar, A.I.; Ozturk, C.; Ozturk, M.; Mollel, M.S.; **Asad, S.**; Hassan, N.U.; Hussain, S.; Imran, M.A. Revenue Maximization through Cell Switching and Spectrum Leasing in 5G HetNets. IEEE Transactions on Cognitive Communications and Networking.

Conference Proceedings and Letters

1. **Asad, S.**; Ozturk, M.; Rais, R.N.B.; Zoha, A.; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Reinforcement Learning driven Energy Efficient Mobile Communication and Applications 2019. pp. 1–7.

2. **Asad, S.**; Dashtipour, K.; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Travelers-Tracing and Mobility Profiling Using Machine Learning in Railway Systems. Month 08, year 2020

3. **Asad, S.**; Dashtipour, K.; Rais, R.N.B; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Employing Machine Learning for Predicting Transportation Modes under the COVID-19 Pandemic: A Mobility-Trends Analysis. UCET 2021 (The 2021 6th International Conference on UK-China Emerging Technologies).

4. **Asad, S.**; Klaine, P.V.; Rais, R.N.B; Hussain, S.; Abbasi, Q.H.; Imran, M.A. Mobility Management in the Applications of 5G and Beyond: A Handover Skipping Topology Analysis, 4th Global Power, Energy and Communication Conference, GPECOM2022, June 2022.

5. **Asad, S.**; Klaine, P.V.; Rais, R.N.B; Hussain, S.; Zhang, L.; Abbasi, Q.H.; Imran, M.A. Blockchain-enabled Handover Skipping for High Mobility Train Passengers, IET Electronics Letters, Under review, Submitted in July 2022.

Best Student Paper Award

1. IEEE 4th Global Power, Energy and Communication Conference, GPECOM22, held on 14-17th June 2022. Best student paper award was presented to **Asad, S.**; Klaine, P.V.; Rais, R.N.B; Hussain, S.; Abbasi, Q.H.; Imran, M.A., for the paper entitled, “Mobility Management in the Applications of 5G and Beyond: A Handover Skipping Topology Analysis”.

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List of Acronyms

2G	Second Generation
3D	Three Dimension
3G	Third Generation
3GPP	3rd Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
AFR	Adaptive Frequency Reuse
AR	Augmented Reality
AWGN	Additive White Gaussian Noise
BPNN	Back Propagation Neural Network
BS	Base Station
CAC	Call Admission Control
CAPEX	CAPital EXpenditure
CDMA	Code Division Multiple Access
CF	Collaborative Filtering
CSI	Channel State Information
D2D	Device to Device
DP	Dynamic Programming
DT	Decision Trees
ECN	Emergency Communication Networks
EE	Energy Efficiency
EICIC	Enhanced Inter-Cell Interference Coordination
EIRP	Equivalent Isotropically Radiated Power
ESM	Energy Saving Mechanism
FFR	Fraction Frequency Reuse
FPC	Fractional Power Control
FQL	Fuzzy Q-Learning
GA	Genetic Algorithm
GD	Gradient Descent

GoS	Grade of Service
GPS	Global Positioning System
HHO	Horizontal HandOver
HMM	Hidden Markov Model
HO	HandOver
ICIC	Inter-Cell Interference Coordination
IoT	Internet of Things
IP	Internet Protocol
ITU-R	International Telecommunication Union - Radio
IT2T	Intelligent Train to Train
IXR	Intelligent Extended Reality
KPI	Key Performance Indicator
LAP	Low Altitude Platforms
LoS	Line of Sight
LTE	Long Term Evolution
LTE-A	Long Term Evolution - Advanced
M2M	Machine to Machine
MC	Macro Cell
MK	Markov Chains
MDP	Markov Decision Process
MDT	Minimization of Drive Tests
MIMO	Multiple Input Muplitple Output
ML	Machine Learning
MLB	Mobility Load Balancing
cMTC	Critical Machine-Type Communications
MOO	Multi-Objective Optimisation
MRO	Mobility Robustness Optimization
MSE	Mean Squared Error
NCL	Neighbour Cell List
NFV	Network Function Virtualisation
NGMN	Next Generation Mobile Networks
NGN	Next Generation Networks
NLoS	Non-Line of Sight
NN	Neural Network
NNS	Nearest Neighbour Search
NP-hard	Non-deterministic Polynomial-time hard
NEWS	North, East, West, and South
OFDMA	Orthogonal Frequency Division Multiple Access

OPEX	OPerational EXpenditure
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Network
RB	Resource Block
RL	Reinforcement Learning
RLF	Radio Link Failure
RNC	Radio Network Controllers
RSRP	Reference Signal Received Power
RSSI	Received Signal Strength Indicator
SC	Small Cell
SINR	Signal to Interference Plus Noise Ratio
SON	Self Organising Networks
SVM	Support Vector Machine
SL	Supervised Learning
TD-Learning	Temporal-Difference Learning
TL	Transfer Learning
TTT	Time to Trigger
UAV	Unmanned Aerial Vehicle
UE	User Equipment
UL	Unsupervised Learning
UWB	Ultra-Wideband
UHD	Ultra High Definition
V2X	Vehicle to Anything
VFA	Value Function Approximation
VHO	Vertical Hand Over
VR	Virtual Reality
XR	Extended Reality

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Chapter 1

Introduction

In the last decade, networks with the intelligent decisions power with respect to mobile networks, have become an essential part of our lives, bringing broad range of automated applications for the potential mobile network operators (MNOs) and end users. For instance, users have the opportunity to perform businesses, transactions, and improve their mobile phone usage while on the move. Furthermore, users can perform adhoc teleconferences, browse internet, watch high definition videos, listen audio on the fly, talk to distant relatives, instantly upload photos or videos onto social media, and many more [1–3].

MNOs strive to play a huge part in solving capacity crunch needs while setting users policies and are uniquely able to provide the resources to make sure mobile services reach every user. Addressing growing traffic demands is a crucial component of the innovation that improves way of life for every mobile user. Therefore, number of devices connected to the network are expected to grow exponentially in next few years [4–6]. Due to the increase, the fifth generation (5G) and beyond 5G (B5G), traffic density needs to be at the cutting-edge with the advancement of Internet of things (IoT), machine-to-machine (M2M) communications, etc. As such, some of the requirements that are recurrent in state-of-the-art literature for 5G networks are [1, 2, 7]:

- Address the capacity crunch needs while planning intelligent mobile networks;
- Provide better quality of service (QoS) and quality of experience (QoE) to users;
- Compatible with different radio access network (RAN) technologies;
- Support a wide range of intelligent mobility management applications;
- Provide higher data rates at the cell edge to avoid interference;

- Support radio latency, resilience, and redundancy;
- Support ultra high reliability;
- Provide improved security such as, advanced encryption methods, blockchain privacy mechanism, etc;
- Provide more flexibility and intelligence in the network;
- Controlled capital and operational expenditures (CAPEX and OPEX);
- Support smart city concept for greener communications focusing on energy efficiency (EE) and reduced CO_2 emissions.

5G would need to be deployed in all layers to meet the above mentioned stringent requirements, facilitating users more than previous mobile networks did. In this regard, several researches have been and are being discussed in the literature in past couple of years, such as, massive MIMO (multiple-input multiple-output), millimeter-waves (mm-waves), control and data plane separation, handovers (HOs) management and skipping, smart city energy efficiency, network densification with small cells (SCs) and macro cells (MC) separation, implementation of self organising networks (SON) functions, and user's mobility prediction and management using artificial intelligence (AI) and machine learning (ML) [2, 8–10].

With these breakthroughs are crucial, the concept of network densification requires considerable amount of changes [11]. The deployment of several SCs would most likely address coverage, capacity and traffic demands and limitations, to end users [2, 12], but in the long term, it would bring new challenges to the MNOs such as, coordination and configuration management of the network. Furthermore, SCs would likely to deal in immense amount of data collection for monitoring network performance, and maintaining network stability. Resulting, in an increasingly challenging tasks when configuring and maintaining network in dynamic environment [2, 9].

By introducing more intelligence in the network, mobility management issues would be resolved. This is where SONs under AI come into place, that provide intelligence to mobile networks, making MNOs life easier. Having a network artificially intelligent, mobile networks would be exploited with resilience, better management and control, simplify network coordination and configuration, reduce overall network complexity, address CAPEX and OPEX issues, and optimise user mobility patterns [1–3, 8–10, 13, 14].

1.1 Self Organising Networks (SONs)

SONs are basically intelligent decisions that are taken to maintain network performance to a level which is considered less humanly operated with more of automation. In contrast to previous generation of mobile networks, it is envisaged to experience optimal outcomes with smart data analysis, efficient resource utilisation, proactive decisions, and flexible algorithms. More specifically, SONs are adaptive to hold the autonomous network recognition for maintaining their objectives intelligently [2,12,15–19]. Based on their continuous interaction with the environment, SONs actions collectively make intelligent decisions and improving their performance while learning on the go. As such, SONs in mobile networks are categorised into: self-configuration, self-optimisation and self-healing; and together they are commonly denoted as *self-x* functions [1,3].

1.1.1 Self-configuration

The ability to execute all the configuration procedures with autonomous operation of the network is termed as, self-configuration [2]. Examples of autonomously configured parameters can be, mobile base stations (BSs), trains visualising tracker net, Internet protocol (IP) address, neighbour cell list (NCL), radio and cell parameters, or those parameters which can be applied to the whole network for policy making strategies, etc. Any addition or removal of the BS would trigger the self-configuration scenario.

1.1.2 Self-optimisation

After self-configuration is done, the self-optimisation functions are triggered. Functions, mainly, procedures to continuously optimise the BSs and associated network parameters for optimal performance guarantee. Self-optimisation examples can be, mobility management, network planning, handover (HO) parameters, energy efficiency (EE), backhaul, caching, coverage and capacity, antenna parameters, load awareness and balancing, resource optimisation, call admission control (CAC), coordination of SON functions, etc [2]. Self-optimisation functions ensure network objectives have been taken care of when reported measurements gather information correctly and continuously.

1.1.3 Self-healing

The function of self-healing is also triggered alongside of self-optimisation. It is to ensure that faults and failures (e.g., software or hardware malfunction) are addressed as soon as they occur. The main focus of self-healing is to continuously monitor the system for assurance of any disorder followed by seamless recovery. Failures event detection and failures diagnosis (i.e., determine why it happened) operate alongside in parallel for compensation mechanisms operation, for network proper functioning. Self-healing in mobile systems can occur in terms of network troubleshooting (fault detection), fault classification, and cell outage management [3, 20–22].

1.2 Motivation

The mobility management in general, and in trains environment, is aggressively aiming to address outstanding solutions with the new paradigms, improving overall network condition. The limitations of using rudimentary methods in the analysis, configuration, optimisation, healing, and monitoring of mobile networks, are negatively impacting the feasibility of 5G and B5G solutions [1, 2]. In addition, the storage, automation, and efficiency are limited when the huge and complex data is concerned. MNOs and train networks need to work collectively to perform readiness action in relation to design intelligent mobility paradigms by potentially using SON functions in order to lead to sub-optimal solutions [12, 14, 23, 24]. This is to avoid human intervention and manual network optimisation and/or configuration. Some other solutions also require expert personnel on site presence for fixing sudden and certain problems out of bound for scheduled works. All these solutions are extremely ineffective and costly to mobile operators [23, 24]. Thus, in order to leverage collected information by MNOs and train operators, adaptable and flexible solutions can be provided to drive intelligent operations with minimal human intervention to address user's mobility prediction needs [2, 14].

1.2.1 Why User Mobility Management is needed?

With the advancement of mobile industry, the ability of users to connect to BSs have become very crucial to address outstanding problems that remained from last decade [3]. In particular, in the emerging field of mobility and self organisation applied to wireless cellular communication networks [3, 22]. Also, in the last decade, the way mobile industry brought a plethora of new applications and services that were impossible before. For instance, distance communication between family and relatives, sharing life experiences through social media apps and website, finance transactions through internet in safe and secure manner, currency exchange or wire transfer from one country to another, etc. [1–3].

Further enhancements in the mobile industry will be possible through the use of technological advances, such as the IoT, M2M, cMTC, IT2T communication, smart cities, DSR, IMS, VR, and many more, which are briefly listed in the Table A.1. Besides, in the future, it is expected to have many more use-cases will be enabled by future mobile networks in relation to the transportation industry [14]. For example, in the case of IXR, AR, and VR devices, extremely high bandwidth with low latency is required in order to guarantee the desired QoS to end-users. Another example is the use-case of cMTC, in which a whole industry is connected via wireless network. High bandwidth, latency and reliability are the challenges and extremely important factors to be addressed [14].

Now, user mobility prediction is one of the key enablers of proactive self-organising and intelligent networks, aiming to effectively manage user trajectories in the HetNets, which are envisaged to be extremely dense and complex due to conglomeration of diverse technologies and challenging environment [8–10, 14, 25–27]. 5G and B5G applications and use-cases have some challenges including mobile networks constraints, which not only physically restricted but have financial impacts of deployment, as higher capacity and QoS comes at the expense of higher costs [12]. Consequently, end-users demands are increasing which is direct in collision to less bills payment. This MNOs have to minimise their network costs while maintaining good QoS and capacity is crucial [2, 12]. Efficient and improved services to fulfil user requirements are needed to evaluate new research paradigms, adding more value to them, and introduce intelligence to the mobile and train networks [2, 12]. Some motivation factors are as follows:

1. User mobility variation are difficult to be dealt with current mobile networks. To this vary reason, current mobile networks are either under-utilised or over-utilised in terms of fulfilling dynamic user requirements. Utilisation of the network depends on the users movement from one place to another which is divided into peak and off-peak hours. This results in a low resource efficiency and congestion, as well as poor QoS and QoE to end-users, respectively;

2. With the 5G networks' concept, network densification is inevitable to populate large number of SCs, that can be deployed not only by the network operators but also by end-users. As such, MNOs are overburdened to manage, configure and optimise an astounding number of SC parameters in order to guarantee QoS;

3. Network densification also boost future mobile networks with a increased load in capacity that would exponentially rise, resulting in a much more

complex and challenging network to be looked after. This leaves manual paradigms of the mobile networks at a risk of being inefficient;

4. Lastly, using mobility management and control by utilising SONs can significantly mitigate operational costs while maintaining QoS. As such, it would provide an intelligent replacement of periodic tests and field analysis while monitoring daily mobility data generated by the network.

In addition to the above, requirement of handling large amount of data, and storing it, is difficult without the use of intelligent mobility management control using large amount of sensors and monitoring devices [2, 8, 9, 14]. As it stands in the current mobile network operations and in the train network environment, despite a huge amount of daily data is generated, is not currently being utilised intelligently to replace manual paradigms to the automation [14]. Furthermore, storing such a great amount of data is a costly exercise which leads network operators to normally discard most of the data generated after its usage [28, 29], which can be dealt more intelligently and effectively.

Finally, current networks lead to sub-optimal network configurations that struggle to cope with the dynamic and changing environment with the inefficiency of adapting themselves. As such, more powerful and robust archetypes with a focus on mobility and data oriented solutions, that involve intelligent environment aware algorithms to build relationships and intrinsic patterns in data, are required. By combining future mobile and train networks with the intelligent solutions, the next generation mobile networks are deemed to operate at its full potential efficiently [2].

1.2.2 Why ML is needed?

The current exponential advances in the technology is a precursor towards an imminent traffic flux, miniaturisation of electronic gadgets, and capacity crunch needs, has challenge companies to effectively manage trillions of bytes of traffic information, in what is known as *Big Data* [12, 24, 30–33]. Such information requires billions of sensors that are able to sense, create and communicate data through a platform which would be artificially intelligent [34–38]. For instance, huge amount of data volume that is generated and collected every second would create better and more profitable solutions if effectively manage [8, 9, 39, 40].

ML-driven algorithms collect and analyse data in order to train intrinsic patterns and relationships between provided input and the output. A model is formed that is able to relate the input to the output, instead of attempting to develop a complex model of the system, resulting, an intelligent learning process which can make smart decisions without human intervention [2, 41–44]. Furthermore, the Moore's Law in computing and recent advances in electronics and cloud computing that is able to store, process and analyse data, justifies the popularity of ML algorithms in recent years [2, 41, 42]. In addition, another clear advantage of ML-driven algorithms is to generalise traffic flux and capacity crunch needs in any environment they are set to put on [2, 8–10, 43]. For example, considering the task of mobile network optimisation according to the passengers traffic flow in train environment, with users in random or designated positions, and all BSs with different power, interference and load levels, it would be impossible without ML intelligence. This is where, ML solutions analyse complex data in order to create a model based on the observations and make predictions if new unseen data is fed into the model [43, 45].

Furthermore, another key advantage of ML algorithms is when dealing with complex tasks in a challenging and complex environment such as underground train tunnels, hidden areas which are difficult to be captured in simple mobile coverage, continuously occurring HO environment, etc. For the use-cases (not limited to) mentioned are impossible to be analytically designed through the use of traditional approaches [1, 2]. For example, considering the task of HOs in high-speed train as to when they shall/shall not occur. What intelligence can be introduced for HO to occur and how?. The mobile network in the underground train environment has mobile coverage with few options to drive HOs and their skipping. These options, as in techniques, are size-aware, location-aware, alternate, hybrid, context-aware, etc As it can be seen from this example, when tasks are extremely complicated and have a lot of variables and parameters to deal with, traditional analytical approaches are not good enough for the solutions required to solve problems, instead they are too complex and costly [1, 2, 46–49]. There are various other examples which would highlight the importance of ML-driven algorithms and their necessity in the mobility management of users/passengers in train/railway network. In summary, the main advantages of ML-driven solutions over traditional and analytical methods are:

- The emerging data needs in the last few years that involve data collection, data storage, and complex data training has become infeasible at a human scale and needs an automation. This is to steer effective management of contingent data and generate near optimal results.

- ML-driven algorithms are capable of analysing and processing a huge amount of data leveraging historical records and learn from it. By analysing previous data, ML algorithms are competent of matching hidden patterns and correlations in order to establish an intelligent model for observed data points. A degree of robustness can be seen when these algorithms produce solutions in accordance with the practical requirements to future predictions.

- Instead of relying on a fixed model, or having to develop a model for every possible new situation, ML algorithms enable generalisation, or simply optimise its models online while improving the learning trends.

- More complexity can be dealt with ML algorithms by relying on data analysis for observed data set fitting and not creating complex and intricate models of a particular problem.

- ML algorithms, and in particular deep learning, have shown improved performance in certain tasks, such as image classification, traffic pattern classification, video games, etc [50–60]. As such, with the constant development of more robust and powerful computers and algorithms, the possibilities of what these intelligent algorithms can do are practically unimaginable.

- The idea of learning by experience or by interaction with the environment is given by [61] in the form of ML-driven RL by learning via a goal-seeking, or trial and error, approach in order to find optimal intelligent solutions. Furthermore, because of this trial and error approach, RL solutions also pose another advantage that they do not require information about the environment (the RL class of Temporal Difference learning algorithms) in order to work, thus they are also termed as, model-free [61]. The interaction between agent and the environment enables RL agents to adjust their behaviour and learn from past experiences, instead of relying in previous examples and data provided by an external and knowledgeable supervisor.

1.3 Objectives

As previously mentioned, this thesis focuses on user mobility predictions and management by using the application of ML algorithms in order to tackle use-cases that belong to user mobility predictions. More specifically, mobility management is utilised to understand user mobility patterns by exploiting ML-driven algorithms in order to perform self-optimisation of future mobile and railway networks. In this realm, different ML classifiers are tested in different scenarios and compared to other current state-of-the-art approaches. A descriptive literature review for this thesis is presented using ML algorithms and SON strategies where the focus lies in the area of self-optimisation. This is followed by contributions which are presented in Chapters 3, 4, and 5.

1. The focus of Chapter 3 is on ML-driven applications such as mobility optimisation, future location precision, ES, encryption, travelers-tracing and mobility profiling. Self-optimisation scenarios based user's mobility predictions are discussed in this study. The key highlights are the optimisation of user-cell association procedures and how to better manage user's mobility predictions based on access, egress, and interchange (AEI) framework. This is to support train infrastructure against congestion, accidents, overloading carriages and maintenance. Analysis is done which studies the impact of ML algorithms on train passenger future movements by using real train dataset. Also, encryption is applied on the passengers data to provide extra layer of security during their journey. In addition, exploiting ML algorithms further with a concept of travelers-profiling, being an essential interventions that railway network professionals rely on managing the Coronavirus Disease 2019 (COVID-19) outbreak while providing safe commute to staff and the public, is elucidated. For delivering the better experiences to end-users and use network resources efficiently, a joint optimisation is proposed, in which users mobility, radio access and optimised network are jointly discussed in a model of mobile and railway networks. The mobility tracking and profiling is done by designating separate routes to daily train travelers in the age-group 16-59 years, and over 60 years (vulnerable age-group), with the recommendations of certain times and routes of traveling, designated train carriages, stations, platforms, and special services using the LUO network.

2. Chapter 4 mainly sheds lights on the paramount challenges of increased carbon emissions in the dense mobile networking environment, by exploiting user mobility predictions-based energy consumption. User mobility predictions-based autonomous energy-aware framework is discussed and proposed for analysing bus passengers ridership through statistical ML and proactive energy savings coupled with CO_2 emissions in heterogeneous architecture using RL. Focus of the analysis remained on the impact of different ML algorithms in driving mobility predictions and saving energy coupled with CO_2 emissions.

3. Chapter 5 presents next generation networks (NGNs) exploiting user mobility by HO skipping and blockchain privacy preservation. This is another emerging topic in the realm of user mobility predictions with self-optimisation of mobile networks with intelligent HO decisions in order to

provide best user seamless experience in high-speed mobility trains.In this study, analysis of HO skipping scenario is done by using novel approach of contact-aware HO skipping in the NGNs. Also, HO skipping and last hop HO scenario by utilising blockchain privacy mechanism are exploited. We focused on deriving solutions to unnecessary HOs throughout the dynamic environment of the train network. Furthermore, the same topic is expanded and analysed in the lights of blockchain technology to supervise mobility in a secure way.

4. Provide future trends and research directions as well as conclusions in the topic of mobility management and ML applied in SON.

1.4 Research Contributions

Based on the aforementioned objectives, this thesis focuses on the user mobility predictions and management by using ML exploiting, self-optimisation use-cases of mobile networks in which different requirements and network constraints are analysed. As such, different optimisation scenarios under the heading of user mobility predictions and management are investigated. The application of ML-driven algorithms for users mobility, energy efficiency, carbon emissions, encryption, mobility profiling, handover (HO) management, and blockchain privacy, is considered for performance evaluation and state-of-the-art solutions. The contributions of this thesis can be summarised as follows:

1. Provide an extensive literature review of ML-driven algorithms for user's mobility predictions applied for the optimisation of mobile and rail networks. The literature review includes the last 15 years of research performed in the area mobility management and future mobility predictions. Furthermore, the application of ML-driven algorithms in SON use-cases for future mobile and rail industry along with future possibilities and aspects are given. For details see [2, 14].

2. Based on the intelligence gained from the mobility model, i.e., user mobility prediction classification and directions, a proactive movement precision is formulated to maximise the advantage of traffic flows in several unexpected directions and instructing passengers to take necessary interchanges. In this contribution the optimisation of parameters both from the network and end users is proposed, with the objective of optimising user movements and encrypt their mobility data. Results show that the proposed approach

performs better than conventional state-of-the-art solutions. In addition to the above, travelers-tracing and mobility profiling is analysed to manage daily train travelers that are in the age-group 16-59 years and over 60 years (vulnerable age-group) with the recommendations of certain times and routes of traveling, designated train carriages, stations, platforms, and special services in a train network.

3. Perform the optimisation of energy by utilising ML-driven mobility predictions, and proactive energy savings coupled with CO_2 emissions using reinforcement learning (RL). In this contribution, k-nearest neighbor (KNN) model to modernise energy savings (ES) conventional limitations, is elucidated. Passengers also been estimated with future location estimations. Furthermore, based on the future cell load information, a proactive ES optimisation problem is formulated to reduce, power and energy consumption by switching OFF lightly loaded, idle or underutilised SCs to reduce carbon emissions. Results show that the proposed approach is robust, dynamic and agile, and that it is able to outperform other methods.

4. Under the heading of next generation networks, passengers mobility is exploited in order to optimise handovers (HOs) by skipping/not skipping. A novel context-aware HO skipping paradigm is discussed in detail to establish best HO skipping technique, called context-aware HO skipping. Real train dataset is used to obtain passenger locations in London Underground and Overground (LUO) train network, followed by mobility tracking for context-aware HO skipping technique. Results show that the proposed framework outperforms in terms of coverage probability, user throughput, HO cost, etc compared to conventional approaches.

5. Within the context of HO skipping, a novel approach called, blockchain-enabled privacy preserving is discussed to first register user entries/exits to/from stations allowing the framework to track the path of users, while users utilise their pseudonym addresses in order to maintain privacy. Based on individual user information, user-specific HO skipping is achieved, leading to a better trade-off in terms of network HO cost, user quality of service (QoS), and last-hop signal quality.

6. Lastly, this thesis finalises with some conclusions and future research directions in the realm of user mobility predictions and management, as well as ML applied in SON.

In addition to the main contributions and publications, co-author contributions are also culminated. For example, the works with Attai, et al. [62] that involved revenue maximisation through cell switching and spectrum leasing. a cell switching and spectrum leasing framework is proposed that is based on simulated annealing algorithm to maximize the revenue of the primary network.

Chapter 2

Background and Literature Review

2.1 Current Mobile Networks Overview

As we have seen in previous years up to now that current mobile industry mainly dependant heavily on manual or human interventions to collect and interpret data for basic mobility functions, such as data assessment, training, configuration, optimisation of radio parameters, etc. Due to the dependencies, this leads to inefficient and substandard solutions with unnecessary costs, undermining revenues, and limiting the network performance with resources waste [1,63]. As such, there should be a shift in archetype in existing and future networks towards a more autonomous and adaptable methods. User's mobility should be managed in order to meet future network needs and complexities resolution to keep the networks scale up, as well as keep on par with current technologies [1, 9]. In the next few sections, a brief overview of current mobile networks and existing mobility methods are presented, followed by an outline of emerging technologies as being the core part of future mobile networks, that can shift archetypes to be fully functional.

2.1.1 Fourth Generation 4G

Contemporary mobile generations drive their models in such a way that theoretical field measurements rely on statistical modelling of mathematics and numbers [64,65]. These models range from mobile network operators analysing traffic patterns for new base stations (BSs) deployment positioning, optimisation of BSs to resolute call data record (CDR) deficiencies, link budgets calculations along with international commission on non-ionizing radiation protection (ICNIRP) and electromagnetic compatibility (EMC) compliance activities, etc. Other examples include drive testing to determine BSs status, parameters, etc [9, 65]. In addition, in order to deploy distributed antenna system (DAS), indoors and outdoors, engineers are sent for data collection about the wireless signal scattering, coverage footprints, path loss, LoS, interference patterns, etc., and build a model of it [64, 65].

As it can be seen by above examples that mathematical models designing have significant importance in the mobile industry where they play a vital role in all aspects such as network assessment, network design and configuration, network training, optimisation and healing. Also, the current exponential traffic flow is a precursor towards an imminent traffic flux, security, network and users mobility, and capacity crunch which leads to several drawbacks, such as [65–67]:

- For an effective traffic management system, deployment of a large number of heterogeneous networks (HetNets) are required that need an accurate mathematical model. This is to achieve the prediction accuracies, user's path, encryption, and manifold capacity gain goal [66]. However, complicated passengers traffic movement are on a direct collision path with unnecessary waste of resources when not captured accurately. Also, even if it were possible to create a mathematical model for such situations there is also the trade-off between the accuracy and complexity where most of the models fail to describe the observations.

- Network infrastructure deployment and optimisation with no future intelligence to adopt mobility behaviours and patterns, might not be feasible for advanced use-cases of the future mobile networks, as current network archetypes lack necessary adaptability and flexibility to dynamically adjust environmental changes such as underground tunnels, traffic variations, etc.

Due to the massive deployments in the small cells (SCs) above issues would be more pressing to cater with an exponentially grown traffic with complex nature [8,9,14]. Furthermore, mobile operators are usually limited in network design options due to the static methods being followed, and usually end-up designing their systems for the worst case scenario. With this, the deployment of a new DAS infrastructure in a building, often network engineers require information of user numbers, their peak/off-peak hours, sojourn time/dwell time in a specific area, users mobility and most visited areas during leisure, etc. All of these questions contribute to build up an assumed scenario with some capacity figures and coverage areas, to design the system accordingly. However, this leads to extremely sub-optimal solutions with building being inactive in terms of crowd, several network resources, as well as revenue, are wasted.

Another example that depicts the inefficiency of these paradigms is whenever sporadic and unplanned events occur, it affects the whole network infrastructure operation. This is due to the lack of adaptability to cope with the unprecedented resulting in the irrecoverable situation to automatically repairing it, unlike intelligent self-reconfiguration or self-healing phases of operation [9, 63, 68, 69]. As such, the remaining infrastructure cannot cope with the unexpected event, nor auto-recovery addresses the required repair, leading to several users fall short of the services. Lastly, the disadvantages of non-adaptable network design is the handling of large user gatherings such as; large concentration of users in a specific area is the case of natural disasters, big events, etc. In such cases, current network paradigms still cannot cope change of behaviours whenever one-off events happen. Leading to several users out of service, capacity blockage, or even loss of connectivity. In this case of under-provisioning network resources, fixed or non-intelligent networks, might not be cost-effective and productive [2].

With these issues related to non-adaptability of auto assess, configure, and heal, user mobility predictions become difficult to be implemented by operators and are rudimentary that relies heavily on past events and associated solutions. They also depend on simple comparisons against a threshold and control loops through feedback from controllers [2]. All of the discussed issues require effectiveness in data collection and assessment to be trained according to the occurrence of events [8–10].

Nowadays, MNOs are gradually introducing ML in their networks for SON capable. However, with some ML being introduced to run SON function, current methods are still underdeveloped and works in reactive manner [13, 47, 70, 71]. Furthermore, current mobile networks rely their SON solutions on assumption basis being a general rule of thumb with the availability of some information such as; coverage gaps, HO ping-pong zones, congestion hot spots or user locations [70, 72]. This is due to the reactive observation that MNOs obtain network information based on alarms on mobile equipment deployed to run the network, and diagnose the triggered events to compensate action utilizing any past experiences. However, this grim reactive nature of mobile networks cannot assess the stringent demands of future mobility to construct dynamic and autonomous model of operation. In addition, the assumption with the partial control over the network activities, events, and mobility patterns are also not completely realistic that would not contribute to an autonomous and adaptable network design [70, 73, 74]. As such, there is a need for an agile, intelligent and robust design in analysing complex nature of real-time data, determining set of problems, and recourse specific actions.

2.1.2 5G and Beyond

Before 5G, mobile networks were focused to provide connectivity to end-users in order for communication purposes. This adherence served users for years before the increasing demands of data and speed which introduced some design limitations due to the high demand of data usage with sufficient speed [12,14,75,76]. As such, the rising demand for bandwidths, latency, and reliability doesn't let legacy design of mobile networks compatible. Furthermore, with the emerging technology advancements, it is expected to have growth in the user numbers along with IoT based on machines communications [55, 77–80]. As it stands, to cover the wide range of requirements not only based on data rates but also future compliance, governance, economy, transportation, environment, and health living will be inefficient with legacy design of previous networks demanded by these new devices. For this purpose, it is vital to aim for new paradigms in addressing modern use-cases and rising needs of emerging technologies. Based on the approach, a brief overview of new 5G and B5G archetypes that would support increasing user/data demands is given below.

Heterogeneous and Dense Networks

Network densification in order to form a heterogeneous network (HetNet) is considered a key element of future mobile networks to cope with increasing capacity demands of traffic and mobility. But on the expense of time, cost, and efforts on complex configuration of thousands of parameters per BS [8, 10, 81–84]. It is also expected to have densification process not entirely in the control MNOs, with end-users also contributing to the deployment of SCs, such as in private mobile networks (PMNs) [14]. This, by its turn, will introduce a challenge in tracking all the users manually specially if they are in confined zones, in underground tunnels, on a high-speed train in their own capsized network, etc. Thus, solutions that to handle such complex situations while dealing with the challenging environments can be extremely advantageous in these cases.

IoT and Machine-to-Machine Communications (M2M)

The IoT provisions to have objects equipped with communications devices in order to communicate with other devices, users, and the core network [55, 85].

Moreover, by assuming the connectivity with integrated devices such as actuators, radio frequency identification (RFID) devices, cellular modules, ticket machines, home appliances, city infrastructure, sensors, vehicles, and many more, the IoT along with M2M communications facilitate wide range of 5G ad beyond applications that are not possible today. This include automation assumed in homes, industries, smart grids, telemedics, smart cities, etc, [23, 86–90]. In this regard, the exponential rise in device numbers requiring Internet access will urge future networks to support billions of heterogeneous devices, with a variety of applications. As a result, 5G and B5G networks driven IoT and M2M communication will have to be radically efficient and diverse to cope with the requirements shift [12, 14, 76].

Reactive to Proactive Shift

As seen in the previous sections, traditional and current mobile networks are designed to perform optimisation actions after detecting an event that have already taken into effect. For example, when congestion is detected in the traffic flow, typically a non-convex algorithm uses mobility past experiences to identify certain aspects of passenger movement. This means, a reactive instead of proactive approach has been into place from some time. In other words, MNOs wait for some inputs from the network for making assumptions and assessment to determine if something went wrong that requires attention [8, 9]. Furthermore, several recent schemes concerning mobility prediction optimisation [8,9] and encryption [91,92], they all seem to have one common approach. The mode of operation is reactive, i.e to optimise the network in response to the problem. To cope with this, a proactive paradigm is required in using AI which would predict the dynamics of network change and advise necessary optimised automation. Through this, extensive periods of outage, unnecessary overhead, poor QoS delivery, loss of revenue, etc, can be approximated beforehand. Therefore, a shift in paradigms is needed to contemplate sudden network behavioural changes for proactively operating future networks. Considering AI networks by using ML-driven robust algorithms can solve the outstanding issues leveraging historical data analysis and assortment before predictions about the future network state [9, 69, 93, 94].

Millimetre Waves (mm-Waves)

The concept of millimetre waves (mm-Waves) has gained increased attention recently in future mobile networks for resolving capacity crunch solutions by having ultra dense SC deployments. The mm-Waves signal propagation in wireless networks would give breathing space to the existent 700MHz to 2.6GHz radio spectrum bands that are currently widely used in mobile communications. Also, ignoring the fact of low penetration in the higher frequencies, MNOs would be comfortable in allocating larger bandwidths to run demanding applications with low latency [95, 96]. The mm-Waves communication is a promising candidate of 5G and B5G networks due to its large quantities of available spectrum handling nature. It requires spatial degrees of high-dimensional antenna arrays in greater numbers along with the mm-Wave radio links usage in satellite and point-to-point backhaul communications which was almost impractical in older mobile generations. By using high-gain smart antennas, the spectrum can be exploited to provide an order of magnitude or more increase in throughput for mobile devices [97, 98]. However, issues specially concerning path loss, line of sight (LoS) and signal attenuation are still being investigated in mm-Waves communications. As such, similarly to massive MIMO, solutions that can adapt themselves in order to optimise network parameters online and solve these problems while the network is operational are advantageous in these situations, such as energy efficiency or beam-forming [99].

Backhaul and Caching

Improved backhaul connectivity is of vital importance in the world of future mobile and emerging networks, or in other terms, the connection between the BSs and the rest of the network. Existing systems are limited to evaluate the connection between the end-user and the BS which needs to be diversified to meet new demands of emerging technologies. Future systems, would however, a wider range of applications and convolutional networks' requirements from users which makes the current mobile networks approach to inappropriate [2, 12, 14, 15, 64]. With that in mind, some researchers spent time in developing solutions to solve the backhaul issue in future networks for safeguarding QoS provisioning performances [100–103], congestion and topology management [7, 104, 105].

For flexible backhaul QoS scheme, authors in [7, 104] have proposed load balancing and management including congestion control mechanisms where test-bed has been introduced with separated control and data plane (CDSA) [106]. In [105], authors utilize a fuzzy logic controller (FLC) for backhaul optimisation in order to arrange the network topology, requiring traffic demands modifications. Other backhaul optimisation solutions are the works proposed by Jaber et al. in [100–103], where authors used Q-Learning strategy for intelligence in association of users with different requirements, in terms of latency, capacity, resilience, and gain in throughput. The relationship of backhaul and users is such that, when backhaul and users need a match, network would allocate users to a particular cell otherwise a new cell is searched for the same match.

In terms of Caching, during recent years, the rapid growth of in the traffic due to proliferation of smart gadgets, demanded stringent data, capacity, and latency to fulfil their rising needs. As such, to address the holistic requirements and to reduce the network load, caching functions are deemed integral part for mobile networks. In [29], Wang et al. gave some highlights on the caching overview as to why it is needed and what benefits could lead future mobile networks on the roads of gains along with challenges. Some other caching solution been discussed by authors in [28,31,107–109] where integration of big data and network resources are combined with caching deployment. In this, big data-driven framework discussed different case studies that relates to mobility scenarios and storage of the complex data analytics. Also, authors in [109], considered mobile network case study to analyse proactive caching not only to alleviate backhaul congestion with random users patterns, but also, explored a social structure of a network that can cache relevant mobility users patterns allowing a device-to-device (D2D) communication. In this work, authors proposed smart solution to learn user behaviours for a targeted domain that can cache contents into the BSs.

Other solutions for that supported cache theory is presented in [107], where caching is modelled as a game theory to tackle optimisation problem of storing the mobility patterns in order to relieve backhaul resources. Similarly, the impact of caching in mobile networks is presented in [108] where authors propose a framework of caching SC networks by first clustering in order to group users with similar content preferences. After that, RL is used to learn the contents to cache and optimise intelligent caching decisions.

Coverage and Capacity

Coverage and capacity are most important factors that future mobile networks have to optimise to address shortfall challenges while achieving the best trade-off between coverage/capacity against cost. Based on this, several authors have proposed intelligent mobile solutions to tackle this problem [2,8,9,12,46,47,110–114]. In [115], for example, the authors proposed a methodology to achieve a better coverage by cell clustering aiming to change cluster sizes and antenna parameters. In [12], the authors discussed key indicators include seamless connectivity, spatio-temporal uniformity of service, perception of infinite capacity or zero latency, and, service cost. No technology can offer infinite capacity or zero latency, however, they can be maintained to a level where maximum optimisation is performed. Mobile operators capitalise on large scale mobility traces based on good coverage and capacity to optimise their network operational behaviour [9,12,62]. Besides, such a scenario supports users mobility by stretching coverage and capacity through, not only, most visited places, but confined locations where coverage and capacity is a challenge [9].

Embracing the world in the 5G era to address coverage and capacity challenges, understanding traffic patterns and human mobility predictions are difficult with limitations experienced by urbanised cellular towers [13, 74, 116]. Extra diligent intelligence is required to fully automate the network that would be a hypothetical remedy against current complexities involved in predicting the traffic flows in the underground train environment [2, 9, 71, 117]. In doing so, by learning traffic flow patterns through ML algorithms leveraging historical data, precise capacity can be calculated which would assist solutions such as, optimisation, traffic and capacity planning, coverage, traffic flow security and encryption, etc. With such a vision of proactively analysing the network, accuracy in administering coverage and capacity through mobility predictions learning can be achieved that will have efficient resource utilisation, improved HO management, and overall network performance [2, 30, 118–120].

Furthermore, Fagen et al., in [121], proposed a method to simultaneously maximise coverage while minimising the interference for a desired level of coverage overlap. Similarly, Engels et al., in [122], developed an algorithm to tune antenna down-tilt angle and its transmit power for optimisation purposes. The trade-off between coverage and capacity via a traffic-light based controller was achieved and analysed. There are many works in the filed of capacity and coverage predicament and optimisation by proposing heuristic approaches [28, 87, 90, 96, 122–124].

Antenna Parameters

Antenna parameters, mainly, antenna down-tilt, azimuth angle, and transmit power have a major impact on the coverage and capacity, and self-optimisation nature of learning. In addition, intelligent antennas do require a parametric set of configuration for spreading its coverage beam of to specific points. In particular, the optimisation of antenna parameters often require intelligent tuning to the original version default by MNOs. In doing so, there is a degree of delicacy while configuring parameters because it requires, not only expertise, but also a lot of precision to perform. Hence, it often becomes costly for the MNOs to perform this level of optimisation. Thus, AI, not only in network but also in antennas and parameters are required to automate the process of self-optimisation when users mobility management is concerned.

In [125], the authors proposed different methods of optimisation to traffic offload of MCs to micros. In [126], the authors develop an optimisation algorithm to find the optimal antenna down-tilt settings while angling it accordingly, and common pilot channel power of BSs. The solution performed an evaluation of the network and analysing the obtained results followed by, an iterative process formed by a control loops. Other works, such as in [127–129] aimed to optimise the antenna parameters such as, down-tilt angle by applying ML-driven algorithms in a mobile network. While in [130], Eckhardt et al., proposed an algorithm for antenna down-tilt angle optimisation considering spectral efficiency of users. The approach considered a mobile network that was based on heuristics to establish the best antenna parameters. All approaches, however, aimed to maximise the coverage and capacity via different methods of either antenna down-tilts or transmission powers coordination, or even monitoring the network by ML-driven algorithms for self-optimisation.

Interference Control

In the world of 5G and B5G communication, interference has always been a a contributing factor that affect performance of communications systems which will continue to contribute in future networks. To mitigate interference, several intelligent schemes have been discussed and in order to cope and control this limiting factor for absolute measurements. For instance, in the LTE-advanced systems users at cell edges are disturbed by the different transmission signals from different BSs. This disturbance refers to the interference. For this reason, to head off and mitigate interference without degrading the service and performance, inter-cell interference coordination (ICIC) was preferred. With the help of ICIC, users can be preserved from being into interference problem. The main aim of ICIC was to free resources from interference. It further improves the performance cells at the edges by increasing the throughput within boundaries [131, 132] with a feedback controller to performing ICIC.

In [133], for example, the authors proposed a distributed self-organising femtocell management architecture in order to mitigate the ICIC between femtocells and MCs. Mehta et al., on the other hand, in [134], developed two solutions in order to address the problem of co-layer interference (interference between neighbours) in a heterogeneous femtocell and MC network scenarios. In [135], the authors also build a self-configuration and optimisation scheme for a network of femtocells overlaid on top of a macrocell network. The algorithm automatically configures the femtocells transmit power and promotes self-optimisation via a feedback controller to automatically control when to turn on or off femtocells in order to reduce interference between macro and femtocells.

Other approach to control interference is mentioned in [53] where, coexistence of a MC and other networks along with development of a distributed algorithm was discussed. In this work, the coexistence of a MC and femtocell network was considered to develop a distributed algorithm for interference mitigation. The carrier allocation problem was solved via ML, while the sub-problem, of power allocation, was remedied using a gradient method. Also, a solution that utilises the RL concept is presented in [136], in which a solution to the ICIC issues considering downlink channel was discussed. Authors used mobile orthogonal frequency-division multiple access (OFDMA) systems in their theory. Adaptive soft frequency reuse concept and the ICIC issues were presented as a control process in order to map the system states into control actions. Lastly, another solution comes from Aliu et al., in [137], in which the authors adopt a novel fraction frequency reuse (FFR) based on GA for ICIC in OFDMA systems.

Mobility Management and Profiling

One of the most important aspect of future mobile networks is the intelligence in predicting user mobility patterns for better management in terms of resources, coverage probabilities, throughput gains, HOs and costs. Managing the mobility ensures the identification of users in specific cells whether they are in SCs or MCs [8–10, 25, 46, 47]. Current techniques use data sets to analyse user mobility patterns, store the movements, make the record of every movement change, and update their databases [8–10, 25, 46, 47, 54, 138]. Some papers, such as in [37, 54, 57, 60, 115, 138–146] use multiple ML techniques to predict user locations in the next cell. The basic idea behind all these papers is to use the concept of ML-driven mobility-based model for every user in the network to assess future location precision and predictions of cells where users most likely to move into.

In [55, 141], for example, the authors develop a method consisting of two cascaded ML models where first being addressing clustering via K-means algorithm and second does classification. Results show that the proposed model achieves better accuracy while combining both classification and clustering. Despite using NNs as primary intelligent strategies, authors in [140] combine the concept of NN with Bayesian learning in order to perform mobility predictions through classification showing Bayesian networks outperformed by 8% to 30%.

Using support vector machine (SVM), a supervised learning technique, in the mobility use-case is one of the widely used technique that is found today [85, 124, 147]. In [124] Zoha et al., proposed a data-driven analytics framework for autonomous outage detection and coverage optimisation. The framework used an LTE network to exploit the minimisation of drive test functionality as specified by 3GPP in Release 10. The approach learns the network profile by projecting the network measurements to a low-dimensional space using SVM-based detection respectively. In [147] Chen et al. build a model that uses only channel state information (CSI) and HO history to determine a user's mobility pattern. Their modelling used users trajectory in current and next cells given the input data (previous cell and CSI sequence). In [85] Daniyal et al., presented an application of wireless sensing at C-band operating at 4.8GHz technology (a potential Chinese 5G band). Assuming indoor environment, a wireless transceiver is used to monitor different body motions of a human experiencing an eclamptic seizure where comparison of ML techniques were performed. The results indicate the SVM's better performance compared to other classifiers used.

In addition, authors from [38] estimated the location of mobile nodes in along with channel noise in an indoor wireless network environment. The solution uses a hierarchical SVM model, that is able to maintain good accuracy for speeds up to 10m/s. Other approaches such as [63, 72, 148, 149] where authors modelled steady state and transient behaviors of user mobility by Markov models. In [148], the authors considered a discrete-time MC in order to represent cell transitions and determine a user's path without being examining training and optimisation. The solution presented in [149], models the network as a state-transition graph for conversion of a problem into a stochastic meaning. Furthermore, authors in [72], built a mathematical model for characterising both steady state and transient behaviors of user mobility in WLANs. Specifically, managing user mobility by a semi-Markov process while obtaining the transition probability matrix. Another work by Farooq et al., in [63], proposed the use of a semi-Markov model together with participatory sensing to predict user mobility prediction coupled with steady state and gain analysis showing maximum prediction accuracy of 90%. Furthermore, a destination and mobility path prediction scheme for mobile networks was developed by [69] that leads to more efficient planning and management of the network's scarce bandwidth resources by analysing probability and Dempster-Shafer processes for predicting the likelihood of the next destination followed by MK process for predicting the likelihood of the next road segment transition.

On the other hand, Yu et al., proposed a novel approach based on activity patterns for location prediction in [150]. Prior to directly predicting user's next location, the solution first attempts to infer user's next activity in multiple phases. The first, the framework tries to infer the current activity of the user, followed by attempts to establish next activity before predicting the user location. This is done by using supervised model to build an activity transition probability graph. Time variation is introduced in the model in different phases of the day. Similarly, the work proposed in [151] used semi-supervised or unsupervised techniques to perform location prediction. The algorithms tends to reduce the effort of gathering labelled data while building a discrete model based on received signals by users for every location.

Handover Parameters Optimisation

The process of moving away from one channel to enter into another including frequency, time slot, spreading code (or a combination of them) during the dedicated more (calling mode) is known as HO. HOs are of utmost importance when considering mobility management of users travelling from one place to another where connections from one cell migrates to another cell. HO can be divided into two categories, i.e., (i) horizontal, in which a user switches between BSs of the same network, or (ii) vertical, in which a user switches between BSs of different networks. Many aspects of a mobile network makes HO parameters optimisation crucial, such as coverage, capacity, load balancing, interference management, energy consumption, mobility profiling, throughput management, etc. [2, 8–10, 25, 36, 46, 49, 90, 152–154].

Another set of solutions from Sas et al., in [155, 156], the problem of users in high mobility experiencing frequent HOs is addressed. The algorithm shown in [155] aimed to classify and match current with previous recorded user trajectories that were stored in the database. The steerer is activated to decide users to be kept within the current cell or to perform a HO to seek for another one. The solution in [156] builds upon the similar concept but adds a mobility classifier module before steerer making a decision. By implementing such classifier, the algorithm categorises users to wither fall into slow, medium or high mobility scenarios before they steered out.

Furthermore, HO parameters tuning are also important to determine if the network is performing as per expectations, such as call dropping and blocking probabilities, ping-pong rate, and early or late HOs [157]. Several ML approaches are being considered and substantial amount of research has been conducted to provide justice to its importance. In [158], for example, the authors assumed the scenario to discuss the impact of A3-offset change, and time to trigger (TTT) parameters which applies to mobility estimation, cell range extension offsets (CREOs), etc., in the HO procedures. The authors also discussed the solution of mobility robustness optimisation (MRO) while demonstrated the performance gains of CREO in a HetNet. On the other had, Soldani et al., in [159], proposed a framework for self-optimisation and evaluated the impact of HOs pruning.

One possible solution for HO parameters to be optimised by using ML-driven algorithms such as in [16, 46–48, 160, 161]. In [160], for example, the authors developed an algorithm to optimise HOs which was based on probabilistic NNs. It was compared with the hysteresis method to tune the results showing reduced number of HOs. This lowered down the cost of the network signalling as well. On the other hand, authors from [16, 161], proposed algorithms to optimise the HO procedure and better determine when an user needs a HO. Similarly, authors showcased some techniques to reduce HOs in [46–48] using stochastic geometry where HO management has been discussed in detail and multiple techniques were used to improve the network performance by reducing number of unnecessary HOs. In [34], Sinclair et al. developed a method to optimise two HO parameters, hysteresis and TTT, that achieved a balance between unnecessary HOs and call drop rates. Results show that the proposed solution reduced the number of dropped calls and unnecessary HOs by up to 70%.

On the other hand, Stoyanova et al., in [162], proposed two different methods to solve vertical HOs optimisation. The first method involved measuring certain metrics, like: signal strength, bit error rate (BER), latency and data rate cast voting in favor of/or against the HO execution. The second approach involved self-organising map (SOM), which periodically measured HO parameters (same as previous method) taking independent decisions for a HO initiation. Results show that the fuzzy solution outperformed allowing a simultaneous evaluation of different HOs criterion. Several algorithm classes of feedback controllers have been tested to reduce unnecessary HOs, as can be seen from [24, 35, 152, 157, 163–171]. All of these solutions aimed to change HO parameters as necessary, such as A3-offset, hysteresis, HO margins, TTT, cell offsets, etc. Thsese works have also aimed to provide stability intervals based on the performance metrics measurement and how far they are from optimal. Limitations of the mobility predictions and HO cases have been detailed by [71]. In [94], future applications based HOs are discussed with state-of-the-art technologies. Similarly, [93] showcased interference predictions in mobile adhoc networks with a general mobility model in order to avoid interference as much as possible with intelligent modelling. Furthermore, a destination and mobility path prediction scheme for mobile networks was developed by [69] that leads to more efficient planning and management of the network's scarce bandwidth resources by analysing probability and dempster-shafer processes for predicting the likelihood of the next destination followed by MK process for predicting the likelihood of the next road segment transition. All of these discussed algorithms used in gathering certain network related metrics and making decisions to optimise HO margins, hysteresis, thresholds, TTT, or any other attributes, for better HO parameters management.

In context of RL, other solutions had optimisation based HO parameters in response to mobility changes in the network. For instance, Mwanje et al., in [172], developed a distributed Q-Learning solution for mobility robustness optimisation (MRO). The claim was to adjust HO settings (hysteresis and TTT) that are major contributors of mobility changes in the network. The solution in [173] using Q-Learning to consider MRO and mobility load balancing (MLB) use cases. The primary goal was to determine HO settings that are optimal to the scenario in MRO case. While MLB, aimed to redistribute load between cells. In addition, the solution proposed by Quintero et al. in [174] shed light onto the HO optimisation problem by using hybrid genetic algorithm (GA) solution. Authors, solved the problem of assigning BSs to radio network controllers (RNC) in a third Generation (3G) network scenario. Another solution that enables every cell of a LTE network to adjust its HO parameters , i.e, O margin, A3-offset and TTT, is proposed to minimize call drop and unnecessary HOs where possible.

HO management scenario is also exploited by [175], in which authors utilised two NNs for a user to handover based on the user's perceived quality of experience (QoE) by measuring number of successful downloads and average download time. Femtocells by Dhahri et al., in [176], were assumed for a network scenario for cell selection in a form of distributed solution is proposed. Secondly, auther presented a statistical solution while relying their hypothesis on game theory. By determining which cell users should connect, the algorithm is able to maximise the capacity and minimise the number of HOs for every user of the network. Another work by Dhahri et al. [177], had two different approaches for a cell selection mechanism in dense femtocell networks. The algorithms relied on Q-Learning mechanism based on previous data. Results show that the enhanced Fuzzy Q-Learning outperforms against conventional Q-Learning where number of HOs are considerably reduced while also maximizing capacity.

Handover Management

Using AI-driven ML techniques are well equipped to support 5G and B5G technologies that are expected to deliver high data rates by presenting some use cases and services in [44, 178–180]. In 5G networks, the footprint of the BSs gets smaller along with the higher frequencies' communications. This concept of more and more BSs in a form of SCs, have risen with high mobility and small coverage area demand. Through this, mobile users can flexibly move among SCs that provide data connectivity and capacity to serve different user requirements and thus, resulting in a HO. The concept of changing the frequency in a SC and the considered HO parameters, affect the QoS and QoE.

In [44], proposed new enablers for 5G networks and beyond, in which, mmWave communications, network densification, IoT, etc. were discussed. According to the authors proposal, HO management provisioned to be more challenging which was proportional to the number of BSs per unit area along with the rise number of connections. Considering intelligent HO management, authors paved the way for tackling these challenges more efficiently and effectively. In [178], presented a survey for mobility management in ultra-dense network considering SCs. Using RL, authors discussed existing surveys for HO management in the densified network scenario. They also discussed the involvement of ML-driven HOs along with future directions and challenges for 5G ultra dense networks. Similarly, in [179], authors proposed a scheme to execute HOs using the functionalities in 5G vehicular networks. Their method was based on the media-independent handover (MIH) and fast proxy mobile IPv6 (FPMIP) standards for both predictive and reactive HO scenarios. Using velocity and alternative monitoring process in the network, proposed work prepared each vehicle for two HO cases. For predictive HO, each time the satisfaction grade of the vehicular user drops below a predefined threshold, the HO is initiated. On the other hand for un-predictive (or reactive) HO execution, the vehicle loses the connectivity with its serving network where it tries to establish connectivity to the available network in the neighbouring list.

In another work [180], the HO performance analysis with different metrics was observed in an urban channel model. Considering 5G SCs, authors analysed the effect of the traditional HO metrics performance on the 5G SC HO procedure. Also, authors in [181] proposed HO management for drones in future mobile networks considering 6G enabling technologies. Authors highlighted a general concept of drone integration in HetNets while discussing specific solutions for addressing possible problems. Furthermore, in [182], authors discussed the challenges in building information modelling (BIM) for transportation infrastructure and its inefficiency to address effective, consistent, and accurate HO management. Using HO management for an underground rail transit project, authors identified several BIM implementation challenges and proposed corresponding solutions.

Load Balancing and Awareness

Future networks are expected to balance the network load via traffic offloading and intelligently cooperating with other BSs for their load bearing contribution [10, 68, 84, 183]. Similarly, in order to cope with the unequal distribution of traffic rising demands flexible networks are required which can build a cost-efficient network intelligently [2]. For instance, we can see one solution in [184], that aimed to propose HetNet for learning and adjusting cell range extension offsets (CREO) dynamically according to the traffic conditions. A regression method is analysed that learned its parameters to adjust the cell range offsets.

Approaches that involved the use of feedback controllers is explained by [17, 185]. In [17], a mathematical framework for quantitative investigations of SON to exemplify basic investigations on load balancing. Target was to exploit functions, such as the signal-to-noise ratio (SINR), the number of satisfied users, or energy efficiency. In addition, the impact of HO parameters optimisation, downlink transmit power adaptation and antenna tilt possibilities. Similarly, in [185], the network performance that requires the load of a cell is used as an input to the algorithm which is able to control HO parameters. Results were compared for basic, regular, and non-regular grid network setup along with different cell sizes. Also, Rodriguez et al., proposed the use of a fuzzy controller with an aim to achieve load balancing in LTE networks, in [186]. Authors also implemented a fuzzy logical controller (FLC) to auto-tune HO margins which in turn automatically balanced the flowing traffic and reduced the number of blocked calls. Muñoz et al., on the other hand simulated a scenario of HO parameters optimisation to achieve load balancing and is described in [187]. This was done by combining the concepts of Q-Learning and FLC. Another similar work to highlight congestion problems in LTE femtocells, is shown in [188] which investigated the potential of different load balancing techniques by tuning either HO margins or, transmission powers. This paper discussed solutions on sole FLC, and combined FLC with RL-based Q-Learning. Results depicted the strategy performed better with larger performance gains when Q-Learning was applied.

Other solutions, for load balancing, such as in [18, 189, 190], were considered in a heuristic way. In [18], an algorithm was developed to unequal traffic balancing through the load while also improving the number of HOs, eventually improving overall system performance. The algorithm relied in heuristics of a greedy distributed solution. In [189], load balancing method was proposed to create clusters interactively via two different methods of heuristics, centralised and decentralized. Similarly, the work of Al-Rawi in [190], by using CRE, authors studied the impact of dynamically changing the range of low power nodes. The solution focused to exploit femtocells to offload users from MCs by adding a CRE offset to the received signal power (RSP) of the users.

A dynamic sector tilting control scheme was proposed by [191] to achieve load balancing by using GAs. Optimisation of sector antenna tilting maximising system capacity, remained the focus of the research for changing both cell sizes and shape. Another solution in [19], considered an approach to balance load among network neighbouring cells consisting of five different parts. It analysed and indicated the required BS to have its traffic handled along with the switching possibility to which neighbouring cell. The proposed method by leveraging historical data analysis, predicted the antenna down-tilt angle possibility to which neighbour and by what degree. Lastly, with the support of control/data separation plane [106], Bassoy et al., in [192], presented an unsupervised clustering algorithm to mainly determine offload traffic from highly loaded cells to neighbour cells. Also, the algorithm authors established the probabilities of their algorithm to work in a high dense deployment scenario.

Resource Optimisation

Provisioning of resources is another important aspect in 5G and B5G networks which needs to be improved and intelligently calculated in order to be allocated according to the situations. One example is discussed in the works by [31], in which the authors explored various angles of integrating big data in the mobile networks for resource allocation purpose. For instance, the authors proposed a framework based on big data and analyses provisioning of resource use their caching, and QoE. Provided solutions were based on the intelligence on how the network can change its parameters with such a big data collection. In this, results were concluded with several benefits to future networks, however there remained challenges that need to be solved significantly.

Some studies proposed the use of NNs in order to optimise network resources. such as in [193–199]. For instance in [193], Sandhir and Mitchell predicted a cell demand after every 10 measurements taken by the system. The framework predicted available number of free channels with each cell resource usage and are reallocated between cells. Similarly, in [194] user mobility predictions were conducted by using two NN modeling. Also in [199], Adeel et al. analysed throughput of mobile users and suggested the best radio parameters through the architecture of cognitive engine development. Random NN was being used to exploit application on future mobile networks with three different learning strategies such as, GD, adaptive inertia weight particle swarm optimisation (AIW-PSO) and differential evolution (DE). The results showed that AIW-PSO performed better and also converged faster. Furthermore, Zang et al., in [195], proposed a method to allocate network resources by using K-means clustering NN and wavelet decomposition in order to observe traffic flow per cell. And, another solution to exploit NN, is the work in showcased in [198], in which authors used a regression based NN with their focus on traffic flow prediction. Authors predicted the path loss of a radio link, for optimising BSs transmission power. In addition, a solution iby Railean et al. in [196], offered traffic forecasting by proposing combined stationary wavelet transforms, NN, and GA. Finally, in the same context, the work in [197], developed a traffic forecasting solution with its primary goal to determine voice traffic demand.

A self-configuration mechanism is discussed in [200], in which Binzer et al. determined the number of BSs needed in the network to be self-optimised according to BSs location and antenna parameters. A game-theoretic approach was presented by Kumar et al., in [201], that optimised the usage of resource blocks (RBs) in a LTE network scenario. A harmonized Q-Learning concept for sharing of resource blocks between BSs was developed by Savazzi and Favalli, in [202] for downlink spatial filtering based on ML clustering algorithm, such as K-means. Authors shed light on the concept of users reallocation to another BS in order to achieve overall system capacity. Similarly, another approach is the work in [203], in which a Q-Learning based algorithm is proposed to adjust femtocells transmission power for capacity increment, limiting the interference.

In [32], in order to redistribute bandwidth allocation, the authors proposed a cluster and feedback loop algorithm. This algorithm explored user and network data in order to increase overall throughput. Similarly, Kiran et al., in [33] developed a fuzzy controller for bandwidth allocation in RAN for LTE-A and 5G networks. Equivalently, Liakopoulus et al., in [204], monitored specific parameters to improve network management that was based on distributed monitoring techniques. Due to the network, BS, and user interaction, BSs can take self-optimising actions after learning the environment. Thus, in [205], the authors analysed fractional power control (FPC) by using Q-Learning in order to reduce blocking rate and file transfer times. Finally, another Q-Learning based solution is proposed in [206], which introduced maximisation of resource utilization that was constrained by call blocking and dropping rates.

Encryption and Security

Encryption based real-time security built into the mobility management to make secure passenger traffic flow recorded by RFID contact-less devices is another existing and futuristic application governed by smart city planning. In the context of encryption, some works have been conducted to alter the data in such a way that it appeared random and irregular [91] when recorded. Therefore, two types of encryption methods, known as symmetric key and asymmetric key were used to highlight its importance. The symmetric key algorithm, in which, keys at encryption and decryption are the same level, while they are different in asymmetric keys on the other hand. In both types of algorithms, the main aim of encryption was to protect the valuable mobility data from attackers. Chaotic systems can produce random data that can be employed in cryptosystem [207]. In the rich literature [207–209], researches reported a number encryption schemes that used chaotic maps. Due to ergodicity, sensitivity and random like behaviour, chaotic systems were well-suited in light-weight encryption. The works produced by [210] had simple self-encryption authentication technique with a global mobility network (GLOMONET) framework based on the concept of distributed security management. The proposed technique provided a solution to reduce the number of transmissions during the authentication phase along with a method to decrease the complexity of mobile equipment. In addition, authors in [211] shed some light on secure communication between wireless hosts and global positioning system (GPS)-based encryption. Therefore, a mobility model was proposed to allow mobile nodes to exchange movement parameters, so that a sender is able to geo-encrypt messages to a moving decryption zone that contains a mobile node's estimated location. Furthermore, authors in [212] discussed visible light communication (VLC) based multiple-input multiple-output (MIMO) system to facilitate IoT connectivity in indoor environments. Using MIMO technique, power-efficient multiple pulse position modulation (MPPM) and long range with low transmission error on-off keying (OOK) were assessed. They used, a lightweight encryption technique for the transmitted data.

Energy Efficiency (EE) and CO_2 Emissions

EE is deemed the most important part of the current and future networks that aroused from smart city planning concept where heterogeneity of the cells consume substantial amount of energy to be regulated. To govern the process of less energy consumption coupled with reduced carbon footprint, several intelligent solutions are being developed [2, 8, 10, 17, 66, 68, 101–103, 213–217].

For introducing network densification, Alsedairy et al., in [11] proposed a framework. The interesting bit in the research work was the consideration on cloud SCs instead of physical SCs to run the fuzzy logic. These cloud cells are smart cells that underlay within the coverage footprint of MCs and work on on-demand basis. As such, by optimising the availability of SCs, the network can reduce its overall energy consumption. Zhao and Chen in [135] also developed a mechanism supporting EE in the mobile network where the mechanism relied on a controller feedback for switching on/off a femtocell. Similarly, authors in [218], depending on the network conditions, built a scheme for modular resources at a BS to dynamically activate or deactivate traffic using RL algorithm. The approach continuously monitor the network conditions in order to adapt itself for making decisions. The decision of turning modules on and off based on the conditions such as, turn on additional BS module, or turn off an already activated module, or even maintain the same condition of the module, etc. Through this, the solution achieved EE network with a very high energy saving, gaining about 80% without increasing user blocking probability. On the other hand, Peng and Wang in [219], applied an adaptive mechanism to increase the quality of energy saving mechanism (ESM). Their framework was to adjust cell sleep intervals based on traffic flow and network load guaranteeing spectral efficiency improvement. Another solution is presented in [220], to address issues remained in the traffic improvement and network implementation by first building a block of supervised prediction models to predict traffic values. Then, use the collected information to plan external network events, thus, improving overall prediction quality. In order to achieve EE, the framework managed to turn on/off certain cells through supervised prediction in the network.

To intelligently associate users with different BSs and to optimise energy, Jaber et al., in [103], proposed a mechanism that was dependant on backhaul connections to turn BSs on and off. Similarly, Miozzo et al. in [221] used Q-Learning to determine which BSs to turn on or off in order to improve the energy usage of the network. Furthermore, the work in [222] optimised the energy of ultra dense mobile networks by utilising big data, together with supervised learning (polynomial regression) which showed promising results achieving the highest cell throughput while maintaining EE, when compared to conventional approaches.

The rising level of greenhouse carbon emissions is driving climate change which needs to be controlled in such a way that transport is responsible for nearly a quarter of global energy-related CO_2 [223]. The subset of zero-emissions agenda discussed BSs to be carbon controlled to lower the emissions as much as possible [1] for cleaner air quality. For instance, Transport for London's (TfL) focus is on measures to promote mode shift to improve Londoners' health and air quality, and to reduce carbon emissions. Similarly, reducing greenhouse gas emissions through a Just Transition to a net zero economy and society, ensuring the journey is fair and creates a better future for everyone [2]. Based on the facts above, few studies have been developed to control carbon emitted by BSs in [223–226]. Their main agenda was to calculate CO_2 emissions using their own frameworks.

[1] Mayor of London Transport Strategy can be found online at: https://content.tfl.gov.uk/the-mayors-transport-strategy-update-2020-21-acc.pdf

[2] Scottish Government Emissions Policy can be found online at: https://www.gov.scot/policies/climate-change/

Edge Intelligence

Another important aspect of mobility management is the edge intelligence in IoT devices that removed a barrier of data fusion while distributing the data and intelligence to the edge. With the success of IoT, user movements and their trajectory patterns recorded by the edge devices to self-adapt or self-optimise without always sending overhead packets back to the network which have been studied by several authors in as [27, 227–231].

In [227], discussed edge resources from roadside units (RSUs) with the deficiency in BSs to match the wide variety of services in future vehicular networks. With the coordination between extensive edge intelligence services and edge resources for vehicular networks, authors proposed an intelligent service oriented mobility management architecture. Authors in [27], identified user design patterns to compute IOT devices, Cyber–physical systems at the edge aiming to keep a balanced trade-off between generality and applicability. In their work, they presented a design pattern model for self-adaptive systems, named Self-organising Coordination Regions (SCR) to focus on organising interconnecting devices into teams. Similarly, authors in [228] showcased 6G-enabled edge intelligence applications for ultra reliable low latencies in order to improve processing and computation capabilities. The advantages of edge over cloud computing were discussed in the paper through which latency and reliability issues in critical applications can be resolved, building intelligence at the edge to compute complex tasks within a negligible time. Furthermore, to deploy storage and computing resources at the wireless network edge, e.g., radio access points, the edge information system (EIS), including edge caching, edge computing, and edge AI, authors in [229] discussed key design issues and methodologies exploiting EIS. Also, edge computing integration with AI by building AI models, i.e., model training and inference, on the edge have been proposed by [230] describing core concepts and the research roadmap. Finally, A mobility-aware cross-edge computation offloading framework for partition-able applications was proposed by authors in [231]. An online-based algorithm using Lyapunov optimisation was proposed to jointly determine energy harvesting and edge site-selection to reduce the latency in data transmission for resource-limited mobile devices.

Blockchain Privacy Mechanism

In the current and future mobile networks, Blockchain is becoming popular that envisages a vision for mobility management. Blockchain was originally developed to support Bitcoin for securing financial transactions without an intermediary like a bank. Some of the innate privacy features of blockchain were evolved to support overall user mobility through a structure that exhibited secure key derivation for mobile HOs. Blockchain, as a secure medium can provide smart contracts, key derivation scheme, and privacy-preserving methods to encapsulate end-to-end user mobility to improve QoS and quality of privacy (QoP) [232–237].

Authors in [232] presented blockchain-based mobility-as-a-service (MaaS) as an application of edge computing where MaaS behaves as an intermediate layer that manages mobility connections between transportation providers and passengers. Their solution improved trust and transparency for all stakeholders while eliminating the need to make commercial agreements with separate MaaS agents. The blockchain-based MaaS has the potential to emerge as the main component for a smart city transportation offering efficiency and reducing carbon dioxide emissions. In order to unlock the 5G and B5G potentials, it became imperative to address the shortcomings of security weakness in HOs as in the previous mobile networks, security schemes didn't support full forward key separation, thus, making networks vulnerable to attacks and prone to latency [233].

Big data smart mobility privacy and security challenges have been discussed in [234], in which, a framework composed of individuals, companies, government and universities was presented. Using encrypted data to the blockchain network participants can perform transactions with other by transaction rules (smart contracts). Due to massive amount of data generation from mobile devices, insight into the user behavior and mobility patterns can be recorded where preserving their data was a concern [235]. Blockchain systems are capable of providing privacy with the implementation of an access control mechanism to the participants. Further, users control the extent of data sharing with the intended audience and been rewarded for sharing the personal mobility data through smart contracts.

Using Blockchain technology, mobile users could offload some mobile devices computations to the nearby geo-distributed Fog servers by Fog computing infrastructure, was the idea presented by [236]. Offloading can be done by mistake and becomes liable to vulnerability introducing privacy leaking and security issues. In order to contemplate with the challenges, blockchain technique into Fog computing can bring some benefits to the privacy. The concept of smart city involves digital strategies implementation that are necessary people-centred and lead into high technology-based innovations expanding capacity and opportunity. Therefore, authors in [237], investigated the possibility to integrate the innovative and multi-purpose blockchain technology in the smart city evolutionary process to form a smart mobility by renewable energy sources traceability.

SON functions Coordination

SON functions yet holds a prominent position to showcase coordination of two or more distinct functions without being interfered with each other while optimising same parameters at the same time [15, 15, 64, 104, 238]. Coordination of SON functions can be understood with a simple example where the network tries maximise its coverage while minimising its interference level. This type of situation should be coordinated to smoothly enable SON functions conflict-free operation and stability of the network.

Lateef et al., in [238], developed DT-based framework to establish policies for avoiding network conflicts related to MLB and MRO mobility functions. Alongside, paper contributed to classify all possible SON conflicts by categorising into five main categories, mainly: parameter conflicts, key performance indicators (KPIs) conflicts, measurement conflicts, network topology mutation conflicts, and logical dependency conflicts. Similarly, another work that tend to resolve the management relating SON conflicts was discussed in [239] where authors analysed the case in a LTE network with a distributed coordination scenario where a feedback loop was modelled as stochastic processes.

Other solutions relating to feedback controllers, can be seen in [240, 241]. In [240], the authors presented SON conflicts by using a hybrid classification system scenario. Based on the feedback controllers, some use-cases of SON conflicts were presented to gather measurements and change SON parameters accordingly. Similarly, in [241], Karla also classified SON parameters to exploit mobile radio system with two classes of parameters in which they showcased a proof of concept scenario of LTE-A evaluation and simulation. Their proposed system first was able to find good set of configuration parameters offline, followed by a feedback controller usage to update itself online.

Mainly there are three SON functions that are used in the 5G abd B5G showcase, they are, (i) Self-configuration Learning, (ii) Self-healing Learning, and (iii) Self-optimisation Learning. Self-configuration Learning is the process which is responsible of parameters auto configuration of a network such as SCs, MCs, Femto-Cells, or any equipment related to BS family. The flexibility in self-configuration is such that, it can be deployed before and after the network is already operable to support any BS alterations to the network. This may happen whenever a new BS is added/removed to/from the network or if the network is recovering from a fault and needs a re-configuration [3]. There are many a self-learning techniques that not only exploit basic operational parameters, but also they have tendency to discover BSs neighbours for radio parameters configuration but at the expense of complex convolutional network. This is due to the increased complexity in the BSs several parameters configuration with many dependencies between each other specially when new BSs joining the network or existing ones disappearing from their neighbours' lists due to faults/errors. The main use-cases for of self-configuration can be defined as [3]:

1. Operational parameters configuration;
2. New BS neighbours and creation of neighbour cell list determination;
3. Other radio parameters configuration and adjustment of network topology.

In terms of Self-healing Learning, due to the current healing methods reliance on manual interventions and cells inspections, the healing procedures are triggered after the event that has been occurred as a fault/error, though a reactive approach. This reactive/passive approach doesn't retrofits and maintain QoS throughout the network introducing loss of revenue to operators [2, 9]. The self-healing function in SON heals failures in response to the events occurred. In addition, it does fault detections and diagnosis in order to trigger corresponding compensation mechanisms accordingly. Furthermore, the expectation of the future mobile systems moving from reactive to proactive paradigms leave self-healing function in vain if faults and anomalies cannot be predicted and remedial measures around it. Due to the advancements in mobile network, self-healing solutions struggle to prove their coexistence with the emerging models [2]. When applying ML algorithms to the self-healing learning, it is easy to label certain data sets, such as in fault classification, however, other data sets that have some outages involved, the measurements appear to be normal or deviate a bit, might be suitable to work with unsupervised algorithms. Following use-cases for self-healing could be defined as [20]:

1. Fault Detection;
2. Fault Classification;
3. Outage Management.

Finally, Self-optimisation Learning is a SON function that takes care of the network while constantly monitoring it and proactively updates its parameters accordingly. Since the performance is based on efficiency which guarantees the network to function proactively, there is no overhead bearing to the backhaul network at every event occurrence [3]. Non-static nature of the network environment gives self-optimisation an edge to tackle BS parameters' adjustments according to user needs. Self-optimisation is a key enabler function to manage user's mobility, traffic flow variations, unknown user movements in underground tunnels, and high-speed trains [2,12,14,15,64]. Therefore, initial self-configuration parameters might have changed during the process and not suitable any more in order to optimise the network's performance. Since, different optimisation parameters are available in the network, several ML algorithms can be applied to collect lots of data during network operation.However, despite its efficiency in collecting large data sets, self-optimisation is still challenging due to parameter dependencies where one small change can alter operation of the network as a whole [2,12,14,15,64]. Based on the literature review use-cases definition by [21], user's mobility management using self-optimisation function can be defined as:

Other Technologies

There are some other technologies which are related to the theme of this report, are, Network Function Virtualization (NFV), Network Slicing (NS), and Massive MIMO. NFV is one of an important enabling technology onto which future mobile networks depend on. It aims at decoupling network functions from specific hardware components gives network a breathing space. The operation is done in the cloud or at high-end servers before sending results back to the hardware [2, 14]. On the other hand, NS accommodates 5G ecosystem divergent service needs, applications, and services in support of vertical industries. NS divides the whole chunk into multiple divergent slices to form a capacity-driven framework. The architecture is cloud based for efficient resource and services sharing including antenna, bandwidth, spectrum, processing power, storage, and networking [75, 242]. The architecture of 5G NR has further evolved from cell-centric radio access nature to a wider multi-beam based user-centric radio access [243]. Also, 5G cellular networks from the start, assumed to enable three types of services from enhanced mobile broadband (eMBB) to new services such as ultra-reliable low latency service (URLLC) and massive machine-type communications (mMTC) [244]. As such, cells densification and massive multiple-input multiple-output (MIMO) concepts became essential to boost capacity demands embracing the intelligence of spectrum efficiency (SE) and energy efficiency (EE) [244]. With the advances of the electronic industry, by being able to miniaturize components, according to the Moore's Law, future network systems could be coupled with arrays containing hundreds of antennas, simultaneously serving many user terminals [245, 246].

2.2 ML an Enabler of User's Mobility

As it is clear from the discussion that, all of these 5G-driven concepts exploiting future mobile networks require some sort of real-time optimisation or past events information from the network to function at their optimal pace. For example, ML drives MNOs to estimate traffic flows for BSs deployment consideration in HetNet environment. Another example is in the case of ML learning communication patterns of IoT and M2M devices. This is done by human interactions with the machines in their daily use when data is gathered to exploit communication patterns. For future approach, ML can proactively support mobile networks leveraging historical data collection into state-of-the-art ML-driven models in order to predict nature of events occurrence. With the variety of functions ML has brought into the mobile world, ML in future mobile networks has a limitless potential inheriting property of data assessment, training, and predictions. ML is expected to play a major role in future mobile networks in order to enable, not only all of these functions, but also the traffic patterns, complex traffic flows in the underground tunnels with limited coverage access, high-speed mobility and handovers (HO) assessment, mobility profiling and travelers-tracing paradigms providing safe travelling facilities, etc. This, by its turn, will make future networks more reliable, efficient, cost-effective and manageable [25, 26, 30, 40, 63, 70–72, 116, 183, 247]. ML relies on computers taking decisions by programming algorithms after analysing given set of data. Or, in other words, the goal of ML is to take an input data and learn a model based on a specific set of instructions (algorithm) that relates the given input with the desired output. ML is usually divided into two main types [39]:

- Supervised Learning (SL), or Predictive Learning;
- Unsupervised Learning (UL) or Descriptive Learning;
- Reinforcement Learning (RL).

A brief description of each ML category is presented by referencing a Figure 2.1.

2.2.1 Supervised Learning

Algorithms that require a data set in order to learn a mapping of both inputs and outputs fall into the category of supervised learning or predictive learning. With the supervisor being learning the process, it also knows the the answers (output) for every input data to be mapped with the output data. As the algorithm iteratively makes predictions during its training process, the supervisor corrects

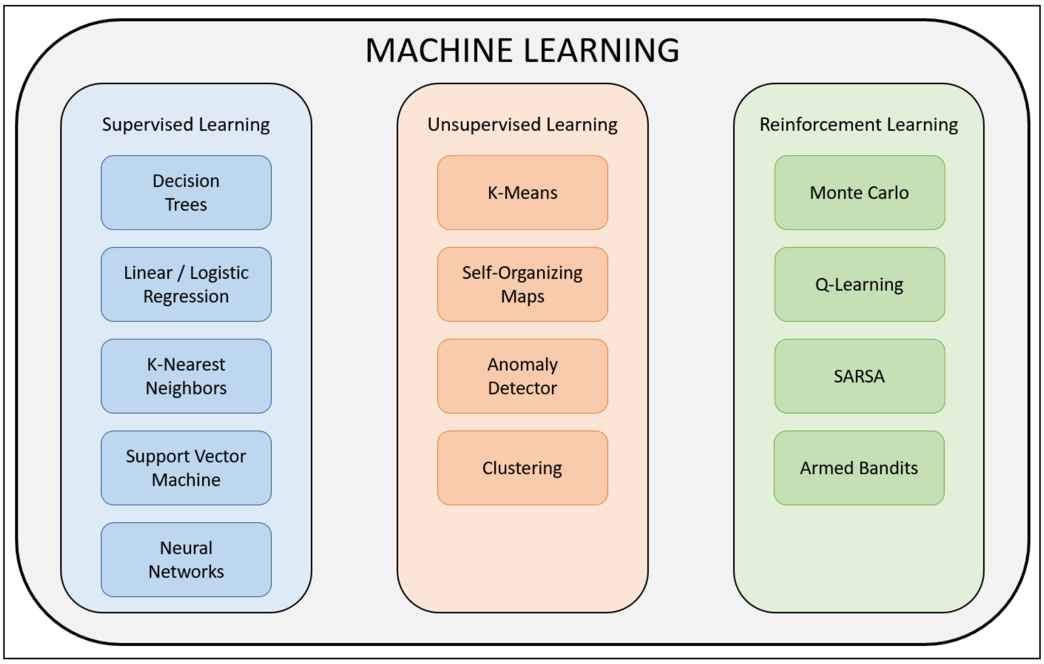


Figure 2.1: Block diagram showing the three main branches of ML and some of its algorithms [1].

it if necessary forming a relationship between input and output data to make predictions for unseen data examples [43, 45].

SL is a classification algorithm which splits into two main categories according to the type of the output variable. If the output variable is a discrete variable, for example: *peak hour traffic* and *off-peak hour traffic*, or *underground* and *over-ground*, the SL problem is referred to as a binary classification problem. On the other hand, if the output variable a continuous value (or a real value), such as a rate of a certain region according to the market prices, then the supervised problem is considered as a regression problem [45]. A range of SL algorithms from linear regression, decision trees (DT), logistic regression (LR), support vector machines (SVM), k-Nearest Neighbors (kNN), to more complex ones, such as neural networks (NN), and its variations, like deep neural networks (dNN), convolutional neural networks (cNN), etc, [50].

2.2.2 Unsupervised Learning

On the other hand, unsupervised learning (UL) also considered as descriptive or knowledge discovery algorithm without information about its output [2, 39] forming an interesting structure. Unlike SL, outputs are not linked with input data sets and as such without having supervisory monitoring. UL objectives usually formed of establishing commonalities in the data set to group of similar examples, in what is known as clustering, or to determine the data distribution [42, 45]. Due to its nature of estimating a model for data without labels, UL algorithm mainly consists of clustering, such as , self organizing maps (SOM), K-Means, anomaly detectors and mixture models, etc, [2, 39].

2.2.3 Reinforcement Learning

RL is a distinct type of machine learning algorithm unlike SL that learns from already occurred events provided by an external supervisor. Although essential, SL learns static models without being interacted to from an interactive problem making desired behaviours difficult or even impractical to achieve [39, 61]. As such, in the situation where interactions are desired in an unknown territory (where one would expect intelligence to be the most beneficial), an agent learns through its own experience with the environment making RL most appropriate interacters [61]. It is rightly said that RL is a ML technique based on a goal-seeking approach [61] that in comparison to other ML techniques, the learner discovers actions by trying them [10, 61].

RL handles wide range of tasks associated with actions where the MC interacts with the network environment, collects system information and compares it with the information it holds. After the learning process is completed, the agent selects its actions and the environment responding accordingly as it can adapt to changing needs driven by actions through continuous learning. Agent's actions are environment dependant to maximise the reward or minimize the penalty. After the execution of each agent's action, resulting state and reward/penalty are evaluated 2.2. Basically, the agent and environment interact continuously at certain time-steps. At each time-step, t, the agent receives a representation of the environment's state and selects an action according to a policy (π). Next, $t + 1$, as a consequence of its action, the agent receives a reward ($r_{\mathrm{t+1}}$) that arrives in a new state. Based on this, a RL system can be divided into four main components [61]:

1. Policy (π): defines the agents behaviour that can be either deterministic or stochastic process.
2. Reward/Penalty ($r_{\mathrm{t+1}}$): special numerical values given by the environment after agent interaction.
3. Value function: indicates the expected value of visiting a state, $V(s)$ – the value of taking an action or state-value function in a specific state, $Q(s, a)$ – action-value function.

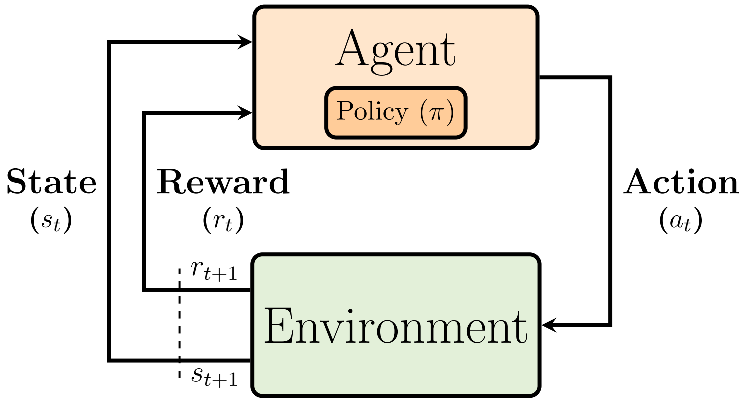


Figure 2.2: RL block diagram where agents actions to learn the environment, receives a reward/penalty, depending on the outcome of its action, and arrives in a new state [1].

4. Environment: comprises everything outside the agent. In addition, the agent holds some knowledge about the environment before action, however, sometimes, a model of the environment is not available that leaves agent to learn from the environment for optimal results.

Furthermore, due to the nature of RL that is based on inheritance of the outcomes, the system of exploring the surroundings and determining probability of possible actions to take, a trade-off factor is always present. Often known as the exploration-exploitation trade-off, is a fundamental RL algorithm dilemma where the agent must not only exploit the best actions currently known, but also explore new possible actions for better cumulative reward based [61, 248]. These algorithms can be further divided into *On-Policy* or *Off-Policy*, depending on how learning is performed [61]:

- On-policy learning: With the assumption of current policy being followed, the agent updates its value function and estimates the return.
- Off-policy learning: With the assumption of different policy being followed, the agent updates its value function and estimates the return.

One of the most commonly used policies in RL is the ϵ-greedy policy, which states that with a probability $p = (1 - \epsilon)$ the action with the maximum value known by the agent is preferred to be chosen, whereas with probability $p = \epsilon$ an action is chosen at random without any known preference. Also, when a decaying ϵ rate is selected, this policy yields a trade-off in terms of exploration and exploitation where in the beginning, because the ϵ is quite larger, the agent likes to explore new actions. And later, due to the decaying ϵ rate, the agent favours the exploitation of the best actions [61].

Q-Learning

Q-Learning algorithm is one of the most common algorithm in RL which is widely used. It was first thought and proposed by Watkins to carry out his research [41]. Q-Learning based on TD learning method acts by learning an action-value function and is represented by $Q(s, a)$ where, expected value of the agent in certain state acts by taking a specific action. At a state s_t, Q-Learning chooses an action a_t by maximizing its value function $Q(s_t, a_t)$ at a specific state according to a reward r. More formally, Q-Learning can be defined by the following equation as [10, 41, 61]:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_{t+1} + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t)], \tag{2.1}$$

where, α is the learning rate, r_{t+1} is an expected reward at the next time step, γ is the discount factor and $\max_a Q(s_{t+1}, a)$ is an estimate of the optimal future action-value function at the next time step, over all possible actions represented by a. In (2.1), right side of the equation determines the backup and the algorithm memory storage. Focusing on the target value function, $r_{t+1} + \gamma \cdot \max_a Q(s_{t+1}, a)$, represents an estimated value onto which the algorithm operates. Previously stored value in the form of error is represented by $r_{t+1} + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t)$ subtracted with the target value [61]. Q-Learning is considered as an off-policy and model-free algorithm which follows different policies in determining the next actions and updates the action-value table where agent does not have knowledge of prior actions being taken in the environment, instead it take actions to obtain environment information [249]. Also, being an off-policy algorithm, Q-Learning utilizes two different policies, (i) generate its behaviour (ϵ-greedy for example), and (ii) evaluate and improve (fully greedy policy). The separation on the policy methods lead to estimate the deterministic decision with another policy controls the agent's behaviour and continue with the sampling all relative and possible actions [61]. As it can be seen from (2.1), Q-Learning algorithm is model-free and a method of asynchronous dynamic programming where it provides agents with the opportunity of learning that finds an estimate of the optimal action-value function by experiencing concurrent sequences of actions [249].

Conventional RL Limitations

There are some limitations in conventional RL algorithms where the task of learning value functions is often considered to be the task of learning the values for different state-action pair entries that are also known as Q-Table entries. Despite this practical assumption, RL is limited to perform well with small number of states and/or actions [61] due to the reliance on periodic lookup table updates and not very practical with the larger data sets or states [61]. In addition to this, RL algorithms generalise the states without differentiating the value of the table between two very similar states due to the concept of Bellman equation as an iterative update [61]. Thus, the value-function not is estimated separately for any given sequence which is a critical issue. As such, in many tasks involving RL, most states that have been encountered will have no experience of the situation beforehand, specially in cases of continuous or complex environments [61]. Therefore, the solution to cope with such kind of issue is to combine RL algorithms and generalisation methods in order to approximate table function. By doing so, the tables can be denoted by a specific function, also known as value function approximation (VFA). According to [61], an algorithm 1 that showcases how VFA can be implemented using RL is presented.

Algorithm 1: RL [61]

```
for Every episode do
    Initialize current state
    for All actions do
        Get features present in current state and action
        Estimate value of Q-Table with VFA
    end
    Choose action according to policy
    for Each iteration do
        Take action
        Observe reward
        Move to next state
        for All actions do
            Get features present in next state and action
            Estimate value of Q-Table with VFA
        end
        Choose next action according to policy
        Update weights by GD
        Current state receives next state
        Current action receives next action
    end
end
```

Chapter 3

Mobility Prediction-based Model

3.1 Introduction

Information and Communication Technology (ICT) enabled optimisation of train's passenger traffic flows is a key consideration of transportation under Smart City planning (SCP). Traditional mobility prediction based optimisation and encryption approaches are reactive in nature; however, AI driven proactive solutions are required for near real-time optimisation. Leveraging the historical passengers data recorded via RFID sensors installed at the train stations, mobility prediction models are able to support and improve the railway operational performance vis-a-vis 5G and B5G. First, the mobility prediction-based optimisation and encryption is analysed with the passenger traffic flows based on access, egress and interchange (AEI) framework in order to support train infrastructure against congestion, accidents, overloading carriages and maintenance. Research predominantly focuses on developing passenger flow predictions using ML along with a novel encryption model capable of handling the heavy passenger traffic flow in real-time. The comparison of the performance of various ML driven flow prediction models using real-world passenger flow data obtained from London Underground and Overground (LUO) is done. Secondly, exploiting ML algorithms further with a concept of travelers-profiling, being an essential interventions that railway network professionals rely on managing the Coronavirus Disease 2019 (COVID-19) outbreak while providing safe commute to staff and the public. Through this, a strategy of safe transportation can be provided while maintaining reasonable social distancing in the mobility of daily travelers. Crowded train carriages, stations, and platforms are highly susceptible to spreading the disease, especially when infected travelers inter-mix with healthy travelers. In this plethora, ML-driven intelligent approach is proposed to manage daily train travelers that are in the age-group 16-59 years and over 60 years (vulnerable age-group) with the recommendations of certain times and routes of traveling, designated train carriages, stations, platforms, and special services using the LUO network.

3.1.1 Related Work

Mobile operators capitalise on large scale mobility traces obtained via mobile phones to optimise their network operational behaviour. Besides, movement patterns aid to develop a scenario where mobile users play a significant role in their movement behaviors through most visited places. Embracing the world in the 5G era, challenges in understanding traffic patterns and human mobility predictions is limited which has been experienced by urbanised cellular towers [13,52,74,250]. Extra diligent intelligence is required to fully automate the network that would be a hypothetical remedy against current complexities involved in predicting the traffic flows in the underground train environment [2, 117]. Traffic flow patterns can be predicted by the ML models by using historical data as shown in Fig 1. This would aid to develop solutions for optimisation and encryption which makes it easier to proactively monitor and predict passengers movements [2, 118].

Several studies on real-time datasets despite randomness in the path of traffic flow, show user movement predictions [71, 83]. The user trajectories from source to destination with regular intervals, expected or unexpected. Several comprehensive surveys for mobility prediction are available in [84, 94, 183] that exploit various methods of predicting user mobility patterns where MK-based is a popular predictor due to being less complex in nature [30, 83, 84]. However, with the limitations of real-time data sets that have complexity involved, ML predictors can be a viable alternative in order to study traffic flow and provide encryption to it. Hence, there is a need to explore the performance of ML predictors for the mobility prediction by using a meaningful and novel AEI framework that with the best knowledge, never been considered before. Several mobility prediction schemes probabilistic approaches for predicting the likelihood of the next destination were discussed in [69, 93, 183, 249]. In context of cellular network optimisation, various machine learning algorithms including decision tree [116], k-means algorithm [55, 56] and artificial neural networks [37] have been employed for predicting user mobility patterns in order to perform network resource optimisation patterns. In context of road networks, NN algorithms [57, 119] have been used for short-term traffic flow prediction, as well for reduce road congestion by analysing traffic information and further relaying the message back to the vehicles [145]. A smartphone based software to recognise traffic flows with high accuracy was proposed by using Random Forests (RF) classification model and positioning technology in [119, 120].

London Underground Limited (LUL) is one of the oldest and largest tubes in the world which is renowned for carrying a large number of passengers in all cardinal directions of the metropolitan city, London. Due to the nature of trains are heavily loaded, it is of utmost importance that user-friendly traffic information within train carriages to prevent superfluous congestion and confusion is provided. It is evident from the fact of the horde of passengers traveling at different times of the day must be facilitated with comfort and safety [67, 251, 252]. Similar contribution was made in the field of train adaptive control when identifying the rolling stock parameters [251] of moving trains. Furthermore, an article was proposed that focused on paradigm of localisation of rolling stocks and its movements, dispatching control and, rail traffic in [252]. A system-theoretic standpoint for establishing transformation and reduction of the parallel paths; reducing overhead was developed in [253]. A similar study was contingent upon robustness into the operational system by analysing the problems of rail transformation of the network to some parallel lists where a taxonomy of the time-optimal criterion is proposed for an ordinary differential [58], however the transformation of the railway doesn't take passenger traffic flows into account through which robustness can be injected into the operation of the rail system. Another illustration in regard to correlations of rail transit traffic flow which impacts the train control system on rail transit service quality [254].

Some works are found in the context of passenger traffic flows, network complexity, and energy efficiency [59]. Real-time traffic information that drives interstation running time monitored by train supervision systems in [60]. In the same context, another work that further classifies the traffic into weights and temperatures is found where the structure of the classification training model was proposed with ML algorithm such as K-Nearest Neighbour (KNN) in [255]. The cellular coverage inside the underground stations are often patchy or in some cases non-existent whereas the traffic flows are quite complex. This makes it quite challenging to control and predict the passenger flow variations and also real-time operational optimisation for smart city planning.

Everyday thousands of passengers use RFID cards to tap in and tap out of the train stations providing an estimate of passenger flows. The use of passive RFID technology requires an RFID card and a reader that is cost-effective and secure based on Radio Frequency (RF) electromagnetic fields. RFID operates in the range of frequencies such as; Low-Frequency (LF) runs at 125 to 134 kHz, High-Frequency (HF) at 13.56 MHz, and Ultra-High-Frequency (UHF) runs at 433 and 860-960 MHz. The database linked to RFID devices stores the passenger data in the form of unique identification numbers through an electronic microchip. In the context of encryption, some works have been conducted to alter the data in such a way that it appears random and irregular [91]. Two types of encryption, known as symmetric key and asymmetric key in [91] are used to highlight the importance of current trends in encryption. In the symmetric key algorithm, keys at encryption and decryption are the same level, while they are different in asymmetric keys. In both types of algorithms, the main aim of encryption is to protect the valuable data from attackers. Chaotic systems can produce random data that can be employed in cryptosystem [207]. In [207–209], researches have reported a number encryption schemes that used chaotic maps. which are well suited for light weight encryption and offer ergodicity, sensitivity and randomness. [207–209]. Therefore, using aforementioned properties of chaos, a scheme for user data protection is discussed. Two chaotic maps, nonlinear chaos map [146] and Logistic map [256] are used in the encryption process which is discussed in more detail.

The world-wide COVID-19 pandemic can be easily spread by nearby people especially in areas with high density where sufficient social distance is improbable between the mobile individuals (e.g., transport network, city centers, etc.). The increase in mobile devices present a new opportunity to combat the challenges encountered by traditional contact-tracing techniques in terms of monitoring, classifying, and advising different age-group travelers about the spread of COVID-19 in densely populated areas, such as overcrowded LUO network. A safe commuting and globally accepted social distancing strategy to mitigate the spread of pandemic while avoiding crowded areas has gained crucial significance [79, 257]. However, there is a need for devising mitigation strategies to further decelerate the disease spread by using AI [10] that exhibits traits associated with the historical mobility of the different age-groups such as vulnerable age-group travelers.

In this direction of research, existing works, but not limited to, show reasonable results in relation to above-ground traffic movements, optimisation of traffic in an urban city environment, encryption of simple data. However, existing contributions discussed in the context of mobility predictions, travelers-tracing and mobility profiling, and encrypting valuable real-time data approaches fall short of the mark for 5G and B5G requirement due to following six limitations:

- Reactive mode of operation: Traditional algorithms rely on the reactive nature of decision making and are not suitable for robust traffic flows modelling. This is due to the LUO environment being dynamic and constantly varying. There is a trade off needed in order to upgrade existing reactive systems at a expense of cost of sacrificing time, resources, and QoS. However, due to the continuously varying dynamics of the passenger traffic flows in LUO environment according to time of congestion on the platforms and stations when a remedy is planned, the conditions may have already changed drastically. This leaves a gap in planning new remedies before it can be influenced. The problem becomes worse in 5G, where complexity of haphazard assortment of different types of passengers traffic in either absence or limitations of cellular coverage within LUO environment.

- 5G optimisation in ultra reliable low latency: Real-time alerts, monitoring and supporting mission critical applications are required to meet certain 5G optimisation and latency standards [12] keeping good QoS and without affecting operational technology (OT) train network. Traffic complexity on stations, tunnels and platforms add unnecessary latency which makes train's operational network in a difficult position to address mission critical applications. Therefore, a demand for predicting passenger flows for low-latency remedies demands is needed.

- User Flow Discovery in LUO Environment: A key challenge to discover a user pattern where users have multiple ways to travel in the LUO network such as Access, Egress and Interchange (AEI) along with the ridership data obtained from Interchange-Alighters and Interchange-Boarders. Existing mobility prediction methods overlook this challenge. User mobility pattern approaches may work in low, medium and high density networks above ground where LTE cellular network is available, however, any studies that address the problem of 5G scalability, measurability and applications in complex LUO ecology are not presented.

- Intelligent transport systems (ITS): Another challenge in the 5G domain is to have an intelligent system that would assist transportation in SCP. Many concepts have been proposed to regulate the mobility of users above ground by using cellular services [10, 68, 70, 72, 125, 149, 183, 231, 238]. But, there is not much work done in the field of ITS using the AEI framework in where cellular services are patchy. With the limitation of cellular services either on-board train modules or ticket machines take the responsibility of traffic flow monitoring. The 5G concept of onboard ITS is fairly new which is yet to be deployed. Train suppliers, for example, Siemens is making splendid efforts in order to deliver innovative trains with special functionality of on-board monitoring concept[1].

[1]Mobility in Metro London can be found online at:
https://www.mobility.siemens.com/global/en/portfolio/references/metro-london.html

- Planning and cost of technology: When 5G brings numerous benefits to the technology, it also brings concerns over planning and deployment costs. There are various methods discussed within the domain of 5G, associated with planning and costs in the energy efficiency, densely populated HetNets, spectrum usage domain, internal logistics and Logistics 4.0, transport systems, etc. However, there seems to have less work conducted in the domain of classification of mobility predictions and encryption modeling considering passenger traffic flows in underground trains.

- Encryption: Advanced Encryption Standard (AES) and Data Encryption Standard (DES) can provide confidentiality but for real-time encryption, a light-weight encryption algorithm is required [146]. Over several years, cryptographers are using chaos-based cryptosystem for faster and real-time encryption. In this work, two chaotic maps known as a nonlinear chaotic map and logistic map that have quick time responses and hold less memory sizes compared to existing schemes have been used. The presented novel scheme would be able to provide an extra layer of security that is difficult to deduce secret cryptographic keys. One can also propose an encryption algorithm with a single map for faster processing but due to lower key space issues, two maps are used.

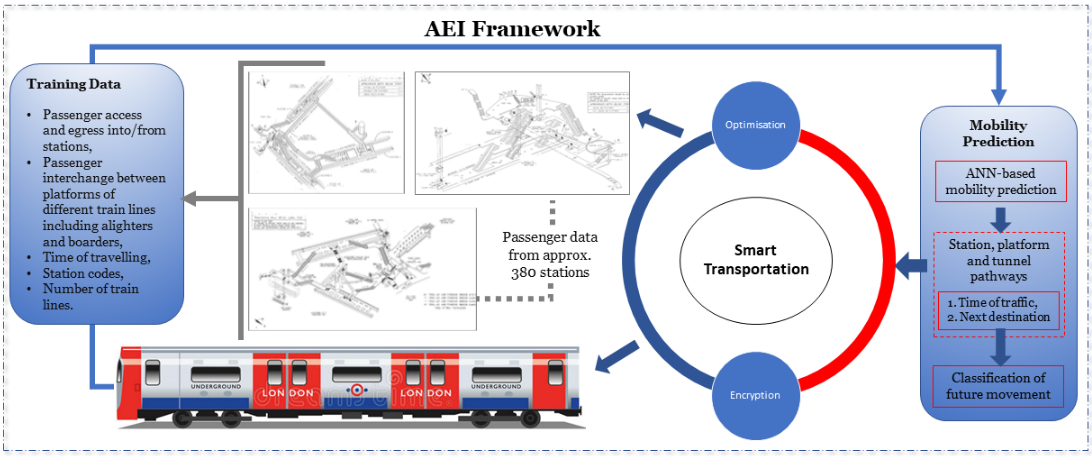


Figure 3.1: AEI Framework with data collection points from approximately 380 stations.

3.1.2 Contributions

To address the aforementioned limitations, a novel AEI based optimisation and encryption framework as shown in Fig. 3.1 is proposed with an aim to make emerging cellular and train systems artificially intelligent and autonomous in order to anticipate and encrypt user mobility behavior within LUO environment. The intelligence obtained from the aforementioned framework can help streamline near-real time operational optimisation. This includes minimisation of congestion at the interchanges, optimal resource scheduling while proactive encryption schemes make sure that passenger data privacy is preserved. The contributions and organisation of paper can be summarized as follows:

- As a building block of AEI framework, an ML driven model that takes into account spatio-temporal characteristics of passenger flows in LUO environment for mobility prediction in large-scale train network is presented. The proposed mobility prediction model overcomes the limitation of conventional ML classification algorithms that failed to incorporate high accumulated passenger traffic in three dimensional states (3D), i.e. number of passengers, travelling time and AEI based passengers travelling and behavioural information (Section 3.2.1 and 3.2.2). Furthermore, a novel method to map the classification results through comparative performance analysis of six ML algorithms, comprehensively is discussed.

- Based on the intelligence gained from the mobility model, i.e., mobility prediction classification and directions, a proactive movement precision is formulated to maximise the advantage of traffic flows in several unexpected directions and instructing passengers to take necessary interchanges. In this way, real-time directions can be exploited for monitoring purposes shown in Section 3.2.3. Classification estimation for the next passenger movements is mentioned in Section 3.2.4.

- An approach to assess and manage daily train travelers that are in the range of ages 16-59 years and over 60 years (vulnerable age-group) by advising traveling in certain train carriages, stations and platforms using the LUO network, is discussed. A mobility-aware travelers tracing sensors in existing railway systems including WiFi, RFID, Bluetooth, Ultra-Wideband (UWB) [258] that collect different age-group travelers data anonymously and pseudonymised it for AI-driven decision analysis in real-time [9]. By these key enablers, improvements have been foreseen to advise travelers with designated safe routes, train carriages, stations and platforms. Also, travelers-tracing enabling technologies outline is presented that would manage traveler profiles according to the intelligent mobility.

- In addition, a novel encryption method to preserve real-time passenger traffic flows where a system incorporates cost, easy deployment, security and privacy preservation aspects (Section 3.2.5) is added to the research. This is benchmarked against the current security parameters and measures that have been used across transportation specifically in train ticket machines using RFID technology. The encryption provides security which is transaction oriented data integrity that is light weight, proactive and provide faster data rates than existing technologies. In addition, an encryption algorithm that is capable of handling the heavy passengers traffic flow in real-time while provide faster processing that can hold an unlimited number of different applications without any limitations of memory sizes discussed in Section 3.4.3.

- System level comprehensive performance analysis of the proposed model have been conducted that complies with multi-tier 3GPP simulations. The prediction accuracies of ML algorithm have been compared using realistic AEI framework. Error margins have been estimated in cross validation of training real-time data to be around 10%.

3.2 System Model

An analytical model development of AEI framework whose foundation is based on the following elements.

- Artificial neural network (ANN) driven mobility prediction.
- Movement precision to map future user location and next movement classification estimation.
- Encryption based real-time security built into the passenger traffic flow recorded by RFID contactless devices at ticket machines.
- Travelers-tracing and mobility profiling.

3.2.1 AEI Framework

The AEI framework focuses on the real-time train network data that covers passenger flows in LUO train stations. Consideration has been given to the total number of passengers movement in a given period of time that have been classified into three main classes; Access, Egress and Interchange. Directions of all passengers using LUO network are known on the principle of their positioning recorded by tap-in and tap-out technology. Assumptions have also been taken into consideration where all passengers use the provided technology without any malfunction. In other words, a model based on full buffer mobility traffic flow, is used for each traveller, i.e there is no defect in data availability and is always present to be monitored with a constant bit rate. For proactive optimisation, a centralised smart transportation architecture is assumed. Furthermore, intersection traces that encompass past and future platform's time and location stamped information such as start and end platform nodes for a particular train line, in-use station's logistic code for all train lines, and all other nodes transitions not in use, are known and assumed to be available to the smart transportation server. Also, a method of encryption is used in the framework that addresses the issue of data privacy while ensuring faster data transfer. Through this would proactively preserve AEI network state information using automated deep learning prediction models with the help of encrypted images. Finally, travelers-profiling is discussed within AEI framework to assess vulnerable vs invulnerable group travelers with key technology enablers.

3.2.2 ANN driven Mapping of Mobility Prediction

ANN is an interconnected group of nodes/neurons consisting of input and output layers. Based on the training data these neurons learns the input-output mapping without being programmed with task-specific rules. Alternatively, the numeric weights are designed in such a way that they can be tuned based on experiences to exploit best possible outcomes when the neural nets show flexibility to inputs and intelligent when learning. An ANN model is implemented to classify passenger traffic flow patterns in the LUO environment and used them to predict future location based on the complex AEI dataset. The movement patterns of 3D layers (number of passengers, time of travelling and AEI) and the relationship between inputs and outputs is described in the following modified equations [39];

$$p_t(y_t = c|w \subset D) = w_o + \sum_{j=1}^{Q} w_j.f(w), \tag{3.1}$$

$$f(w) = f(w_{0,j} + \sum_{i=1}^{P} w_{i,j}.\, x_{t-i}), \tag{3.2}$$

where, p_t is the probability of three classes c within the AEI dataset D which depends on x_{t-i} as inputs (1, 2, ...,P), $w_{i,j}$ (i=0,1, 2, ..., P; j=1,2, ..., Q), w_j is (0,1, 2,..., Q) are connection weights. P and Q are represented as input and hidden nodes, y_t is the output that depends on integer t transition of layers from 0 to 2 of the indices in dataset D, and $f(w)$ is the transfer function depends on number of weighted nodes. There are various functions used in ANN such as; linear, logistic, quadratic, hyperbolic and gauss. The most common function used in hidden layers is called logistic function. Therefore, for producing best possible outputs, ANN performs a relationship among its inputs and outputs through nonlinear functionality which is shown in the equation [39] below;

$$y_t = F(x_{t-1}, ..., x_{t-P}, w), \tag{3.3}$$

where, w represents connection weights as a vector and function F is nonlinear based on the parameters and structure of the network. In this study, ANN outperforms against all the other algorithms discussed for mobility predictions. Therefore, detailed ANN mapping as a best classification algorithm in the following section is shown. The passenger positioning below ground and the number of passengers in a given period of time are the most important parameters in the mobility prediction schemes. With the deployment of 5G HetNets in the LUO environment offering better cellular coverage and capacity, the accuracy of the ANN driven prediction models will improve if they take into account mobility traces as an additional input.

ANN-based mobility model is trained by large number of inputs called training samples associated with different traffic flow categories. In addition to the training matrix, the weights and biases are adjusted to satisfy ANN mechanism for proper mapping of inputs (AEI) and outputs (prediction accuracy) and, adapt to new passenger positioning according to classified three classes. The AEI-based topological mapping of ANN is shown in Fig. 3.2 to minimise errors occurred by locations associated with the optimisation of weights and biases.

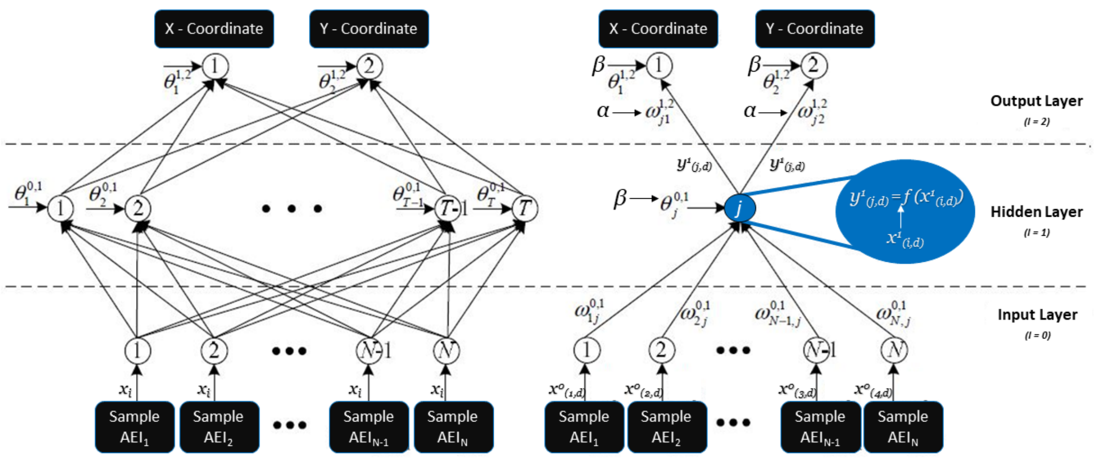


Figure 3.2: Topological mapping of ANN-based mobility prediction for LUO environment.

Now, w, x and y as weights, inputs and outputs. Layers l are denoted as

0, 1, 2 for input, hidden and output layers, $w_{i,j}^{l-1,l}$ represents the relationship of weight's connection through input, hidden and output layers, $x_{i,d}^{l}$ represent the input values from the dataset d with the perceptron i and $l = (0,\ 1)$ is the transition layer from input to hidden layer. The parameter $y_{j,d}^{l}$ represents the output values with the perceptron j and $l = (1,\ 2)$ is the layer transition from hidden to the output layer for the sample dataset d. Following are the equations that satisfy the relationship for each perceptron to classify number of inputs, their weighted transitions and best predicted outputs [39];

$$
\begin{aligned}
x_{i,d}^{l} &= f(y_{j,d}^{l}) = \lim_{y(0 \to 1)} \frac{1}{1 + exp(-y_{j,d}^{l})}, \\
y_{j,d}^{l} &= \int_{j} \sum_{i=1}^{D(l-1)} (w_{i,j}^{l-1,l}\ x_{i,d}^{l-1}) - \theta_{j}^{l-1,l}\ dx, \\
D(l);\ j &= \begin{cases} D, & l = 0, \\ T, & l = 1; \\ j, & l = 1, when\ j = 1, ..., T, \\ j, & l = 2, when\ j = 1\ or\ 2, \end{cases}
\end{aligned}
\tag{3.4}
$$

The optimal weight and bias calculation is performed by iterating several times to reach to a optimum state where training error is the minimum. The error minimisation equation is as follows [39];

$$
\Delta_{(y,z)} = \frac{1}{2} \left[\sum_{d=1}^{D} \sum_{j=1}^{2} (y_{j,d}^{2} - z_{j,d})^{2} \right] \tag{3.5}
$$

where, $\Delta_{(y,z)}$ is the difference margin of training error depends on $y_{j,d}$ and $z_{j,d}$ vectors. D is the dataset training samples, $y_{j,d}$ represents the output of x and y coordinates and, $z_{j,d}$ denotes the training phase coordinates with the expected x and y. Utilisation of back-propagation (BP) method would essentially provide the essence of neural net training in order to obtain optimal weights and biases by practicing fine-tuning. Following are the equations from [39] for optimal weights and biases tuning which are modified according to the AEI framework;

$$
\begin{aligned}
w_{i,j}^{l-1,l}(k+1) &= w_{i,j}^{l-1,l}(k) - \frac{\alpha \partial \Delta_{(y,z)}}{\partial w_{i,j}^{l-1,l}(k)}, \\
&= w_{i,j}^{l-1,l}(k) - \alpha \int_j \sum_{d=1}^{D} \delta_{j,d}^{l}(k)\, y_{j,d}^{l-1}(k)\, dy, \\
\theta_j^{l-1,l}(k+1) &= \theta_j^{l-1,l}(k) - \beta \int_j \sum_{d=1}^{D} \delta_{j,d}^{l}(k)\, y_{j,d}^{l-1}(k)\, dy,
\end{aligned} \tag{3.6}
$$

$$
\delta_{j,d}^{l}(k) = \begin{cases} \acute{f}[x_{i,d}^{l}(k)] \sum_{m=1}^{2} \delta_{m,p}^{l+1}(k)\, w_{j,m}^{l,l+1}(k), & l = 1, \\ \\ [y_{j,d}^{l}(k) - z_{j,d}]\acute{f}[x_{i,d}^{l}(k)], & l = 2, \end{cases} \tag{3.7}
$$

where, i is (1,..., N) when l=1 and, (1,..., T) when l=2. Similarly, j is (1,..., N) when l=1 and, (1 or 2) when l=2. Number of maximum iterations are represented by $k \leq K$. The α and β as rate of learning weights $w_{i,j}^{l-1,l}$ and biases $\theta_j^{l-1,l}$. Finally, $\delta_{j,d}$ being an iterative process for the acquirement of optimal weights and biases, it is a reminiscent of neurons that adjusts outputs of various inputs through contrast enhancement.

3.2.3 Movement Precision to Map Future User Location

When aiming to establish optimal movement patterns while their location precision in LUO environment, it is undoubtedly a challenge to come up with a accurate outcome which would comply to all geometrical parameters. Therefore, ANN-based precision matrix is chosen for underground stations, platforms and tunnels to analyse relative distances and recorded AEI information received from different ticket barriers using tap-in and tap-out technology. TfL train lines called, Jubilee Line and London Overground are chosen for the test scenario on one of the stations in London which has several AEI points as shown in the Fig 3.3. The mean $\bar{M}$ values are calculated from different ticket barriers through which passengers get in and out of the stations to terminate or carry on their journeys. Now, the mean for AEI framework would be calculated with the help of passengers access A, passenger egress E and, passenger interchanges I, being the three correlation factors to determine the precision coordinates [39];

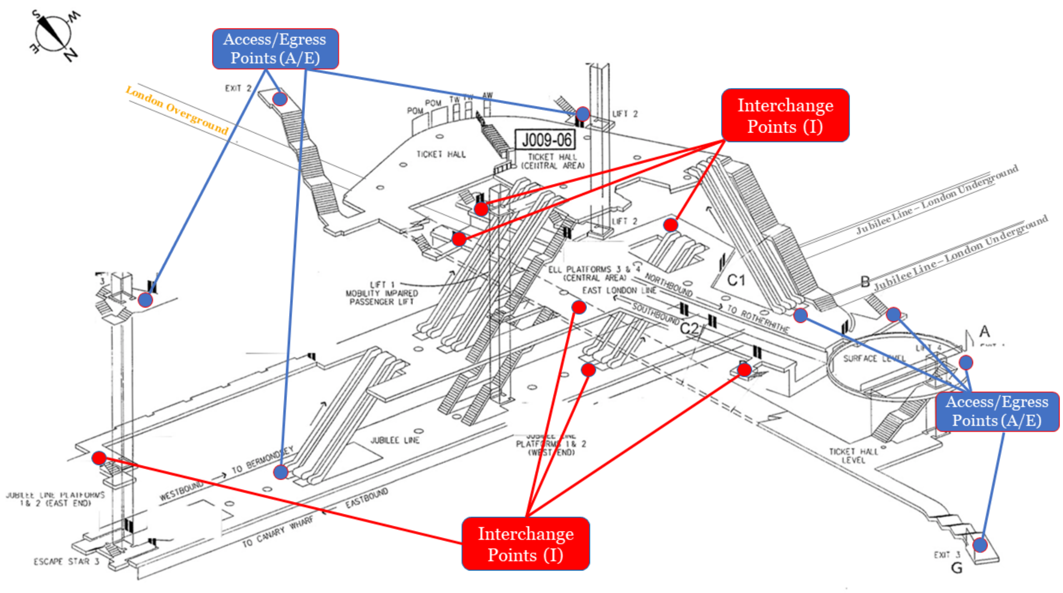


Figure 3.3: Test scenario layout.

$$A_k(x,y) = A_{k,x,j} + A_{k,i,y}\ ,$$
$$A_k(x,y) = \frac{\int_j \sum_{i=1}^{n}(M_{i,j}-\overline{M_{i,j}})(i-\bar{i})\ dj}{\sqrt{\sum_{i=1}^{n}(M_{i,j}-\overline{M_{i,j}})^2 \sum_{i=1}^{n}(i-\bar{i})^2}} + \frac{\int_i \sum_{j=1}^{n}(M_{i,j}-\overline{M_{i,j}})(j-\bar{j})\ di}{\sqrt{\sum_{j=1}^{n}(M_{i,j}-\overline{M_{i,j}})^2 \sum_{j=1}^{n}(j-\bar{j})^2}}, \tag{3.8}$$

$$E_k(x,y) = E_{k,x,j} + E_{k,i,y}\ ,$$
$$E_k(x,y) = \frac{\int_j \sum_{i=1}^{n}(M_{i,j}-\overline{M_{i,j}})(i-\bar{i})\ dj}{\sqrt{\sum_{i=1}^{n}(M_{i,j}-\overline{M_{i,j}})^2 \sum_{i=1}^{n}(i-\bar{i})^2}} + \frac{\int_i \sum_{j=1}^{n}(M_{i,j}-\overline{M_{i,j}})(j-\bar{j})\ di}{\sqrt{\sum_{j=1}^{n}(M_{i,j}-\overline{M_{i,j}})^2 \sum_{j=1}^{n}(j-\bar{j})^2}}, \tag{3.9}$$

Since, the interchange precision is a combination of multiple points' coordinates which include all the interchange-alighters, interchange-boarders and all the possible movements, $f(IP^k_{i,j})$. The following equations [39] which would provide accuracy in capturing all the possible movements under interchange;

$$
\begin{aligned}
I_k(x,y) &= I_{k,x,j} + I_{k,i,y} + IP^{k}_{i,j}\ , \\
I_k(x,y) &= \frac{\int_j \sum\limits_{i=1}^{n} (M_{i,j} - \overline{M_{i,j}})(i - \bar{i})\ dj}{\sqrt{\sum\limits_{i=1}^{n} (M_{i,j} - \overline{M_{i,j}})^2 \sum\limits_{i=1}^{n} (i - \bar{i})^2}} + \frac{\int_i \sum\limits_{j=1}^{n} (M_{i,j} - \overline{M_{i,j}})(j - \bar{j})\ di}{\sqrt{\sum\limits_{j=1}^{n} (M_{i,j} - \overline{M_{i,j}})^2 \sum\limits_{j=1}^{n} (j - \bar{j})^2}} + \\
&\frac{\int_{i,j} \sum\limits_{i,j=1}^{n} (M_{i,j} - \overline{M_{i,j}})(i - \bar{i})(j - \bar{j})\ d(i,j)}{\sqrt{\sum\limits_{i,j=1}^{n} (M_{i,j} - \overline{M_{i,j}})^2 \sum\limits_{i,j=1}^{n} [(i - \bar{i})(j - \bar{j})]^2}},
\end{aligned} \tag{3.10}
$$

where, $M_{i,j}$ is the mean value of the traffic flow provided by LUO from multiple reference points for kth iterations and $\overline{M_{i,j}}$ represents $M_{i,j}$ mean values. $A_k(x,y)$, $E_k(x,y)$ and, $I_k(x,y)$ denotes access, egress and interchange coordinates on x-axis and y-axis. $\Gamma_k(x,y)$ is defined as a function to provide relative x, y values according to AEI framework from equations (3.8), (3.9) and (3.10);

$$
\Gamma_k(x,y) = A_k(x,y) + E_k(x,y) + I_k(x,y), \tag{3.11}
$$

3.2.4 Next Movement Classification Estimation

For the purpose of classification estimation using the novel AEI framework, a softmax function has been used which is ANN network-based classifier in the final layer. The aim is to train the AEI information under cross-entropy approach [39] for optimal results. In mapping two probability distributions p and q, the set of events can be identified that measures average number of bits vital for identification of drawn events from the given set of underlying set of events. Here, p is true distribution and q is an estimated probability distribution. The distribution using both probability distributions p and q for the dataset is [39];

$$
\begin{aligned}
f(d)\ [\eta_k(p,q)] &= -\sum_{x \in X} p(x)\ log\ q(x), \\
f(c)\ [\eta_k(p,q)] &= -\int_X P(x)\ log\ Q(x)\ dr(x),
\end{aligned} \tag{3.12}
$$

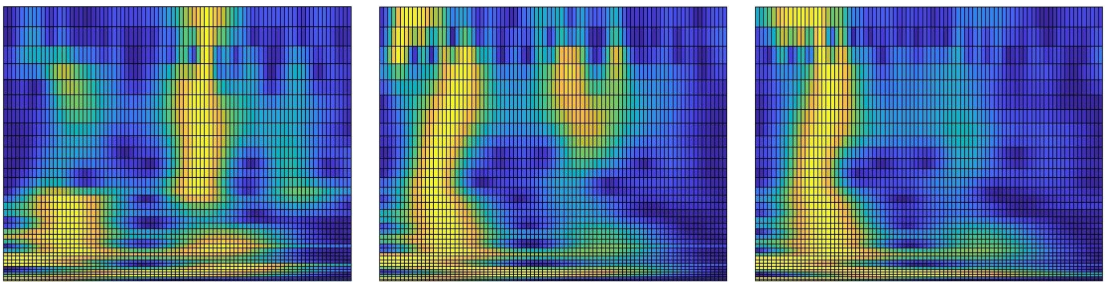
where, $\eta_k(p,q)$ is the entropy function, X being the dataset in a precise notion in both discrete and continuous distributions. In particular, for continuous distribution, assumption has been made that p and q are absolutely continuous associated with their reference measures r. Using 3.12, an $\eta_k(p,q)$ for three different variables is;

$$
\begin{aligned}
f(d)\,[\eta_k(p,q)] &= -\sum_{x\in X}\sum_{y\in Y}\sum_{t\in T} P_k(x,y,t)\; log\; Q_k(x,y,t),\\
f(c)\,[\eta_k(p,q)] &= -\int_X P_k(x,y,t)\; log\; Q_k(x,y,t)\; dr(x,y,t),
\end{aligned}
\tag{3.13}
$$

where, x, y and t are number of passengers, AEI dynamic information and, travelling time.

3.2.5 Encryption of passenger traffic flows

AEI is a highly important information and eavesdropper(s) can access this sensitive information for any means. Fig 3.4 shows plain text data that can reveal important information regarding the AEI framework which, through the following method, would be encrypted to form a designated encrypted model. Following novel encrypted model is used to detail the steps;



(a) Access. (b) Egress. (c) Interchange.

Figure 3.4: Plain text AEI data.

1. Let A is a plain text data having size $A \times B$. Apply secure hash algorithm (SHA-512) on A and get a 128 hexadecimal value. Store SHA value in ψ.

2. Convert ψ into decimal and store value in ω.

3. Get an initial value for chaos map using below Eq:

$$x_n = \frac{\omega}{2^{512}} \tag{3.14}$$

4. Provide x_n seed parameter to Nonlinear chaos map given below [146]:

$$x_{n+1} = (1-\beta^{-4}).\cot(\frac{\alpha}{1+\beta}).(1+\frac{1}{\beta})^{\beta}.\tan(\alpha x_n).(1-x_n)^{\beta}, \tag{3.15}$$

where the seed parameters are defined in the Table 3.1;

5. From Table 3.1, we have defined seed α and β parameters for chaos mapping and iterate the map for $3 \times (A+B)$ in order to get random sequences and save sequence in Γ.

6. Convert plain text information into three different channels, i.e., Ω, Ψ, and Φ. Now shuffle rows and columns of each channel with the sequence obtain from the chaos map and store value in Ω_p, Ψ_p, and Φ_p, respectively.

7. Logistic map is written as [256]:

$$y_{n+1} = r(y_n)(1-y_n), \tag{3.16}$$

In above equation, $y_n \in [0,1]$ and $r \in [0,4]$ are initial conditions of map. Iterate Logistic map $3 \times A \times B$ times and multiply the obtained value with 10^{14} and save result in a row matrix R. Apply the modulus operator and save result in S:
$S = Rmod(256)$.

8. Reshape S into three separate matrices i.e., S_1, S_2, S_3 and Apply XOR operation:
$C_1 = \Omega_p \oplus S_1$.
$C_2 = \Psi_p \oplus S_2$.
$C_3 = \Phi_p \oplus S_3$.

9. Combine C_1, C_2, C_3 and save value in C that is the final encrypted sensitive information.

3.2.6 Travelers-Tracing and Mobility Profiling

In this part, AEI framework has been exploited against travelers-profiling. A symptomatic or asymptomatic individuals are locomotive throughout the LUO network. When the age-groups, 16-59 years or over 60 years comes in contact with the LUO network, the probability of being exposed is β_u and β_o respectively. Generally, the rate of propagation is affected by contact intensity which is determined by the contact frequency and duration. Hence, it can be state

Table 3.1: Seed Parameters for Chaos Mapping

Data type	Value
Chaos map combination 1	$x_n \in (0, 1)$
Seed parameter for chaos mapping input 1	$\alpha \in (0, 1.4]$
Seed parameter for chaos mapping input 2	$\beta \in [5, 43]$
	or
Chaos map combination 2	$x_n \in (0, 1)$
Seed parameter for chaos mapping input 1	$\alpha \in (1.4, 1.5]$
Seed parameter for chaos mapping input 2	$\beta \in [9, 38]$
	or
Chaos map combination 3	$x_n \in (0, 1)$
Seed parameter for chaos mapping input 1	$\alpha \in (1.5, 1.57]$
Seed parameter for chaos mapping input 2	$\beta \in [3, 15]$

that the rate of propagation is directly proportional to contact intensity. Human tracking in the railway systems is dependant upon travelers-tracing enablers such as; WiFi, RFID, Bluetooth, UWB where wireless cellular network signaling, Global Positioning System (GPS) are either not available or limited. The collected data is pseudonymised and aggregated by the railway systems portal for data analysis and decision-making. The main focus of this study is relies on the travelers-tracing dependant decision-making process to exploit different age-groups mobility management. The average contact intensity between the two age-group travelers i and j in the discrete time span τ can be denoted as [78]:

$$\delta_{i,j}(t) = \frac{\sum\limits_{x=1}^{\alpha^c_{i,j}(t)} \tau(x)}{\alpha^c_{i,j}(t)} , \tag{3.17}$$

where, $\alpha^c_{i,j}(t)$ is the total number of contacts before the time slot t, and $\tau(x)$ is the corresponding contact duration. Given the dataset with different age-groups, 16-59 years and over 60 years, the vertex ω representing daily travelers by using Eq. (3.17) and probabilities β_u and β_o would be:

$$\omega_{i,j}(t)(i|j \subseteq D) = \delta_{i,j}(t) \left[\sum_{i=1}^{\alpha^u_i(t)} \beta_u + \sum_{j=1}^{\alpha^o_j(t)} \beta_o \right] , \tag{3.18}$$

where, $\alpha^u_i(t)$ and $\alpha^o_j(t)$ represent the 16-59 years and over 60 age-groups' neighbors. Let $\mathbb{U}(t)$, $\mathbb{O}(t)$, and $\mathbb{D}(t)$ denote travelers in age-group under 60 years, over 60 years, and available resources at LUO network to accommodate travelers accordingly. The optimisation to advise certain safe routes to different age-groups is expressed in the following equation;

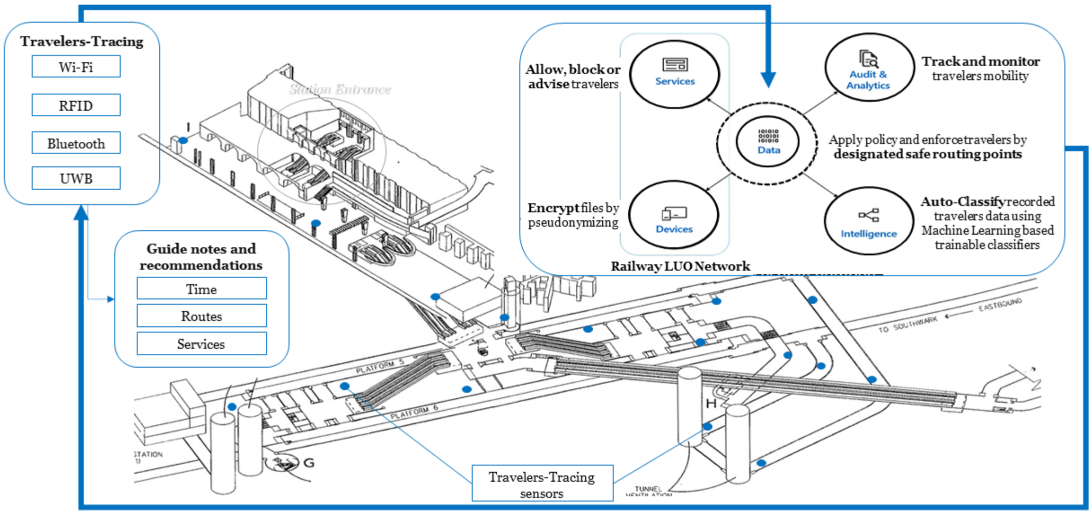


Figure 3.5: Mobility-Aware travelers-tracing and profiling strategy using Real-Time Railway Tracker Network (RRTN).

$$\sum_{D} \int_{1}^{T} \frac{\mathbb{U}(t)}{\mathbb{O}(t)}\, dt, \tag{3.19}$$

where, $\{\mathbb{U}(t), \mathbb{O}(t)\} \leqslant \mathbb{D}(t)$ in the given time t.

3.3 Methodology

Based on the novel AEI framework results, first analysis of the proactive ML-based automated classification of mobility prediction using ANN-based algorithm is done. Second, two chaotic maps known as nonlinear chaotic and logistic maps for encryption are considered. An encryption algorithm with a single map is used for faster processing but due to lower key space issues, the two maps in this work that can hold an unlimited number of different applications without any limitations of memory sizes due to their lightweight nature are used. The measured performance from the comparative analysis in the first part has been benchmarked against five algorithms (i) KNN, (ii) Support Vector Machine (SVM), (iii) Discriminant Analysis (DA), (iv) Naive Bayes (NB), and (v) Decision Tree (DT) [39] by using 3D information including, number of passengers, time of traveling and AEI. Three classes of AEI have been used to classify the best possible mobility predictions. In the second part, the best chosen algorithm against classification modeling, movement precision and classification estimation for future estimation.

Table 3.2: Simulation Scenario and Settings ($M = millions, hrs = hours$)

Data type	**Value**
Number of stations (Access/Egress)	380
Number of platforms (Interchanges)	270
Total number of passengers	12.15M
Total number of passenger (Early)	0.41M
Total number of passenger (AM Peak)	3.18M
Total number of passenger (Midday)	3.02M
Total number of passenger (PM Peak)	3.34M
Total number of passenger (Evening)	1.51M
Total number of passenger (Late)	0.68M
Number of classes	3
Area of passenger movement probability	100%
Total simulation duration	21hrs

3.4 Simulations and Results

3.4.1 Simulation Settings and Data Set

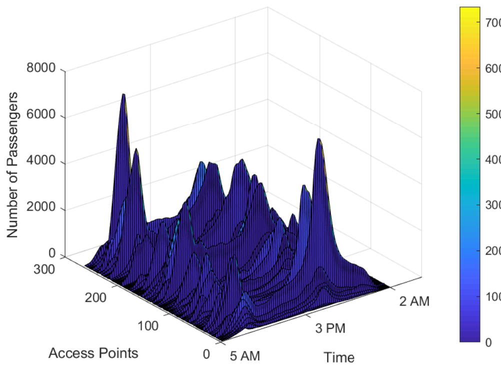
Simulations are completed by considering a typical LUO environment based train traffic flow distributions leveraging 3GPP standard compliant algorithms that perform classification of network topology supported by MATLAB. The details of simulation parameters are given in Table 3.2 which explains the dataset for a week captured in the year 2017-18, where M is referred to million counts. The modeling of traffic flow is based on real-time recorded data where passengers are distributed non-uniformly in the LUO areas such that the passengers were clustered around station, platforms, and tunnels in each of the three classes. The Monte Carlo style computational algorithms are used for simulation evaluations in order to establish mean performance of the proposed framework. The selection of the mobility model was a real challenge when the objective is to represent the behavior of passengers on the move in the LUO environment.

There are several models in the recent works in literature which provide mobility pattern of users end-to-end, some inspiration can be taken from well known models such as truncated levy walk, SMOOTH, SLAW, etc., [40], however in this work, none of the mobility model best fit to the scenario. Based on deep analysis in relation to find a close match, the research concludes that some references can be used to define the AEI framework in light of SLAW (Self-similar Least Action Walk) [13]. References of the mobility model would be realistic when it exhibits real-time efficiency of passengers flow pattern, i.e., (i) truncated flights: the length of passengers flights which are either straight line or haphazard trips with directional changes or pause, (ii) dissimilar mobility areas: passengers mostly move in their daily suited routes according to shortest times and less number of train line changes whereas different people may have different approaches when choosing routes such as disability access, step-free access etc, (iii) truncated inter-contact times: elapsed time between two stations including interchanges in-between by the same passenger, (iv) fractal way-points: passengers are used-to of their most visiting places and attractions, (v) convenient mobility areas: passengers are attracted to the specific travelling zones according to their daily budget. Therefore, the accuracy of AEI framework is based on the mobility traces obtained from the dataset that already contained such information mentioned in proximity of SLAW. The mobility model was utilised to analyse parameters mentioned in Table 3.2. From the table, it can be seen that, the data frame is divided into multiple scenarios according to different times of the day, number of passengers in the given time and classes associated to measure passengers in given time and traffic flow. The classification of mobility prediction interval was set to 21-hours from 05:00 AM to 02:00 AM in the simulation as of negligible traffic flows monitored in the remaining hours of the 24-hour day. The proposed encryption scheme is dependent on nonlinear chaos map and Logistic map. The initial seed in the proposed work are x_n, α, β, r, and y_n. These all seed are used as a key and must be kept secret from eavesdropper. During simulation, set $x_n = 0.1$, α $=1.45$, $\beta = 10$, $r = 3.7$, and $y_n = 0.001$.

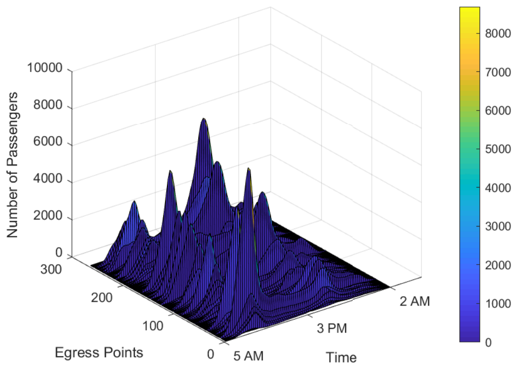
3.4.2 Mobility Prediction Accuracy

For ANN-based prediction accuracy benchmarking, the research model is trained on 7 days of a week (the year 2017-18) training data. The equations (3.4) and (3.6) are utilised to predict traffic flows dependant on weights and biases for every l, layer in k intervals. At each k interval, weights are observed and the accuracy of classification is then calculated by adding all the values in every layer for all time instants. Furthermore, the model is benchmarked against the movement precision of all the traffic in all the stations, platforms and tunnels by using x and y coordinates for three classes access, egress, and interchange. The calculations are reliant on the number of access points, the number of egress points and the number of interchanges within one station is represented as interchange points are obtained from (3.11). Interchanges include passengers who alight on the same platform to take other train lines, passengers who alight on different platforms to take other train lines and passengers who board onto the same train line but going in different directions from the same platform. All of these are dependant on the traffic movement at different times of the day (early, peak time travellers in AM and PM, passengers in midday, evening movements, and late-night traffic as shown in Fig. 3.6.

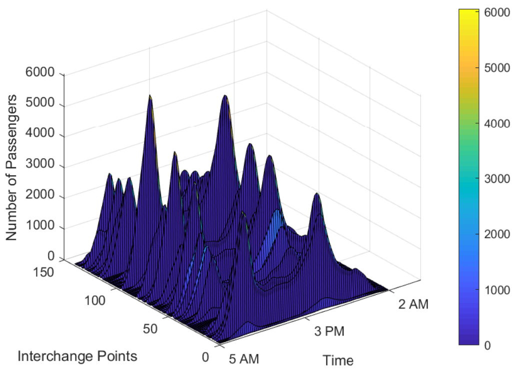
The presentation is based on the simulation results obtained from a heavily loaded dataset such as AEI dependant number of stations, number of passengers and their time of travelling. This is shown in Fig. 3.6. Also, a classification analysis of mobility predictions by discussing six ML algorithms is presented to showcase the performance of the best classification algorithm according to the prediction accuracies of high accumulated passengers traffic flows.



(a) Access.



(b) Egress.



(c) Interchange.

Figure 3.6: Simulation results for train traffic flows AEI framework considering three dimensional (3D) dataset for 1 week in the year 2017-18. Plotted LUO dataset is from 05:00 AM to 02:00 AM (21-hours) by different train lines on multiple stations with specific station numbers.

For further details; KNN classifier with k as the distance metric of nearest neighbours set to 3; SVM classifier with RBF kernel for the parameters setting where γ and C are set to default with the kernel size 200; DA with linear function; NB with normal function; DT with maximum splits set to 50. Rest of the values are set to default and to get optimum results; single hidden layer of 10 neurons for ANN; and ten-fold cross-validation was used for all the ML classifiers. Out of huge and complex dataset, a total of 677 observations were used for all three activities, AEI, as a use-case. Observations were selected based on their relevance to the empirical modelling from and between train operational hours from 05:00 AM to 02:00 AM (21-hours). Accuracy has been used as a performance metric for mobility prediction using the aforementioned classifiers that are presented in Table 3.3. It can be observed that the NB algorithm provided the worst classification accuracy for all three classes providing overall accuracy of 48%. The DT, SVM and KNN algorithms performed almost similar, delivering overall classification accuracy of 80%. The ANN classifier performed better than five classifiers by 10% providing overall classification accuracy of more than 90%.

The confusion matrices obtained using the ANN algorithm are presented in Fig. 3.7 which demonstrates the overall classification of mobility prediction accuracies by using ANN-based classifier in the AEI Framework for all the developed classes. The total number of available observations were divided into three parts, training, validation and test datasets. To train the ANN algorithm, 70% of samples (473) while remaining 15% (102) for validation and 15% (102) for a test are used. Looking at Fig. 3.7, the number of correct observations for Class A (Access) are 69 that account for 75.8%. Similarly, for Class E (Egress) and Class I (Interchange), the correct classification is 90% and 87%, respectively. Moreover, as far as classification of validation is concerned, 63%, 88% and 81% true classification rate are obtained for Class A, Class E and Class I, respectively. The dataset for testing the performance of ANN classifier, the 102 data samples were used. For class A, a total of 14 samples were used where 12 were correctly classified and 3 were misclassified. A total of 52 samples were used for Class E, where 49 were correctly identified and 3 were misclassified. Lastly, for Class I, 32 out of 35 samples correctly classified and 3 as misclassified. The overall test accuracy for all three classes while comparing all mobility prediction algorithms was obtained as 91.17% through ANN classifier, a best optimal result. There is about 9% margin of error remained in the classifier which is a statistical measurement that differentiates between actual and projected results. This margin of error allows the framework to gauge the level of unpredictability in data and research outcomes, and can be further improved when sampling more data feed into the model.

Accuracy (%) is originally employed to evaluate the performance of all the algorithms in all possible scenarios using the AEI framework (i.e., for all train stations, passenger behaviours, and combination of their movements). The Receiver Operating Characteristic (ROC) curve is presented in Fig. 3.8 for the best

Table 3.3: Classification of Mobility Prediction Accuracies

Machine Learning Algorithm	Accuracy
Artificial Neural Network (ANN)	91.17%
Discriminant Analysis (DT)	80.18%
K-Nearest Neighbour (KNN)	79.61%
Support Vector Machine (SVM)	79.47%
Decision Tree (DT)	76.37%
Naive Bayes (NB)	48.18%

performing model ANN-based on percentage accuracies in different passenger movement scenarios then metrics like precision (recall), Sensitivity (True Positive Rate (TPR)), specificity (True Negative Rate (TNR)) are calculated to assess the detailed performance. True positive rate is higher like 0.87, 0.95, and 0.95 for Access, Egress, and Interchange, which is well above threshold.

3.4.3 Encryption

The proposed encryption method is explained in Section 3.2.5 where encryption is applied on plain text images shown in Fig. 3.4. Encryption results are highlighted in Fig. 3.9. From encrypted results, one can see that plain text and encrypted information are different and an intruder cannot get information from the encrypted data. However, one visual inspection is not sufficient and hence the proposed scheme on several security parameters have been evaluated . Interested readers can find more details on these parameters in references [92, 146]. Results are highlighted in Tables 3.5, 3.6 and 3.7. Security of the proposed scheme is evident through lower correlation, homogeneity and energy values. Furthermore, higher values of entropy, key sensitivity, number of pixel change rate (NPCR), unified average change intensity (UACI) and contrast also highlight higher security of the encrypted data in all cases of the AEI framework.

3.4.4 Intelligence Enabled Railway Systems

Existing LUO railway network intended to manage travelers of different age-groups, i.e, 16-59 years and over 60 years mobility and to ensure designated routing while using travelers-tracing method [78] against COVID-19 spread are exploited. The explanation of the key enablers is given which will play an instrumental role of travelers-tracing in existing railway systems as shown in Fig. 3.5. In this part, first the idea of analysing mobility of all age-groups as shown in

Table 3.4: Results of security parameters

Table 3.5: Access Data

Security Parameter	Plain text	Encrypted form
$Corr\ Coff$ (H)	0.5890	-.0021
$Corr\ Coff$ (V)	0.7438	0.0032
$Corr\ Coff$ (D)	0.4077	0.0193
$Entropy$	7.1273	7.7068
$NPCR$	NA	99.6314 %
$UACI$	NA	33.4710
$Contrast$	3.7399	10.5089
$Homogeneity$	0.6809	0.3899
$Energy$	0.0854	0.0156

Table 3.6: Egress Data

Security Parameter	Plain text	Encrypted form
$Corr\ Coff$ (H)	0.5579	0.0341
$Corr\ Coff$ (V)	0.7593	0.0201
$Corr\ Coff$ (D)	0.3981	0.0186
$Entropy$	7.1273	7.7068
$NPCR$	NA	99.6140 %
$UACI$	NA	33.5032
$Contrast$	3.9899	10.4951
$Homogeneity$	0.6831	0.3881
$Energy$	0.0828	0.0156

Table 3.7: Interchange Data

Security Parameter	Plain text	Encrypted form
$Corr\ Coff$ (H)	0.6240	-0.0071
$Corr\ Coff$ (V)	0.7705	-0.0309
$Corr\ Coff$ (D)	0.4199	0.0190
$Entropy$	7.1273	7.7068
$NPCR$	NA	99.6338 %
$UACI$	NA	33.4917
$Contrast$	3.5455	10.5004
$Homogeneity$	0.6922	0.3887
$Energy$	0.1042	0.0156

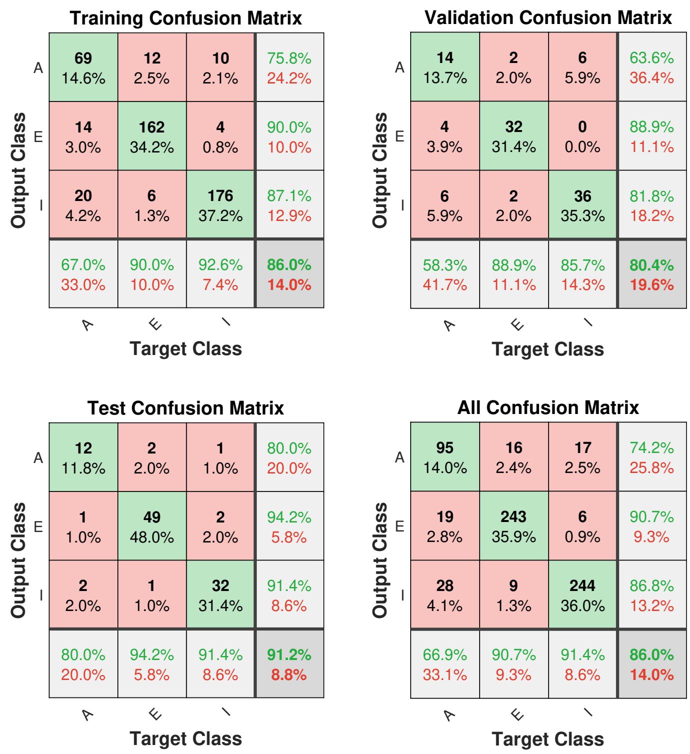


Figure 3.7: ANN algorithm based simulation results for the classification of train traffic flows AEI framework mobility predictions using three classes; Access (A), Egress (E) and Interchange (I).

Fig. 3.10, followed by the results obtained from ML-driven classifiers are presented in Tables 3.8 and 3.9, is presented. Since, almost everyone carries cellular mobile devices which do not serve as always-on human trackers, therefore, the multiple technologies are exploited for travelers-tracking in railway systems. More specifically, the higher the number and mobility of user equipment (UEs) recorded by travelers-tracing enablers, the higher the number and mobility of people lying in different age-groups to be served and advised accordingly. Daily train travelers according to the travelers age-groups, (i) 16-59 years, and (ii) over 60 years in LUO environment are assessed in ML-driven algorithms. Modelled dataset is classified by considering different age-group travelers to take necessary actions such as; monitoring potential contacts/proximity travelers, advising the travelers mobility to certain safe mobility pathways/routes to safeguard the vulnerable age-group travelers from the outspread disease. By using MATLAB libraries, six classifiers to obtain accuracy, precision, recall, and F1 score results as shown in Tables 3.8 and 3.9 are modelled. As it can be seen that SVM classifier with default RBF kernel parameters settings and 200 kernel size outperformed in both age-groups compared to other classifiers.

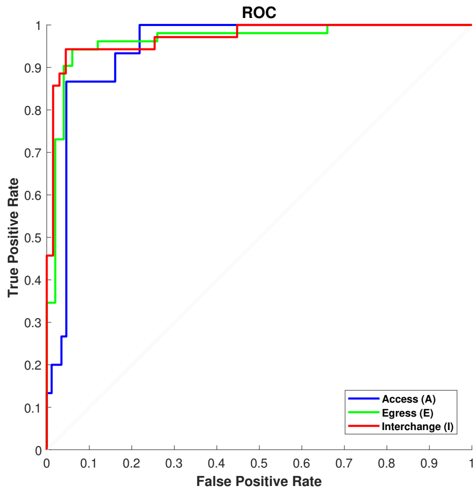


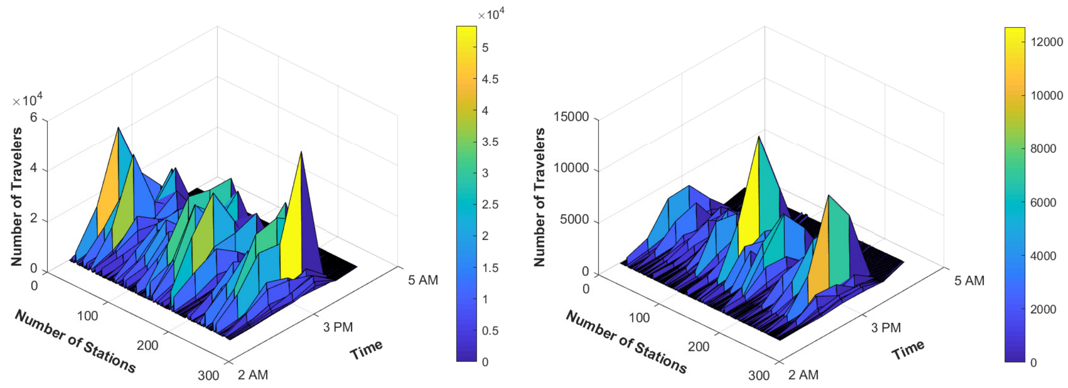
Figure 3.8: Receiver operating characteristic (ROC) curve for three classes Access (A), Egress (E) and Interchange (I) representing the specificity pair corresponding to a AEI Framework decision threshold. Grey line in the middle of the plot is a threshold line between True Positive and False Positive Ratios.

(a) Access. (b) Egress. (c) Interchange.

Figure 3.9: Encrypted text AEI data.

3.4.5 Travelers-Tracing & Profiling Enablers

According to a recent studies [259, 260], severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) remains viable in aerosols for up to three hours exhaled by unhealthy people while speaking, coughing or even breathing, whether symptomatic or not [10]. The main focus is given to the vulnerable age-group (over 60s) travelers scenario to remain protected against the disease spread. This age-group will be recommended of certain times, safe train carriages, stations, and platforms in order to travel. All areas of the LUO where human mobility is possible are considered as 'high-risk' as daily commuters use the network without knowing the contagious people traveling with them. The main objective is to detect high-risk age-group travelers by using travelers-tracing enablers, allowing prioritisation for further monitoring and risk management.



(a) Crowd density of 16-59 years age-group. (b) Crowd density of over 60 years.

Figure 3.10: Simulation results for daily train travelers considering three dimensional (3D) approach for 1 week in the year 2017-18. Plotted age-groups are from 05:00 AM to 02:00 AM (21-hours) on multiple stations.

Table 3.8: Age-group 16-59 years Mobility Prediction Classification

ML Classifier	Accuracy	Precision	Recall	F-Measure
Logistic Regression (LR)	79.10	0.78	0.77	0.77
Multi-layer Perceptron (MLP)	80.91	0.80	0.79	0.79
Support Vector Machine (SVM)	86.43	0.86	0.84	0.84
Random Forest (RT)	83.36	0.83	0.81	0.81
K-Nearest Neighbour (KNN)	84.91	0.84	0.82	0.82
Decision Tree (DT)	85.63	0.85	0.83	0.83

- WiFi: There is a wide availability of Wi-Fi currently being used within railway systems which in particular have been deployed in more than 97% of all LUO stations to facilitate users[2]. The ubiquity of WiFi access through the deployment of WiFi access points within the LUO network can be exploited to obtain traveler's mobility safe routes. The uniqueness of mobility traces provides a traveler's movement from one station to another accurately when Wifi is switched on. The information of recently visited stations, platforms, and train carriages [9] is pseudonymised to prevent the identification of the travelers. This method plays an important role in determining designated safe routing to combat the spread of epidemics including COVID-19 [257].

- RFID: It is one of the major and widely-used technologies that are in operation in railway systems, covering almost all parts of train carriages, railway stations, and platforms. RFID is an electromagnetic waves-based identification method that has numerous applications including public transport, trains movement monitoring from depots to main lines and vice versa, building access, patient monitoring, inventory, assembly lines & supply chains,

[2]http://content.tfl.gov.uk/review-tfl-wifi-pilot.pdf

Table 3.9: Age-group Over 60 years Mobility Prediction Classification

ML Classifier	Accuracy	Precision	Recall	F-Measure
Logistic Regression (LR)	75.21	0.75	0.73	0.73
Multi-layer Perceptron (MLP)	76.59	0.76	0.74	0.74
Support Vector Machine (SVM)	81.96	0.81	0.79	0.79
Random Forest (RT)	77.86	0.77	0.75	0.75
K-Nearest Neighbour (KNN)	79.24	0.79	0.77	0.77
Decision Tree (DT)	79.60	0.79	0.79	0.79

food tagging, security identification, localization, etc. [257]. UHF RFID uses passive tags connected to smartphones and objects in the LUO environment where tracking of different age-group travelers is possible using tap-in and tap-out touch system in Real-Time Railway Tracker Network (RRTN). Antenna in the RFID tag with beam steering capability detects the RSSI, bearings, and logarithmic points along an axis estimated by applying ML techniques.

- Bluetooth: It is a widely-used wireless technology for data transmission between fixed and mobile devices in short distances. The Low-power Bluetooth Communication (LBC) with shorter wavelengths, UHF radio waves collect surrounding information. By regular scanning, access point indicators (APIs) to locate nearby Bluetooth devices in real-time [261]. Phones with Bluetooth stores and pairs the list of Bluetooth devices. With the Bluetooth pairing, different age-groups can be determined and stored in the central railway database to advise certain actions to certain age-groups. In case vulnerable age-group (over 60s) traveler enters into a station, the list of Bluetooth devices it has encountered can be fetched, and a notification would be generated to the travelers to follow certain safe traveling routes, train carriages, station or platforms.

- UWB: It is one of a radio technology that has short-range and high bandwidth communication on a low energy level by using large antenna arrays and ultra-wide bandwidths, a decimetre level accuracy (minimum accuracy) in location systems becomes viable. Minimum accuracy with the precise range measurement to estimate the distance between target and reference base station can be achieved by using UWB technology, unlike Bluetooth or Wi-Fi where RF signal's time difference of arrival (TDOA) or Time of Flight provides more precision[3].

[3]UWB Ofcom document can be found at:
https://www.ofcom.org.uk/__data/assets/pdf_file/0015/25152/uwb.pdf

3.4.6 Recommendations

The strategy and overall life-cycle of travelers-tracing and profiling is to collect the information through travelers-tracing enablers provided on each station at the LUO network. Recorded data is sent to the railway database by using RRTN for daily monitoring. Simulation results are presented for daily train travelers in order to obtain ML-driven classification accuracy, precision, recall and F-measure scores. It can be seen that the SVM classifier outperformed than all other five classifiers with an overall classification accuracy of 86.43% and 81.96% in age-group 16-59 years and over 60 years. Below are the few recommendations that certain age-group travelers would be designated in the context of RRTN realisation through safe mobility routing against COVID-19.

- Time - to ensure the time-specific mobility for age-specific travelers would be assigned for safeguarding vulnerable age-group from others. This would mean to allot off-peak day travel time-slots between 10 am to 12 noon and 2pm to 4pm with the guidelines available at stations and platforms. Staff can be asked to assist in this regard, alternatively guideline notifications can be sent through travelers-tracing enablers on user smartphones.

- Route - to provide safe routes at the stations and platforms by designating specific routes which can be color coded to prominence for travelers according to their age-groups.

- Train carriage - for optimum safety, one train would be divided into blocks of virtual train carriages with different age-group markings assist the vulnerable travelers.

- Station - to facilitate train travelers to board, alight or freight in specific stations of the train network for vulnerable age-group safety in the times of disease spread. Certain stations equipped with extra assistance and ancillary services as ticket sales, waiting rooms and baggage/freight to be used for different age-group travel in different times of the day.

- Platform - at least one track-side platform would be assigned to vulnerable age-group travelers with extra assistance and services such as luggage carts, user friendly electronic boards, emergency call facility, etc.

- Special services - to further ensure the safety of the travelers and train drivers, new limits to the number of travelers on board at any one time shall be introduced. In case of congestion at the stations, alternate bus services would be arranged to facilitate/help vulnerable age-group travelers mobility.

3.5 Summary

The novel spatio-temporal mobility prediction based optimisation and encryption technique proposed, can solve numerous future B5G network pathways and traffic movement problems. The AEI framework employs the robust concept of future passenger location estimations and accuracies through which the advantages of futuristic optimisation can be maximised. It relies on classification of mobility prediction and preserving important passengers data with encryption. The proposed approach provides state-of-the-art heuristic techniques for; traffic movement predictions, network pathway implementation, implementation of encrypted traffic flows and, practical solutions to address optimisation problems ahead of time in the underground train network. With this outset, B5G ambitions regarding address latency and QoS issues can be met. Therefore, the proactive ML based mobility prediction classification, mapping of the optimal classification algorithm, and an encryption algorithm with a single map for faster processing, will have a detrimental affect on intelligent mobility. Simulations based on real-time traffic employing realistic classification of mobility predictions using the AEI framework can achieve 91.17% with ANN algorithm as compared to other ML algorithms. Comparative performance analysis with movement precision of train traffic flows indicate adequate stability and robustness of the proposed AEI framework towards predicting accuracies and hence it also provides advanced encryption to the sensitive information. Furthermore, an introduction to a new strategy is given that addresses crowded train carriages, stations, and platforms that are highly susceptible to spreading the disease supported by mobility prediction accuracies using ML classifiers. The main strategy is to exploit the technologies including WiFi, RFID, Bluetooth, and UWB to effectively track daily train travelers with different age-groups in the LUO network. So that, the different age-group traveler's mobility can efficiently be monitored in order to issue recommendations of designated safe track routes, certain train carriages, stations, and platforms.

Chapter 4

Mobility Prediction-based Energy Optimisation

4.1 Introduction

A paramount challenge of increased CO_2 emissions prohibit network densification to deliver the 5G cellular capacity and connectivity demands, while maintaining a greener, healthier and prosperous environment. Energy consumption is a demanding consideration in the 5G era to combat several challenges such as reactive mode of operation, high latency wake up times, incorrect user association with the cells, multiple cross-functional operation of SON, etc. To address this challenge, a novel model, mobility prediction-based autonomous energy-aware framework is proposed for analysing bus passengers ridership through statistical ML and proactive energy savings coupled with CO_2 emissions in HetNet architecture using RL. Furthermore, comparisons using ML algorithms considering bus passengers ridership obtained from London Overground (LO) dataset, have been made.

4.1.1 Related Work

Recent years have seen major technological developments in mobile communication networks, including network densification, split of control and data planes [106], and network virtualisation, etc. Technology will continue to advance rapidly and across the world billions of pounds will be invested in the development of 'new mobility services', eventually bringing more challenges to the dense networks [12]. Transportation, zero emissions, economy, governance, and environment [66, 262] are the smart city key functions that drive the population density where one of the vision is to support coherent and seamless mobile connectivity. Currently, ICTs account for between 5% and 9% of total electricity consumption, and their development suggests a deep transformation of energy systems, from smart networks to customer management or decentralised energy exchanges [1]. With the versatility of mobile devices and their up-scaling numbers, there is a need to devise some statistical methods to cope up with the 5G trends of communication where the ES and CO_2 reductions are highly important [10].

Due to the exponential increase in user demands, the requirements for data-intensive wireless services are also boosted at an unprecedented rate encumbrancing current wireless systems and providers [52,263]. Remedies are currently under immense discussion and development to satisfy ubiquitous up-scaling demands which is further expected to rise manifold [12]. 5G compared to earlier generations not only addresses physical layer problems, however, it also introduces modern applications being run by the use of ML and RL methods. Hence, the deployment of Ultra-dense small cells (UDSCs) is on direct collision path with the challenges in modern smart city concept such as, transportation, zero emissions, economy, governance, and environment [9,10,264] that impacts directly the vision of 5G as shown in Fig. 4.1. This is because UDSCs are power hungry network elements that satisfy user demands by "always ON" strategy. Consumed power has a direct relation to the total amount of energy being drawn coupled with CO_2 emissions and operational costs (OPEX). SCs as compared to MCs have relatively low energy consumption, however, the always ON approach in HetNet architecture with densely deployed SCs increases overall energy consumption [10,81,265]. The high energy consumptions in SCs is the circuit power component (load independent power consumption) that enacts a much larger portion of over-all energy consumption [93]. Various reasons when load component gets overloaded are inefficient use of SCs drawing unnecessary power, and incorrect mobility prediction of daily passengers ridership across deployed SCs. As a result, with the concept of UDSC deployments the need for CO_2 reductions driven by ES schemes using RL and mobility predictions driven by ML algorithms will be even more compelling.

In cellular systems, CO_2 emissions driven by energy consumptions can be lessened significantly by switching OFF underutilized, lightly loaded, or idle SCs during peak and off-peak intervals by offloading their load to their Macro Cell MC within the same HetNet or by managing users mobility patterns [9, 13, 183]. In this way, minimum energy coupled with CO_2 emissions are consumed per bit transmission [71, 82, 94, 216]. To exploit these approaches, SON function by 3GPP [12,265] has adopted ES and has extensively been studying the ripple effects of ES and user's mobility on the environment. ES improvement with a focus

[1] https://www.enerdata.net/publications/executive-briefing/between-10-and-20-electricity-consumption-ict-sector-2030.html

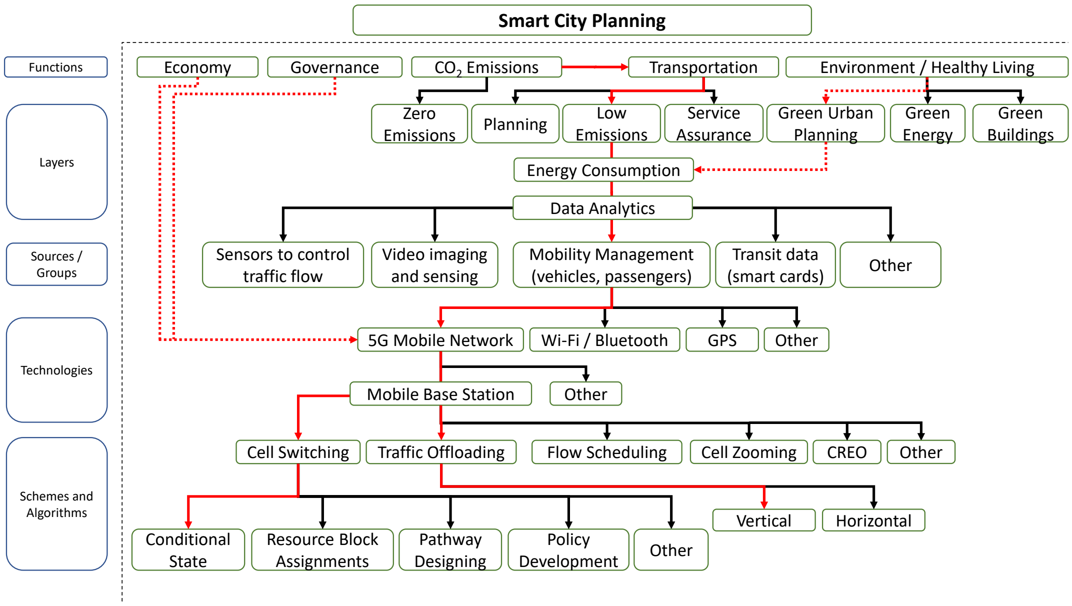


Figure 4.1: Smart City Planning structure.

on mobility prediction and resource allocation has been studied more extensively despite its relatively small gain compared to switching On-Off underloaded BS [71, 82, 94, 216]. ES gains by switching On-Off operation would improve the situation to only a limited degree for a given throughput until they are further enriched with the proactive and autonomous approaches by intelligent switching methods. In this direction of research, some recent works show promising results in terms of potential ES [40, 66, 68, 70, 71, 84, 94, 266, 267]. However, they fall short of the mark for 5G demands due to the following five limitations:

1. Sensitive mode of operation: Typical ES SON algorithms are susceptible to reaction that achieves ES at the expense of QoS after an event has been completed. Given the well-populated city dynamics with bus passenger ridership in relation to deployed cellular environment, by the time SCs overloading or under-loading is detected and a realistic algorithm is opted to solve the known issue, the conditions may already change [265]. In the 5G environment, this problem can further escalate when disparate passenger ridership and plethora of cell types responsible to support smart city eco-system are not in harmony.

2. SCs wake up time: Sleeping SCs require a specific amount of time to wake up [268]. Any passenger entering a SC footprint that is still in a sleeping state would add high latency experience. Thus, there is a need to modernise conventional paradigm pro-actively to maintain low latency requirements of 5G in a more agile fashion i.e, pro-active ES by passengers mobility

prediction.

3. User Association to sleeping SCs: A key challenge in the HetNet cell On-Off switching strategy is to establish user associations (bus passengers ridership association) to the correct serving SCs that are switch ON while passengers are within its coverage footprint [68]. Thus contributing to overhead challenges. Existing ES schemes have not apparently provided evidences to address this challenge where 5G QoS demands low-overhead, low-costs and highly efficient architectures.

4. SON upright design: Conventional ES solutions when implemented together in a HetNet environment are susceptible to conflicts [12] that require intelligence to resolve. SON use-cases that are liable to be conflicted are; traffic offloading while SC switching [10,84] and prediction of passengers to neighbouring cells [9]. For the first conflict, Cell Individual Offsets (CIOs) along with transmission power settings play a major role whereas correct distancing metric for classification of mobility predictions is the second one. Furthermore, traffic offloading through vertical, horizontal or both are important methods when BS transmit power is concerned [71]. In horizontal offloading, SCs have low transmit powers within the certain cell range to offload the traffic of neighboring cells. Therefore, between SCs, horizontal offloading can not always be realized. Consequently, vertical offloading often becomes the only choice for some SCs to go into sleep mode if its neighboring SCs are not in the proximity.

5. CO_2 Emissions: This challenge coupled with ES is either overlooked by researchers or lacks comprehensive quantization [10, 262] to the extent of ES saving impact on CO_2 emissions.

4.1.2 Contributions

Energy-aware framework (Fig. 4.2) to address the aforementioned limitations by analysing bus passenger ridership dataset using multi-tier self-organising HetNet is proposed by considering with 1 MC and 9 SCs in Central London location [12]. The main focus is to anticipate the passengers mobility behavior travelling in a bus who are passing through a HetNet architecture so that concerned SCs become artificially intelligent and autonomous. This AI would be used to formulate a novel ES optimisation problem through mobility management for proactive SCs scheduling and offloading satisfying QoS requirements. Following are the summarized contributions of this research:

1. As a building block of novel energy-aware framework a spatio-temporal mobility prediction framework by analysing statistical KNN model to modernise ES conventional limitations, is elucidated.

2. A novel method of passengers future location estimation is proposed to map the next cell spatiotemporal HO based on the idea of landmarks using multiple K values in KNN model and a detailed comparison.

3. Another novelty of this proposal is; based on the future cell load information and CIOs as optimisation variables for load balancing among SCs, a proactive ES optimisation problem is formulated to reduce, power and energy consumption by switching OFF lightly loaded, idle or underutilised HetNet SCs. Intelligence in load balancing would exploit specifically lightly loaded SCs to be switched OFF while satisfying QoS.

4. Based on the information achieved from mobility prediction of passengers ridership and ES awareness, a novel scheme of CO_2 reductions is also quantified.

4.2 System Model

In this section, analytical model development of energy-aware framework whose key corner stones are as follows, is presented.

- Statistical KNN-based Passengers Mobility Prediction.
- Passengers Future Location Estimation.
- Proactive ES, and CO_2 Reduction.

4.2.1 Energy-Aware Framework

The energy-aware framework proposed considers the downlink stream with 1 MC and 9 SCs as shown in Fig. 4.2. MC is equipped with directional antennas whereas all the SC antennas are assumed to be omnidirectional with constant gains. Same frequency band is utilised by all cells in the framework with frequency re-use factor of 1. Constant bit rate service with full buffer data utility is available in a centralised C-SON architecture with system-wide proactive-energy saving optimisation based CO_2 reduction. Moreover, historical traces of mobility that include time, location, number of passengers, associated cell IDs, and received power

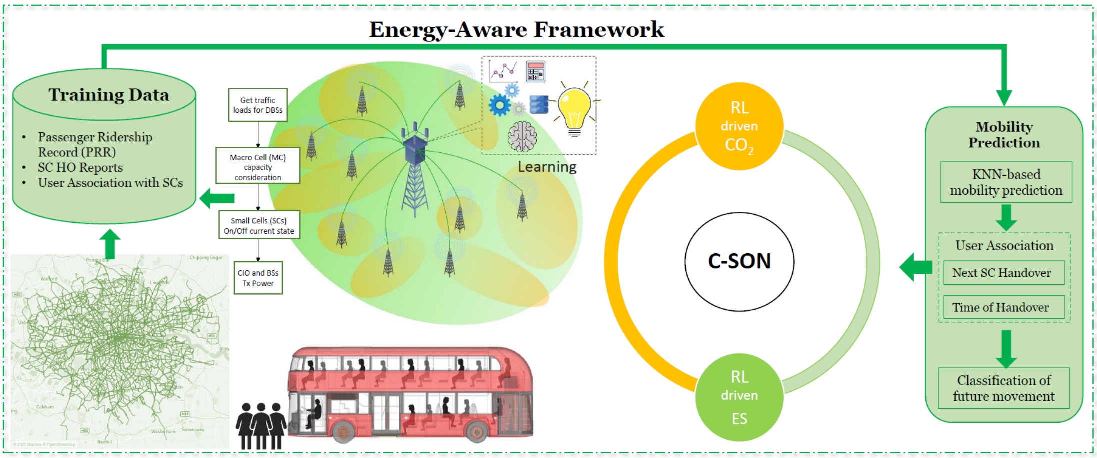


Figure 4.2: Network model comprising a 1 MC and 9 SCs (Data Base Sations - DBS) in HetNets deployment with CDSA. Energy-aware framework with bus passenger ridership dataset as an input.

levels (RSRP) are assumed to be available to the C-SON server. For Proactive-energy saving optimisation based CO_2 reduction, consideration has been given to a two-tier HetNet model consisting of a live MC and 9 live SCs along with their traffic information in separated control and data planes. Signalling is carried out by the MC with the responsibility of low data rate services while the backhaul MC-connected SCs offer high capacity services. When SCs monitor low traffic activity, they tend to switch-off while offloading their traffic to the MC provided there is enough capacity in the MC to accommodate the offloaded traffic load.

4.2.2 Statistical KNN-based Passengers Mobility Prediction

A non-parametric KNN classifier segregates a model in which the alteration of both distance metrics and the number of nearest neighbors are done simultaneously for optimum results and comprehensive comparison. The reason for simultaneous parameters settings is that the KNN classifier stores training data which can be easily tuned and modelled to compute re-substitution predictions. Alternatively the model can be classified to train new observations using the predict method. The following modified equation is to be considered [39]:

$$p(y = c|x \subset D, K) = \frac{1}{K} \sum_{i \in N_{\mathrm{K}}(x,D)} I(y_{\mathrm{i}} = c), \tag{4.1}$$

where, p is probability of classes x_{i}, which depends on peak time x_1 and off-peak time x_2 test inputs within the framework, $N_{\mathrm{K}}(y, D)$ are the K nearest points to an integer y in the dataset D and $I(e)$ is an indicator function when e is 0, for false and 1, for true. This method provides flexibility whether learning could be instance-based or memory-based. Commonly, Euclidean distance metric is used to set the parameters of KNN classifier, however, $Mahalanobis$ distance metric is used in this research for optimal classification results evaluation. This simply "looks at" the K points in the training set that are nearest to the test input x_i. Input "peak" and "off-peak" bus passenger ridership data is used as an input with multiple values of K. KNN classifiers work fine with low inputs; however, they do not function nicely with inputs with high dimensions. Computation with $Mahalanobis$ distance metric, using a positive definite covariance matrix C between each pair of elements of a given random vector. The default value of the matrix C is the sample covariance matrix of X, as computed by nancov(X). The following modified equation is to be considered [39, 269]:

$$d_{(i,j)}(x, \mu) = \sqrt{\left(x - \mu\right)^T \Sigma^{-1} \left(x - \mu\right)} \ , \tag{4.2}$$

where, $d_{(i,j)}(x, \mu)$ is the distance between a data vector x and the mean vector μ with $(i, j) = 0, 1, 2, ...$ The $Mahalanobis$ distance metric is a vector distance that uses a Σ^{-1} norm and is a stretching factor on the space and is the inverse of variance-covariance matrix Σ between x and y [269]. Number of nearest neighbors in X used to classify each point during prediction, specified as a positive integer value which can be less than the number of rows in the training data. Note that for an identity covariance matrix $\Sigma_i = I$, the $Mahalanobis$ distance becomes the familiar Euclidean distance.

4.2.3 Passengers Future Location Estimation

Let the association of users u to their SCs according to the geographic locations at time instant k be $\mathbb{U} \in M_k = (x_k, y_k)$ and the predicted cell HO tuple for each user mobility be $(\mathbb{M}_u, \mathbb{T}_u)$. The future cell associations in next time intervals are, $k + \bar{k}$ as $M_{k+\bar{k}}$. Taking references from [13, 266] that the nodes (passengers) usually move around in such a way that; daily passengers move to complete their routine tasks with fairly regular landmarks; and tourists for well-visited landmarks, their mobility logs are utilised to estimate, (i) most probable landmarks of daily commuters, and (ii) visited landmarks by non-frequent travellers in each SC. By harnessing mobility information, trajectories from current location to the most predicted locations would be estimated by cell sojourn HO time $\mathbb{T}_{HO}$ and multiple distance metrics mentioned in the section above. Let the coordinates of the most probable landmark for users u mobility in the next cell $\mathbb{M}_u$ be $\mathbb{U} \in M_{\mathbb{M}_u} = (x^{lm}_{\mathbb{M}_u}, y^{lm}_{\mathbb{M}_u})$ and the unit vector $\widehat{v}$ based on current coordinates in the direction of $(x^{lm}_{\mathbb{M}_u}, y^{lm}_{\mathbb{M}_u})$ is given as:

$$\widehat{v} = \mathbb{U} \in \left(\frac{\Big[M_{\mathbb{M}_u} - M_k\Big]}{||\Big(M_{\mathbb{M}_u} - M_k\Big)||} \right), \tag{4.3}$$

where, $||.||$ is the *Mahalanobis* norm operator. The future coordinates at time interval $M_{k+\bar{k}}$ can be estimated as:

$$M_{k+\bar{k}} = M_k + \int^{K} \left[\frac{\sqrt{\Big(x^{lm}_{\mathbb{M}_u} - x_k\Big)^2 - \Big(y^{lm}_{\mathbb{M}_u} - y_k\Big)^2}}{T_{HO}} \right] * \widehat{v}\ d\bar{k}\ , \tag{4.4}$$

The pseudo-code for the users mobility prediction in terms of future location estimations is given in the Algorithm 2.

Algorithm 2: Passengers Future Location Estimation

Input : Passengers current location parameters M_k, $\mathbb{M}_u$, $\mathbb{T}_u$, $M_{\mathbb{M}_u}$, $SojournTime_{max}$

Output: Passengers next move mobility prediction $M_{k+\bar{k}}$

```
for u ∈ 𝕌 do
    if u(Sojourn − time) ≥ max(Sojourn − time) OR no(Training − samples) i.e, M_𝕄u = ∅ then
        Initialize M_{k+k̄} = M_k;
    else
        Execute Equation (4.4)
    end
end
```

4.2.4 Proactive ES, and CO_2 Reduction

For a wireless network performance evaluation, the state-of-the-art is to analyse RAN components at system level where multiple components in a typical BS contributes to power consumption depending on traffic load profiles. These components include, power amplifiers, back-haul links, amplifier efficiency, signal processing and generation, air conditioning and others. Following equation is to be considered.

$$BS_{\text{tot}} = \ S\left[(\tfrac{A_{\text{Tx}}\ P_{\text{Tx}}}{\eta_{\text{eff}}}) + Pr_{\text{t}} + Pr_{\text{d}} + Pr_{\text{g}} + Pr_{\text{c}} + Pr_{\text{o}} \right] + Pr_{\text{l}} + Pr_{\text{a}}\ , \tag{4.5}$$

where S is the number of sectors in a cell, A_{Tx} is the number of antennas transmitting per sector, P_{Tx} is the input power of the antenna, η_{eff} is the power amplifier efficiency, transceiver as Pr_{t}, digital signal processor as Pr_{d}, signal generator as Pr_{g}, AC-DC converter as Pr_{c}, back-haul link as Pr_{l}, air conditioning as Pr_{a}, and Pr_{o} are the other BS components. Given the movement of all passengers in the next tuple with future movement estimated location $L \in M_{k+\bar{k}}$, cell switching mechanism for SCs is discussed, in which, in the next interval as $k+\bar{k}$ in order to control overall energy consumption of the framework. On-Off switching schedule would comply with coverage KPI and QoS requirements of each UE to be at its estimated next move $L \in M_{k+\bar{k}}$ while ensuring each BS loading constraints. The total instantaneous power being consumed by a cell is the sum of transmit power and circuit as [10]:

$$
\begin{aligned}
P_{\mathrm{tot}} &= \rho\Big(BS_{\mathrm{tot}}\,.P_{\mathrm{cir}} + \lambda\,.P_t) + P_{\mathrm{HetNet}}, \\
P_{\mathrm{HetNet}} &= P_{\mathrm{mc}} + \sum_{k=2}^{K} P_{\mathrm{sc}}^{k} \;\; \in= \begin{cases} P_{\mathrm{mc}} = BS_{\mathrm{tot}}^{\mathrm{mc}} + \lambda_{\mathrm{mc}} P_{\mathrm{tx}}^{\mathrm{mc}} \\ \\ P_{\mathrm{sc}}^{k} = BS_{\mathrm{tot}}^{\mathrm{sc}} + \lambda_{\mathrm{sc}} P_{\mathrm{tx}}^{\mathrm{sc}}\,, \end{cases}
\end{aligned}
\tag{4.6}
$$

where, P_{tot} represents total instantaneous cell power, P_{cir} is the constant circuit power which gets drawn when a BS in a given cell c changes its state from being active to sleep mode while reducing significant power, P_t represents cell transmit power, λ is the load variable that depends on the capacity of the cell, the indicator variable ρ defines the On-Off state of BS in cell c, P_{HetNet} is total HetNet power consumption that employs 1 MC and 9 SCs in this case, P_{mc} and P_{sc}^{k} are the power consumptions of MC and K-th SCs respectively with $k = \{2, 3, 4, .., n\}$, is the number of SCs surrounded by a MC. Energy savings leveraging the performance metrics defined by energy consumption ratio (ECR) [81, 270] is one way to quantify a cell energy behaviour in $Joules/bit$, given as:

$$
ECR = \int_{c} \frac{P}{\sum\limits_{U \in c} B^{u}(w)\,.f(\gamma_u)}\,, \tag{4.7}
$$

where $f(\gamma_u)$ denotes a function that returns user's u achievable spectral efficiency at a given SINR, $B^{u}(w)$ is the user specific bandwidth, and P is the amount of power consumed. The SINR γ_u at future movement estimated location $M_{k+\bar{k}}$ when associated with a cell c is defined as the ratio of a user's reference signal received power $RSRP_u$ from a cell c to the sum of all cells i RSRPs such that

$i \subset C$ with the noise N.

$$\gamma_u(k+\bar{k}) = \left[\frac{P_t.G_u\bar{G_u}\delta\alpha(\Delta_u)^{-\beta}}{N + \sum_{i\subset C}^{n} P_t^i .G_u\bar{G_u^i}\delta\alpha(\Delta_u^i)^{-\beta}}\right]_{k+\bar{k}}, \tag{4.8}$$

where, cell transmit power is P_t, user equipment gain is G_u, transmitting antenna gain seen by user u is represented by $\bar{G_u}$, signal variant shadowing is represented by δ, path loss constant is α, estimated user u location distance $M_{k+\bar{k}}$ is given by Δ_u, and path loss exponent is represented by β. Next time steps $k+\bar{k}$ are reliant on the time subscript enclosed within $[.]k+\bar{k}$ throughout the paper. Shadowing is assumed to be available for user u estimated locations with minimal errors. The SINR expression of fully loaded cells along with the interference from neighboring cells for data transmission can be given as:

$$\gamma_u(k+\bar{k}) = \left[\frac{P_t.G_u\bar{G_u}\delta\alpha(\Delta_u)^{-\beta}}{N + \sum_{i\subset C}^{n} \rho_i P_t^i .G_u\bar{G_u^i}\delta\alpha(\Delta_u^i)^{-\beta}}\right]_{k+\bar{k}}, \tag{4.9}$$

where ρ_i denotes the cell load of a cell i. The process of compensating a distorting factor for received interference power from each active cell yields a particular coupling of the total interference when multiple cells are utilized. Heavily loaded cells are more power interfering contributors than less loaded ones [10, 265]. For a HetNet arrangement, instantaneous cell load is the ratio of active physical resource blocks (PRBs) obtained during a transmission time interval (TTI) with the available PRBs available in the cell. Hence, for monitoring UL/DL total PRBs usage, the ratio act as a standard measurement indicator. QoS and achievable SINR are influenced by the number of PRBs allocated in an SC(s). PRBs are directly proportional to the required data rate to maintain QoS. Hence, more PRBs are assigned to a user, the higher the QoS and lower the SINR. The total cell c load for each time stepping intervals $k+\bar{k}$ is defined as:

$$\lambda(k+\bar{k}) = \left[\frac{1}{RB_n}\sum_{i\subset C}^{n}\frac{\tau_u}{B^u(w)\; log_2 1+\gamma_u}\right]_{k+\bar{k}}, \tag{4.10}$$

where, $B^u(w)$ is a resource block bandwidth, RB_n are the number of resource blocks in a cell c, τ_u is the transmission rate, and $i \subset C$ are the number of active users u in a cell c. The load as a virtual load which is allowed to exceed one to monitor the cell loading state. The minimum bit rate τ_u is required to maintain QoS requirements by continuously serving users u in each cell c. There are number of methods used to calculate the required user throughput by calculating required resources to service the user. In the 3rd Generation Partnership Project (3GPP) standards, a mechanism known as QoS Class Identifier (QCI) is used to prioritise active users based on the resource type allocation and requirements through model transmission bit rate τ. Furthermore, functional of users behaviours, their service request patterns, levels of subscription and, their in-use applications would be modelled using transmission bit rate τ [12]. The user u association criterion to the SCs is;

$$\mathbb{U}_i(i \subseteq C) = \left[u \in \mathbb{U} \, | i = \underset{i \in C}{\text{argmax}} \Big(P_{r,u} + P_{CIO} \Big) \right] , \tag{4.11}$$

where, $P_{r,u}$ (dBm) is user reference signal power from a cell i.e, 1 MC or sum of 9 SCs, and P_{CIO} (dB) is Cell Individual Offset (CIO), a biased parameter depends on load of the cell that has a main function to offset lower transmit power of all the SCs in the HetNet in order to transfer load when lightly used or idle. When under utilized SCs are turned off, the load would be transferred to MC provided there is sufficient capacity. The downside of this activity is; users would no longer be associated with the strongest SC; backhaul overhead would increase when loading and off-loading occurs. This would turn the SINR to be lower with higher CIO values. However, CIO measures loads to be balanced, which would eventually drop the capacity due to SINR drop and affects the QoS. Therefore, to partially offset the SINR of the serving cell, available PRBs would be allocated to that user u which are more in comparision to the available PRBs the previous serving SC. As a trade-off knob to control the load balancing, Energy Consumption and CO_2 Emissions of the cells and overall HetNet architecture, CIO parameter is highly important. Now, the equation of general energy consumption for each of the time steps $k + \bar{k}$ for all cells c within HetNet architecture [10, 68, 70] is;

$$min(\rho, P_{CIO}) \;=\; \sum_{i \in C} [ECR]_{k+\bar{k}} \quad , \tag{4.12}$$

The main objective of this work is to optimise the HetNet energy consumption based on cell switching and traffic offloading so that CO_2 emissions are reduced and optimal policies are enforced to automate the network. To do this, load and CIO parameters $(\rho, P_{CIO})$are required to be optimised for all the SCs such that overall energy consumption ratio in all SCs within HetNet is minimised, consequently reducing the CO_2 emissions. The first two limitations define the CIO limits and on/off state array respectively and will determine the solution search space size, whereas the third limitation is to ensure the minimum amount of coverage to all the users u through means of HetNet collective contribution.

The minimum received power that a user u would require is P_{th} and ϖ is the area of coverage probability that the users would be within it that would maintain QoS requirements, and 1(.) denotes indicator function. Minimum required bit rate is the fourth constraint that depends upon the QoS requirements. In order to maintain the ECR minimum objective, switching off lightly loaded SCs would impact received $P_{r,u}$ (dBm) minimum user reference signal power and make it worse, leading to worsen SINR and throughput. Therefore, fourth constraint guarantees minimum amount of SINR to be maintained for all users in all cases. This would require cell load ρ to be less than total load threshold ρ_T (0, 1). Cell switching On-Off, CIOs and cell load index is a non convex optimisation problem on a large scale [70, 72]. The complexity of user association in Eq. 4.11 per SC is expected to grow exponentially when dealing with multiple constraints concurrently, therefore RL techniques to compare and obtain optimal results as shown in Fig. 4.6a have been analysed. The modelled scenario has CIO as an optimisation variable with ten possible values available at each SC and 1024 possible iterations. Energy-aware framework devises optimal On-Off state array and all SCs CIO values proactively aiming to minimize the energy consumption ratio of the whole network that would further extrapolate the CO_2 emissions. Energy-aware framework has a direct impact on CO_2 emissions and is directly proportional. The total integral sum of all the ECR ratio values in a HetNet architecture would be calculated with the help of CO_2 conversion factors in [10, 66]. Therefore, from (4.7);

$$\Delta_{CO_2} = \psi \int_0^T \mathbb{U}_i(i \subseteq C)\ \ ECR\Big(P_{\text{tot}}\Big)\ dt, \tag{4.13}$$

where, Δ_{CO_2} is carbon footprint that depends on the total energy consumption ratio $ECR(P_{\text{tot}})$ obtained from total power consumption P_{tot}, ψ refers to emissions per unit/conversion factor and t represents the time duration.

4.3 Proposed Approach

The results, based on the novel energy-aware framework where, first, an analysis on the energy saving coupled with CO_2 emissions is discussed through RL-based Q-learning and then ML driven classification accuracies using KNN algorithm with distance metrics. First part is benchmarked against, (i) No-Switching (NS), (ii) Exhaustive Search (ES), and (iii) Greedy approach where as the second part has been benchmarked against five algorithms (i) KNN, (ii) SVM, (iii) DA, (iv) NB, and (v) DT and, (vi) ANN, by using geographic BS locations and user cell association, and number of passengers in peak and off-peak times.

4.3.1 ML-driven Classification Accuracy

In addition to the RL in the above section, ML-driven classification accuracies to predict peak and off-peak passengers travel within HetNet environment has been proposed. ML was invented from pattern recognition to automate machines for intelligent decision making while learning from history and adapt to the testing environment [37, 261]. For the optimisation of peak and off-peak activities, ML algorithms proposed in [37,55,56,254] are used to model traffic identification and user association to the BSs for classification of moving patterns.

First, classification mechanism is KNN which is a non-parametric classifier that it searches for K-points in its training set that are are nearest to its test inputs. It performs counting of its member classes and returns observational fractions as estimated values [9, 39]. Distance based metrics for KNN algorithm are comprehensively discussed in Section 4.2.2. Second, classification mechanism is DA which is based on independent variables to perform predictions for classification individuals into groups with two objectives (i) classification of new inputs by predictive equations or, (ii) predictions of individual variables to comprehend relationships [9,39]. Third, classification mechanism is SVM which is also known as a large margin classifier with the set of inputs classification of high dimensions through the liner and non-linear mapping. Output results are reliant on on a subset of the training data, known as support vectors [9, 39]. The model takes a decision based on boundaries to construct distance bound nearest training samples in a form of hyperplane.Fourth, classification mechanism is DT which is often called classification and regression trees (CART) model that recursively partitions the input space of individual local models in each resulting region. It can be represented by a tree with one leaf per region [9, 39]. Fifth, classification mechanism is NB which is another mobility classification algorithm that classifies vectors of discrete-valued features [9, 39]. It has class labels through which training classes (peak and off-peak passengers) have demonstrated the product which is called NB model. Finally, the sixth classification mechanism is an ANN that classifies the interconnected group of nodes/neurons consisting of input and output layers. Neurons learn the training data without being programmed with task-specific rules. Numeric weights are tuned on experiences to exploit best possible outcomes when learning the neural nets [9, 39].

4.3.2 RL-driven Energy Savings

Energy-aware framework proposes SC On-Off switching operation by using RL algorithm where MC senses the environment and takes an action which is rewarded or penalised depending on the conditional state of action being taken. RL has been opted to support SC On-Off switching operation due to its suitability of making decisions out of a wide-range of options. MC interacts with the network environment, obtains SCs traffic information and user u association criterion to make decisions. Hence, RL copes with the dynamic environment via adaptability through learning and then deciding the required actions to maintain QoS. Q-learning algorithm is adopted [2,10,249] to solve the constraints. Q-learning is one of the most popular RL algorithms that has a proven capability of working in dynamic environments [93,183]. QL is an off-policy method that follows different policies to determine next possible action state in conjunction with action-value table update. The six main components in QL are: (i) agent, (ii) environment, (iii) action, (iv) state, (v) reward/penalty, and (vi) action-value table. Agent takes actions by interacting with a given environment in order to maximize the reward or minimize the penalty. After each action that the agent takes, resulting state and reward/penalty are evaluated [10,84].

The consideration is given to a simple HetNet live model which has a MC and 9 SCs have been distributed geographically in one of the busiest streets in Central London. The state space will be small enough to apply a simple look up table (Q table), which is updated for every state action pair. In designing the SC switching mechanism, main goal was to find the best switching strategy with low ECR coupled with CO_2 emissions that is dependant on the selection of the best set of SCs to switch off, out of all possible set of SCs.

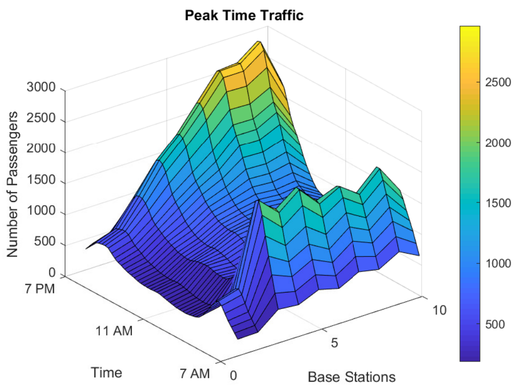
4.4 Performance Evaluation

The proposed energy-aware framework is divided into two parts for the analysis of peak and off-peak dataset obtained from the bus passenger ridership in Central London. Typical LO environment based bus passenger distributions leveraging 3GPP standard compliant RL-based QL and ML-based six classification algorithms for multiple purposes as described in Section 4.2 are generated. Due to the dynamics of the busy environment, number of passengers vary over time. The modelled 21-hours from 05:00 am to 02:00 am to cover peak and off-peak travel is shown in Fig. 4.3. For the first part of this model, bus passengers are distributed within HetNet cells to find the optimum cell On-Off switching and overloading method. Total power consumption of the HetNet architecture is calculated from

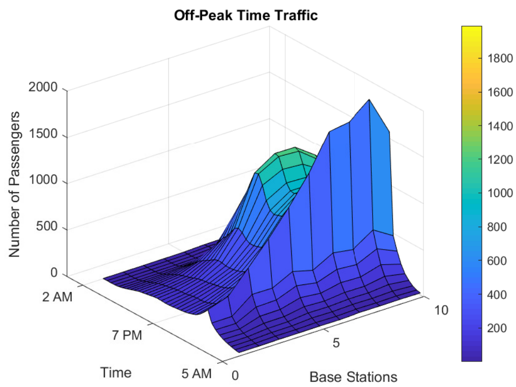
Eq. (4.6) where the cell load λ is normalised for the calculation of transmitted power P_t from Eq. (4.10). Average mean values of 100 iterations for power and energy consumptions are plotted. CO_2 emissions based on user associations with the SCs and the ECR is obtained from from Eq. (4.13). For the second part of this model, bus passengers are classified and compared against different ML algorithms to establish optimum mobility prediction based approach in dense mobile networks. For both parts, network topology is supported by simulations in MATLAB for which simulation parameters are mentioned in Table 4.1.

Table 4.1: Simulation Scenario and Settings ($M = millions, hrs = hours$)

Data type	**Value**
Number of BS	10 (1 MC and 9 SCs)
Bandwidth	20 MHz
Frequency	2.6 GHz
Physical Resource Blocks (PRBs)	100
Number of iterations for RL	100
Number of iterations for ML	100
Total bus routes	673
Total number of passengers (Peak)	0.5 M
Total number of passenger (Off-Peak)	0.2 M
Number of classes	2
Area of passenger movement probability	100%
Total simulation duration	21hrs



(a) Peak Time.



(b) Off-Peak Time.

Figure 4.3: Simulation results for Peak and Off-Peak travel for 10 Base Stations. Plotted dataset is from 05:00 AM to 02:00 AM (21-hours) by different buses.

4.4.1 Classification Prediction Accuracy

Six ML classifiers are used in the MATLAB libraries to simulate classifiers in such a way that; KNN classifier from Eq. (4.1) and Eq. (4.2) with several values of K

as the distance metric of nearest neighbours that is discussed in Section 4.2 where $K = 1$ belongs to the distance metric called *Mahalanobis* outperforms compared to other metrics as shown in the Fig. 4.4. This proves the simplicity of the algorithm in classifying new data points based on similarity principle. Similar to the $K = 1$, when $K = (2, 3, 4, ..)$ the output value stays closer to the $K = 1$ results, meaning test points from the training dataset, the classifier have memorised the last movement to the correct label and the classifier will achieve minimal error rate response; DA classifier with linear function being used; SVM classifier with default RBF kernel parameters settings but kernel size used is 200; DT classifier with maximum splits set to 50; NB classifier with normal function; ANN classifier with neurons set to multiple values to train weights and layers in each k intervals; and rest of the values are set to default. A total of 840 observations were used for peak and off-peak time travel for a performance metric mobility prediction accuracies using the six ML classifiers as shown in Table 4.2. It can be seen that the ANN algorithm failed to provide good accuracy of the classification and listed at the bottom of the table with only 73.09%. The NB provided overall accuracy of 86.94%, whereas DA, SVM and DT algorithms performed in a somewhat similar fashion, delivering overall classification accuracy of more than 97.00%. Finally, KNN classifier in the Energy-Aware framework performed better than all five classifiers with overall classification accuracy of 98.82%.

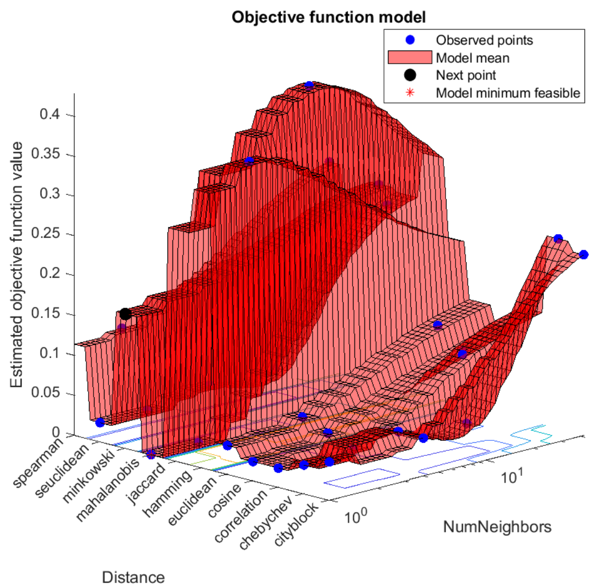


Figure 4.4: KNN Functional Model with the observed optimal values and next point classification.

Table 4.2: Classification of Mobility Prediction Accuracies

Machine Learning Algorithm	Accuracy
K-Nearest Neighbour (KNN)	98.82%
Discriminant Analysis (DA)	98.75%
Support Vector Machine (SVM)	98.75%
Decision Tree (DT)	97.78%
Naive Bayes (NB)	86.94%
Artificial Neural Network (ANN)	73.08%

4.4.2 Energy Saving, Benchmarking and Metrics

In this section, the performance evaluation of the proposed QL-based cell switching algorithm is assessed by considering live BSs. The learning rate, λ_r is set to 0.3 whereas the discount factor, ϕ is 0.9 [77]. The energy efficiency performance of the proposed QL assisted approach is compared to various cell switching approaches, namely *NS*, *Greedy*, and *ES*. In no-switching case, the SCs are always kept on, while the SCs are always switched off regardless of the available capacity of the MC in Greedy approach. ES, on the other hand, goes through all the possible switching options to find the best option which reduces the total energy consumption of the network without exceeding the capacity of the MC. Fig. 4.5 demonstrates the power consumption of all the approaches. As expected, the

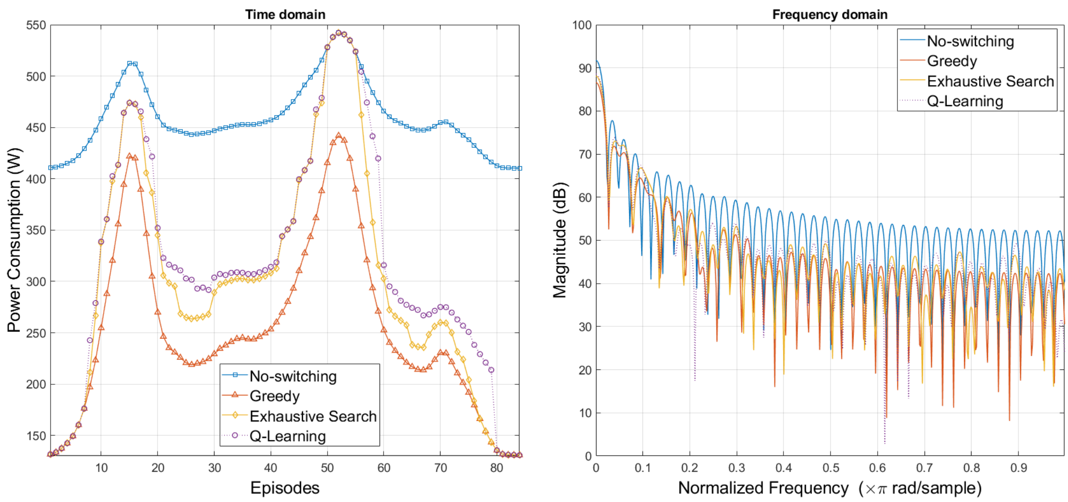
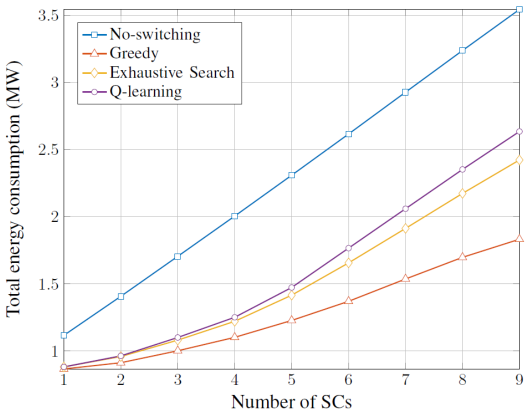
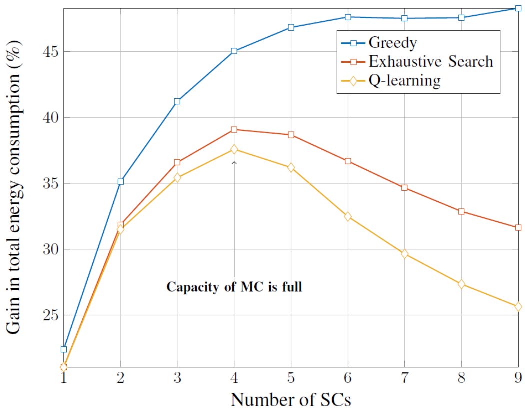


Figure 4.5: Power consumption of various approaches when the number of SCs is 9. Episodes refers to the instances in the network.

Greedy approach outperforms all the other methods, as it does not consider the availability of the MC. Thus, its superiority in terms of power consumption comes at the expense of exceeding the MC capacity, which decreases the QoS, since the users are kept unconnected when there in not enough capacity at the MC. The ES approach finds the best trade-off between power consumption reduction and the capacity of MC and as expected the proposed QL assisted approach converges to ES. In other words, the QL assisted proposed method reduces the power consumption of the network without degrading the QoS. Total in a form of ECR of all the approaches included in the HetNet is shown in Fig. 4.6a, while Fig. 4.6b presents the gains of NS, Greedy, and ES approaches. As shown in Fig. 4.5 and Fig. 4.6,



(a) Total HetNet energy consumption.



(b) Gain for different methods compared to the NS approach.

Figure 4.6: Results for total ECR of the HetNet and the Gain provided by different switching approaches.

the number of SCs is the most contributing factor for saving power and energy. As can be seen from Fig. 4.6a, the total energy consumption of the network increases almost linearly with rising number of SCs. Therefore, it is expected that the ECR increases with the growth of component numbers. Thus maintaining CIOs are significant without dropping out capacity for QoS demands. Results in Fig. 4.6b show that the energy saving increases with increasing number of SCs, but only to some extend (when the number of SCs is 4). The reason is that the contribution of the SCs on the total energy consumption becomes more significant when their quantity increases, and thus the ECR improves by switching off the SCs. On the other hand, the energy consumption gain starts decreasing once the number of SCs exceeds some certain quantity, which is 4 in this proposed model. The reason behind this is that the capacity of MC becomes insufficient to accommodate more users; hence, the is no more room to switch off additional SCs. In other words, the MC reaches its limit in terms of capacity, or put it another way, the number of SCs that can be switched off also reaches to the limit. Consequently, the network cannot save more energy even with additional SCs, and the relative gain starts decreasing, as the total energy consumption of the network increases. Finally,

CO_2 emissions are directly proportional to ECR which keeps on increasing with the ratio being increased and is shown in Fig. 4.7. On comparing all methods discussed in this proposal, the overall HetNet gain in terms of energy consumption coupled with CO_2 emissions between NS and Greedy approach is approximately 45.63%, between NS and ES is approximately 35.60%, and between NS and QL is approximately 31.83%. For the proposed statistics methods, the presented robust framework is concluded to save considerable amount of energy and subsequent carbon emissions.

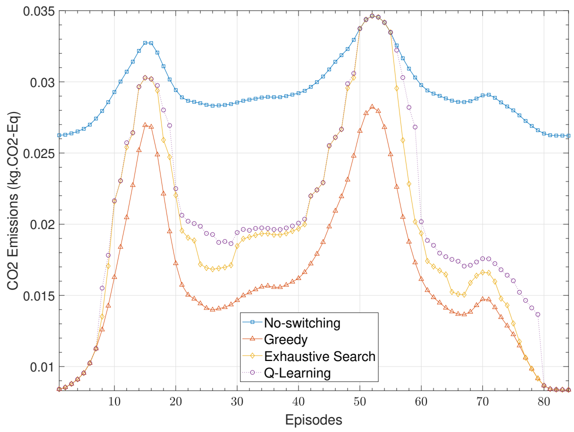


Figure 4.7: Total CO_2 emissions of the HetNet for various number of SCs.

4.5 Summary

The novel mobility prediction-based autonomous energy-aware framework using ML and RL techniques is proposed to address multiple challenges including peak and off-peak time passenger ridership and future location estimations supported by mobility prediction accuracies and energy consumption of the HetNet, analysing the overall impact of HetNet CO_2 emissions in a two-tier model by using cell On-Off switching and offloading scheme. In the first part, ML-based comprehensively discussed algorithms and optimal mapping of classification prediction accuracy can achieve 98.82% with KNN classifier were analysed and assessed. Comparative study of peak and off-peak time passenger ridership and future location estimations indicate adequate robustness. In the second part of the proposed framework, RL-based QL algorithm is used to establish an optimal way of underutilized cell On-Off switching operation and SCs that emit unnecessary CO_2 emissions. Based on the proposed framework, energy savings gain coupled with carbon emissions of up to 31.83% are achieved.

Chapter 5

Mobility Management in NGNs

5.1 Introduction

5G spectral efficiency requirements foresee network densification as a potential solution to improve capacity and throughput to target NGNs. This is achieved by shrinking the footprint of BSs, effective frequency reuse, and dynamic use of shared resources between users. However, such a deployment results in unnecessary HOs due to the cell size decrements, and limited sojourn time on a high train mobility. In particular, when a train speedily passes through the BS radio coverage footprints, frequent HO rate may result in serious communication interruption impacting QoS. First, a novel context-aware HO skipping framework is proposed that relies on passenger mobility, trains trajectory, travelling time and frequency, network load and SINR data. The framework is based on modelling of the passenger traffic flows in cardinal directions i.e, North, East, West, and South (NEWS) employing realistic Poisson point process (PPP) for real-time mobility patterns to support mobile networks from overloading and congesting. Spatio-temporal simulations leveraging NEWS mobility prediction model with ML-based SVM classifier shows an accuracy of 94.51%. ML-driven mobility prediction results integrate into our proposed scheme that shows comparable coverage probability, and average throughput to the no skipping case, while significantly reducing HO costs. Secondly, a novel blockchain-enabled privacy preserved HO skipping mechanism is discussed that uses train mobility dataset from the city of London. Using the dataset parameters, the modelled passenger traffic flows considered a specific train line as a use-case, while the blockchain is used to register user station entries/exits, allowing the framework to track the path of users utilising their pseudonym addresses in order to maintain privacy.

5.1.1 Related Work and Background

Worldwide increasing traffic demand entails the continuous use of electronic gadgets such as tablets, mobile phones, and other handheld devices. Such proliferation plays an active role in driving the evolution of small BSs, such as micro, pico, and femto, to traditional macro BSs in order to address the capacity crunch needs. For instance, the 5G evolution for cellular networks brings mobile devices and cellular subscriptions more prevalent with increasing data traffic demand and subsequently straining out the available resources [47]. Due to the increasing traffic in high mobility trains, a major consideration of cellular services need to be looked for all passengers at all times. The need to access mobile networks while travelling have been considerably expanded with the limitations from legacy wireless technologies, challenge high train mobility passengers without conforming their needs of modern day travel. Due to the rapid mobility of the high-speed trains, data transmission suffers from high HO rates, which has been a long-standing challenge for high-speed mobility passengers in cellular networks. Unnecessary frequent HOs incur a lot of communication and computational overheads and thus, affecting the overall QoS [48, 49]. Increasing traffic demands can be addressed by deploying more BSs under 5G wireless communications and beyond, as there is an expectation to serve more passengers providing tremendous data rates with resilience and support high-mobility passengers with low end-to-end latency. Densifying the BSs within the same geographical region shrinks the footprint of each BS, which results in the expansion of capacity with the increase in spatial-spectral efficiency and QoS. However, the increasing inclination of capacity gains is at the expense of a proportionally increased HO rates [47, 48].

Ultra-dense networks (UDNs) require more HO management due to their composition based on dense deployment nature of SC [66]. HO executions occur more frequently along the passengers trajectory where users move inside each SC for a limited time at an expense of significant HO cost and resources and overall mobile users' performance (i.e., throughput). Such important negatives where the impact of BS densification (i.e., HO rate) and management of QoS to underline the overall benefits to stationary and mobile passengers are usually overlooked [12]. The cell dwell time for different shaped cells is characterized in [73]. Mobility prediction based HO management optimisation is proposed in [25, 74, 271] to understand mobile traffic patterns, predicting human mobility, and travellers profiling. Self-organising networks (SONs) driven HO management is proposed in [2, 12, 14, 15] to trim the needs of unnecessary HOs in multi-tier networks and fulfil passenger demands by running various distributed learning algorithms at the edge of the network.

AI-based mobility prediction and encryption leveraging historical passengers data recorded via RFID sensors was discussed in [9]. By using ML classification, authors analysed LUO network user mobility to support and improve the railway operational performance which includes, QoS maintenance, HO optimisation, effective resource management, etc. Bus passenger ridership mobility using multi-tier HetNet is discussed in [8] with the main focus being adherent in the anticipation of the passengers mobility behavior crossing HetNet architecture. ML-based algorithms use geographic BS locations, user cell association, and number of passengers in peak and off-peak times have been modelled by using six ML algorithms. Several studies [10, 39, 85, 117, 261, 272–275] use ML classifiers to present their model that discussed 5G limitations, opportunities, and directions. ML algorithms such as LR, SVM, and multilayer perceptron (MLP) are compared to predict passenger daily traffic. Some other algorithms such as RL, KNN, ANN, DNN, DT, NB, and DA, are trained to classify inputs to obtain predicted intelligent outputs. However, none of the aforementioned works shed light on ML-driven HO skipping techniques in the context of load-awareness. Also, their works are rare to use train data as inputs into ML model for data training. Therefore, a ML driven context-aware HO management is required to intelligently drive the HO process in cellular networks.

For instance, efficient models to improve the HO performance along with the QoS have been extensively addressed in the mobility context of cellular network literature. In [49], data transmission suffers from severe penetration loss in high speed railways and when the train moves from one BS to another, there are huge amount of HO occurs. Using of mobile relay node (MRN) can improve the HO overheads in fixed-trajectory group pre-handover authentication mode with better security properties. A mobility model called self-similar least-action walk (SLAW) [13] is able to produce synthetic mobility traces containing statistical features such as, heavy-tail flight and pause-time distributions; heterogeneously bounded mobility areas; truncated power-law intercontact times; destinations of people in a self-similar manner; and users current waypoints where they are more likely to choose a destination. Due to the shrinking of the BSs led by network densification, the number of HOs increases. Therefore, a cooperative HO management scheme devising HO effect mitigation via cellular network densification is discussed in [276]. Several other techniques that discuss mobility predictions based HO management are studied in [69, 71, 93–95, 116] for multi-tier downlink cellular networks.

Implementation of seamless HO between first tier (macrocell layer) and second tier (small cells) is one of the key challenges to fulfill the QoS requirements.

In [123], authors discussed HO procedure details for information gathering, decision strategies and the BS exchange process. In [277], authors presented a model of HO cost reduction is one of the important targets in LTE-Advanced SON based on a HO optimisation algorithm on users mobility state. A comparison between HO reduction method and the traditional HO control algorithms was made. In [278] co-channel interference and HO management especially for cell edge users were discussed with the examination of HO management problems and cooperative interference mitigation in an HetNet SC network. In [279], a relation between the desired link distance and the nearest interference sources has been discussed in the research that shows performance bounds for multi-tier and cognitive cellular wireless networks using stochastic geometry. User-centric BS cooperation and its complex HO patterns which are the contributors of user performance degrade are discussed in [280] with an aim to to quantify the number of HO in user-centric cooperative wireless networks.

A systematic review of mobility communications high-speed railway systems has been discussed in [281], where key challenges and opportunities are summarised. Their survey includes, communication operations, high mobility channels, and signal processing techniques such as Doppler diversity along with the mitigation techniques high mobility systems. A cross-tier HO analysis between a MC and a SC in HetNet architecture, that can provide sojourn time expressions inside a SC by using tools from stochastic geometry has been proposed in [282]. For velocity estimation, the user's trajectory path is exploited by spatial randomness in [47, 48, 283]. HO skipping scheme and its alternatives have been introduced in [46–48] to reduce the HO rate which also proposed an alternative HO execution along the user's trajectory while associated with either its closest or second closest BS. This work is extended in [46] with the topology-based HO skipping concept on a user's distance from the target BS and the size of the cell. However, none of the aforementioned studies undertake the interaction between user throughput, multi-decision HO protocol as a function of the BS density. Nor the consideration was given to the train environment (underground and overground) where users move along a predefined trajectory. In addition, our NEWS framework examine multiple users simultaneously which fall short in the existing works such as [47, 48] where only a single user was considered.

The main source of inspiration behind this work is the interplay of HO rate associated with the mobility of passengers within the metropolitan city of London where locations of BS deployment are known. Furthermore, rigorous analytical studies based on stochastic geometry [46, 282] exploit HO rates dependant on

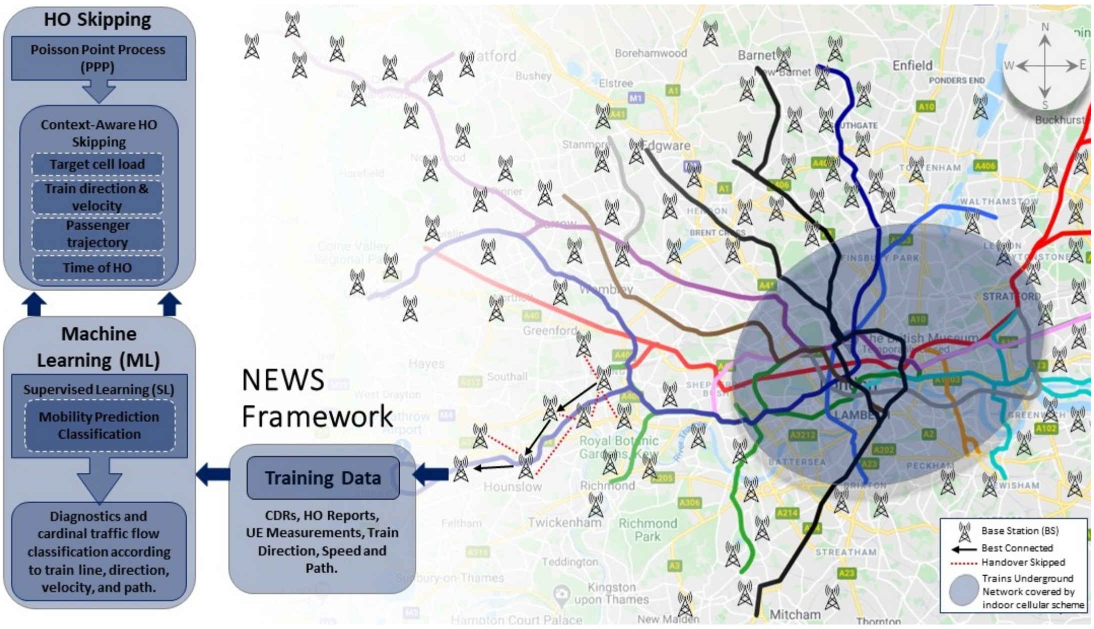


Figure 5.1: NEWS Framework with LUO train map and assumed number of BSs plotted onto the image for indicative purposes. Multiple colours are representative of different train lines operate within LUO train network.

the cardinal passenger traffic flows in the LUO train network [1]. To achieve estimated results of coverage probability, the PPP is best [47, 48] in its ergodicity rate quantification for realistic BS deployment in the LUO train network. The coverage probability associated with passenger traffic flows and ergodic rate in multi-tier cellular network has been used by Poisson cluster process (PCP) where cell clustering captures and integrates the deployment of several SCs in congested regions [284]. The single and multi-tier scenarios were assumed to produce HO rates of user's mobility in PPP cellular networks in [46, 282, 285]. Some studies on HO rate analysis are conducted in [36, 153, 154]. However, none of the aforementioned studies investigate the combined effect of network densification along with cardinal passenger traffic flows that exploit both the HO overhead and the throughput gains in the LUO train network.

As it can be seen, most HO skipping schemes considered in the literature involve some sort of data collection from users. However, with more users being aware of their privacy nowadays, it is becoming increasingly complex and challenging to convince users to share their data, as there are several concerns in terms of how their data is utilized [286, 287]. Therefore, there is a need for novel approaches that are able to anonymously and securely collect data from

[1]LUO is the London Underground and Overground network with 270 stations and 11 train lines stretching deep into the Capital's suburbs, and beyond. For more details visit, https://tfl.gov.uk/corporate/about-tfl/culture-and-heritage/londons-transport-a-history/london-underground.

users, and with their consent. There are traditional methods used for user tracking such as, TraceTogether App powered by Bluetrace [288] protocol and Google Apple Contact Tracing. Both methods used Bluetooth low energy for discovery of users in proximity. In TraceTogether, users' devices are always in the active mode, i.e., broadcasting state to locally record clients but on the compromise of mobile battery. There are also some security threats such as, its vulnerable wireless interface, jamming, sniffing, etc. Due to the high risk of security, the Bluetooth physical layer has to sacrifice on the hardware identification for keeping it concealed against attacks. Other method, Google Apple Contact Tracing has a different privacy mechanism compared to TraceTogether App. In this tracing, users' identities are not kept by the provider, hence becomes privacy preserved. But their dependency relies on the central server for contact matching and notifications which consecutively brings a concern of trajectory attack on user's privacy. As this method is central server dependent, it builds and modifies users' profiles with the access information available in the server, resulting potential exposures of users private data.

There is another application which was a joint production of Apple and Google to keep the users' identities preserved, relied on Bluetooth [289]. Similarly, there is an existence of digital contact tracing (DCT) that utilizes electronic platforms to synchronize healthcare database and keep it updated with the necessary information of patients [290], or the making the use of well-known GPS in combination with Wi-Fi for users' trajectories and positioning [291]. Thus, whenever users are in proximity an alert gets generated. In [25], safe commute to staff and public was provided by ensuring necessary arrangements managing daily train travelers with the specific travelers-profiling. There were designated routes for different age-groups such as, 16-59 years and over 60 years (vulnerable age-group) proposed with designated train carriages, stations, and platforms. On one hand where technology is supporting contact-tracing, there are issues with the privacy being preserved on the other. In the aforementioned techniques, the dependency remained on the third party server to address any alerts and provides resolution [25,288,289]. Moreover, there are other threats to the mentioned approaches due to their centralised server nature. As such, one promising way forward is through blockchain, as it can provide a decentralized data management framework [287]. Since blockchain does not rely on a central authority, it is less prone to failure, it is more transparent as every transaction is public, more secure due to encryption, as well as anonymous, as users are behind pseudonym addresses [292].

In this direction of research, passenger traffic flows based on novel cardinal directions NEWS framework employing realistic PPP that can produce real-time mobility predictions to support LUO train infrastructure from overloading and congestion has been studied and modelled. For this, an intelligent HO skipping technique called context-aware HO skipping is proposed to efficiently manage HO rate associated with cardinal passenger traffic flows. Our paper contributions are as follows:

- Real dataset: To examine a real scenario, the dataset from Transport for London (TfL) in order to predict the number of passengers at each train station have been utlised. Multiple colours are representative of different train lines that operate within LUO train network as shown in Fig 5.1.

- Mobility Tracking and Future Location Estimation: mobility prediction classification by using ML algorithms for passenger traffic flows in cardinal directions have been considered. Realisation of passenger's mobility and trajectory in the LUO network that comprises of several train lines integrates with the HO skipping techniques.

- Context-Aware HO Skipping: Based on ML results obtained via classification and cell topologies (current cell and the cells which are going to be visited next), the passenger association with its closest BS while on the move, have been analysed and presented. To address passenger's mobility, a context-aware HO management is required to intelligently drive the HO process in cellular networks. Therefore, the proposed intelligent HO skipping technique exploits multi-decision protocol for taking automated decisions to carry out a necessary HO. In contrast to the proposed techniques in [47,48], not only managed to reduce the randomness of the passenger's association with the BSs but also enhanced the overall performance of the HO skipping phase with improved SINR, and average throughput. A HO is skipped when BSs intelligently report their traffic states by issuing collective neighbouring reports. Context-aware technique takes multiple parameters into account such as passengers trajectories, velocities, path, travel direction, and cell load for a HO to be skipped, thus improving the overall performance of our NEWS framework.

- Blockchain: The NEWS framework is exploited against blockchain technology to track individual users through train stations, providing a secure and private platform in order to collect users data throughout their trajectory, and based on individual user information, user-specific HO skipping is achieved, leading to a better trade-off in terms of network HO cost, user QoS, and last-hop signal quality.

HO Fundamentals

The arbitrary user association with the serving BS determines the need for HO when in motion. The criteria is for a UE to be associated with the serving BS based on the best serving participant which has high average received signal strength (RSS) level. A higher RSS level BS continues to serve a UE within its boundaries until the UE decides to change its association while moving from one BS to another domain. Traditionally, this method of user association was effective until the heterogeneity within cellular networks was introduced. Nowadays with increasing traffic demands, HetNets play a vital role in densifying cellular networks further to enhance the capacity. Increased demand for HetNets also brought developments in determining the best serving BS, cell load balancing, throughput maximizing, delay tolerance, and resilience recorded in the call detail records (CDRs) [8,10,13,25,47,48,216]. Despite of the selection rule, UE mobility requires an advanced level of intelligence to exploit the best HO rates with the densification of BSs. Hence, a trade-off is needed to utilise HO cost in line with the BS density.

There are three main phases of HO: initiation, preparation, and execution. Initiation phase determines user reports that contain reference signals measured from serving BS neighbours. In the 4G LTE, but not limited to, the key point indicators (KPIs) consists of RSRP and RSRQ [15, 46]. Downlink and/or uplink signal measurement reports also contribute to the HO initiation process. The preparation phase allows signalling to be exchanged between serving and targeted BSs along with the admission controller. The key player to decide whether HO is necessary is the admission controller which initiates the HO process based on a set of protocols defined in the HO criteria. Once the defined HO criteria is met, with the use of random access channel (RACH), the user discharges its association from the serving BS and attempts to synchronise and access the target BS. The UE then notifies the execution of HO, which is completed to the network by sending a confirmation message upon synchronisation. The HO procedure is performed but at the cost of some overheads which degrade the overall performance of the network. This involves the interruption of smooth data flow between UE and serving BS due to signalling. The occurrence of such interruptions depends on BS intensity and user velocity where the duration of each interruption is an important measure denoted as end-to-end HO jitter [76]. The aim is to decrease the frequency of such HO delays in user's mobility at both slow and high velocities. Usually, the slow user's movement doesn't trigger the HO due to the sufficient sojourn time. However, high mobility is incumbent upon setting up certain measures in order to avoid unnecessary HOs. UE speed has a great influence on HO rate and is an important aspect of the overall performance. Frequent cells and several BSs shift take place when a passenger moves in high mobility train leading to HOs, thus increasing call drop ratio and failure rate alongside [216]. Therefore, optimisation of hysteresis and time to trigger (TTT) should be carefully monitored to satisfy passengers wireless communication requirement in high-speed train mobility. In our case, the LUO train network has high mobility trains that run on different speeds to cover distances. For instance, the average speed on the London Underground (LU) is 20.5 mph (33.0 km/h) whereas, London Overground (LO) trains tend to travel at over 40 mph (64 km/h) and can reach speeds of 62 mph (100 km/h) in the suburban and countryside areas [293]. For the multiple speeds and different time thresholds, some empirical experiments and have chosen their values based on the best trade-off in terms of HO cost and user throughput.

State-of-Art in HO Skipping

The movement of the trains in cardinal directions require a strategy when they pass through SCs connected to macro base station (MBS) through backhaul as shown in Fig. 5.1. The main goal of the PPP mobility prediction model is to ensure that our novel NEWS framework defined context-aware HO skipping would produce best connected results when compared to other HO skipping techniques in LUO train environment. This means, to remain under mobile coverage footprint, when trains move from one BS to another, they receive coverage requests from several BSs located within the proximity of its movement. In our research we have discussed multiple HO skipping techniques such as, alternate HO, location-aware HO, size-aware HO [48], and context-aware HO. Preferring one SC to another requires a strategy to overcome unnecessary overheads, waste of resources and HO costs. PPP mobility prediction model driven HO skipping technique can maximise the throughput with the best SINR and reduced HO costs. The no skipping is shown in Fig. 5.2 (scheme a), where a black line indicates the train line, white circles indicate the train stations over the train line. BSs are represented by blue dots, with their coverage areas defined by the blue borders. In case a BS has its area painted in green, it means that the users have connected to that BS, whereas if it is in yellow, it means that the BS has been skipped.

1. Alternate cell switching based HO skipping: The alternate HO skipping scheme accounts for the alternate automated procedure for cell selection and HO skipping when a passenger is on the move in certain direction of travel [48]. The passenger's trajectory decides which BSs to latch and skip

on alternating basis regardless of cell location, size, and load. The alternate HO skipping is illustrated in Fig. 5.2 (scheme b).

2. Location-Aware HO skipping: The HO skipping technique based on location triggers skipping when shortest possible distance between the user trajectory and the target BS is accounted [48]. In other words, users exceeds the predefined threshold L when covering minimum distance along the trajectory to target a BS. In our work, threshold L can be designed in such a way that passengers skip the BSs along their cardinal directions through the cell edge only. HO skipping based on location scheme is illustrated in Fig. 5.2 (scheme c).

3. Size-Aware HO skipping: When BSs' footprints are less than the predefined thresholds, s service areas, the passengers tend to skip the HOs based on BS cell sizes [48]. This HO setting reduces the service area of the BS that leads moving passengers to skip the cell and form a connectivity to other cell. In this concept, cell dwell time is dependant on the BS footprint size that aims to avoid time duration for far-reaching blackouts.In this contingency, SCs are skipped by the passengers where large footprint-based cells serve the requirement and allocate resources. HO skipping based on cell sizes scheme is illustrated in Fig. 5.2 (scheme d). Service areas are assumed to be correct and known by the mobile network operators (MNOs) that deliver services around LUO train network.

4. Hybrid HO skipping: Alternate, location and size aware HO skipping techniques fall short to accurately observe the true cell dwell time. Therefore, on combining all techniques, more precision and enhanced inference about the cell dwell time can be achieved which is shown in Fig. 5.2 (scheme e) [48]. This way, the factor of improvement in the HO skipping decisions and performances can be handled more accurately and precisely. Consequently, the combination of all techniques set out the accountability of user location and cell areas while making the HO decision. One of the most important aspect is to estimate user's trajectory where we have used known trajectories associated with daily passengers on the LUO train network. This makes our HO skipping strategical which can be triggered on known passenger's location and cell size thresholds.

Fig. 5.2 also shows our proposed context-aware HO skipping (scheme f) which is presented in Section IV of this paper.

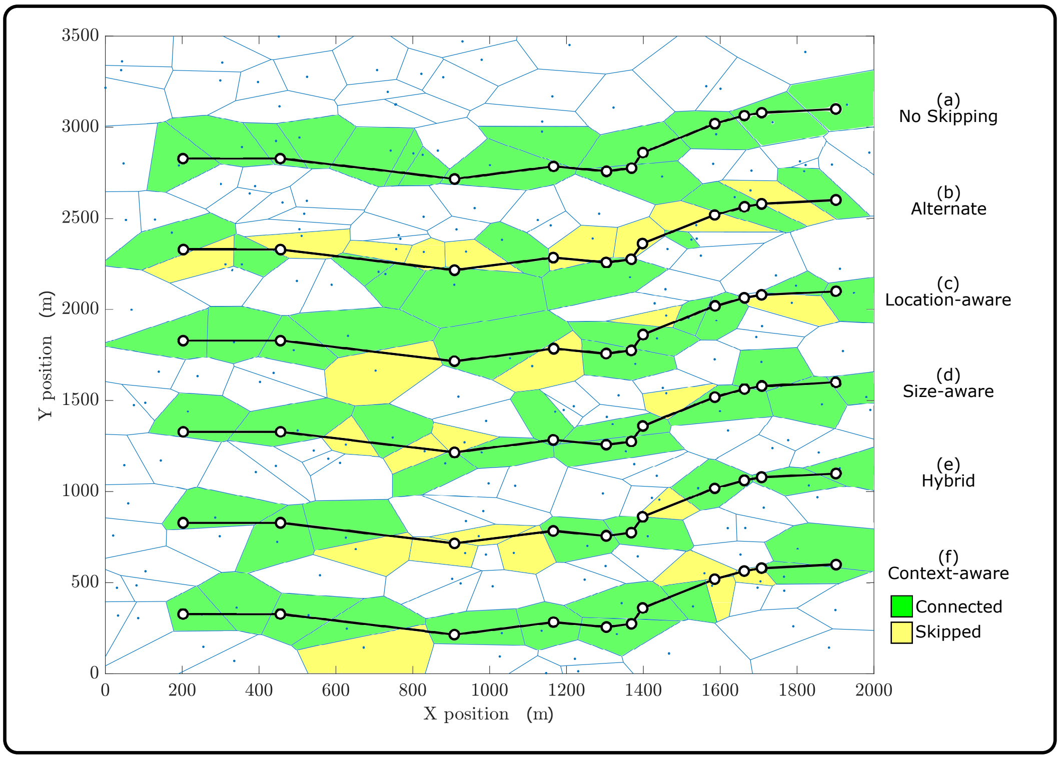


Figure 5.2: Representation of PPP based single tier cellular network where green and yellow cells are indicative of connected and skipped cells. HO skipping schemes (a to f) represent no skipping, alternate, location-aware, size-aware, hybrid, and context-aware HO skipping schemes, respectively. Black line represents a specific train line moving East to West.

5.2 System Model

5.2.1 NEWS Framework

The proposed NEWS framework considers the downlink stream with number of BSs spread over an area based on the city of London. The area consists of a rectangle of sides L_1 and L_2 that covers one of the train lines for simplicity. In this area, a certain number of BSs are evenly deployed according to a PPP, with rate λ across several train lines as shown in Fig. 5.1. Moreover, we also assume that the city of London is covered by N_o distinct MNOs and that each operator is considered to have the same total available bandwidth W. Each BS is equipped with multiple directional antennas with constant gains and Tx powers, each BS has N_s sectors, with each sector supporting a fixed number of RBs, N_{RB}. In addition, a frequency reuse factor of 1 with constant bit-rate service is assumed. For context-aware HO skipping establishment, consideration has been given to a single-tier network model consisting of assumed BSs spread around multiple train lines in cardinal directions with their traffic information in separated CDSA [106]. In CDSA, a MC controls the signalling with low data rate activities whereas data based stations (DBS) or simply SCs offer high capacity services. In the NEWS framework, train lines move in specific direction using a specific path defined by the TfL as shown in Fig. 5.1 whereas, there are number of movements to define the trajectories of passengers such as boarders, alighters, station entry/exit passengers, link and passengers frequency, etc. For the movement of trains, each colour in Fig. 5.1 represents a train line. For instance, Piccadilly line which is represented by a blue colour in the figure moves in East-West (and vice-versa) direction. Similarly, Northern line represented in black colour travels from North to South and vice-versa.

5.2.2 PPP-based BS distribution model

Experiments yielding numerical values of random variable x, the number of outcomes occurring in a specific region in a given interval of time are referred as Poisson experiments. With the use of Poisson experiments, a number of observations can be generated for a random variable to formulate set of given values in a PPP process [294]. NEWS framework employs PPP to model HO rate during passenger traffic flows in cardinal directions via topology-aware HO skipping techniques. The presented equation is to define how observations are calculated to perform Poisson experiments,

$$P(r;\lambda t) = \sum_{x=0}^{r} p(x;\lambda t) = \frac{e^{-\lambda t}\,(\lambda t)^{x}}{x!} \ , \tag{5.1}$$

The mean number of outcomes are computed from $\mu = \lambda t$, where t denotes the specific time of HO occurrence and λ is the rate of arrival that can be represented by a symbol $P(x;\lambda t)$. λ is the average number of outcomes per unit time and region, $x = 0, 1, 2, ...,$ and $e = 2.718$. According to this model, in the proposed framework BSs are then evenly deployed in the rectangular area following a PPP.

5.2.3 User Parameters

To perform user association, our framework models passengers to associate with the BSs based on their distances with the set of all passengers $\mathbb{U} = 1, 2, ..., u$ and all BSs $\mathbb{B} = 1, 2, ..., b_k$. Once the distance is known, RSRP measurements are calculated by locating the passenger within a train, its association to the closest

BS while on the move per each evolved node-B (eNB), and signal availability at a each location. Therefore from [48] we can calculate the RSRP of each user as,

$$\mathrm{RSRP}_{u,b_k} = T_x \cdot h \cdot d_{u,b_k}^{-\alpha} \ , \tag{5.2}$$

where, T_x is the eNB transmit power, h is the channel power gain, which follows a Rayleigh distribution with unit variance, d_{u,b_k} is the distance between user u and BS b_k, and α is the path loss exponent. The average sum of the RSRP signal received from passengers (wanted reference signal) to the average sum of interference and noise N (unwanted signal) is measured by SINR, which is given as,

$$\mathrm{SINR}_{u,b_k} = \frac{\mathrm{RSRP}_{u,b_k}}{N + \sum\limits_{i=1, i \neq b_k}^{b_k} I_i}, \tag{5.3}$$

where, N corresponds to the additive white Gaussian noise (AWGN) and interference from all other BSs, except the one that the user is trying to connect to, is denoted by $\sum_{i=1, i \neq b_k}^{b_k} I_i$.

In addition to SINR, the coverage probability is also determined. In general, coverage probability is dependant on the SINR where a UE exceeds a certain defined threshold. NEWS framework exploits coverage probability affected by SINR when the mobility of passengers outstrips by predefined threshold parameters. Therefore, the coverage probability can be calculated as [48],

$$C_{u,b_k} = \mathbb{P}\Bigg[\mathrm{SINR}_{u,b_k} > T\Bigg], \tag{5.4}$$

where T is a predefined threshold.

Users are then allocated to specific BSs according to not only SINR, but also the available resource blocks (RBs) at each BS. Without loss of generality, it is assumed that each user consumes 1 RB when connecting to a BS and that for a user to associate to a BS, the following criteria must be met:

$$\Psi_{u,b_k} = \begin{cases} 1, & \text{if } \mathrm{SINR}_{u,b_k} \geq \mathrm{SINR}_{min} \ \& \ \mathrm{RB}_{rem} \geq 0, \\ 0, & \text{otherwise.} \end{cases} \tag{5.5}$$

In other words, if the user has a SINR above a minimum requirement SINR_{min} and there are enough RBs available at the target BS, the user is associated with its preferred BS. Otherwise, if none of these conditions are met, the user then looks for the next best BS available. If none of these conditions are met, the user is then assumed to be out of service, until a new BS can be found that meets these criteria.

5.2.4 User Mobility

Since in this work it is considered that users are on-board trains, it is assumed that a train moves with a constant speed of v and that users inside the train are positioned in the center of mass of the train plus an additional random offset, defined by coordinates $(x_c, y_c) \pm (x_o, y_o)$ meters. In addition, it is considered that the train travels in between a certain number of stations, and that whenever the train passes through a station certain passengers board, while others leave the train. It is also assumed that only a percentage of passengers, N_{active}, require connection while being on a train.

As the train moves through the considered area, it traverses the coverage zones of BSs. In case no BSs are skipped, passengers always associate to the best available BS, according to (5.5). When skipping is performed, whenever passengers skip a certain BS, they maintain their association with the previous serving BS and avoid looking out for nearest BSs regardless of their proximity. Alternatively, they tend to HO to the next target BS based on the relative distance. To simultaneously serve moving passengers by both serving and the next target BSs, mutually load dependant intelligent transmission is required, being the main focus of our NEWS framework, relies on full or partial coverage availability in the LUO network.

5.2.5 HO Cost

For HO skipping, we define HO cost associated with the coverage probability and SINR derivatives in light of multiple HO skipping techniques as [48],

$$\overrightarrow{HO_c} = \min(\hbar_t \cdot \tau,\ 1)\ , \tag{5.6}$$

where, $\hbar_t$ is the rate of HO per unit time and τ denotes the delay tolerant of each HO in seconds. Therefore, the $\overrightarrow{HO_c}$, being unit-less, is used to observe the costs associated with the HO techniques to quantify the fraction of time along the passenger's trajectory. In other words, the time taken by a UE switching from serving BS to the targeted one due to HO signalling. For the useful transmission, $\hbar_t \cdot \tau \geq 1$, this means that the HO delay is greater than the cell dwell time. Therefore, HO signalling wasted the entire time where $\overrightarrow{HO_c}$ is set to one, meaning, there wasn't any useful transmission. Now, PPP based HO rate for passenger's trajectory [285] is defined as,

$$\hbar_t = \frac{4v}{\pi}\sqrt{\lambda}, \tag{5.7}$$

where v is the speed of the train, and λ is the PPP rate. The number of HOs per unit length have been calculated for HO rates followed by the velocity v multiplication. The number of HOs per unit length $\hbar_l$ is obtained from the the trajectory length. Thus, $\overrightarrow{HO_c}$ can be defined as,

$$\overrightarrow{HO_c} = \hbar_l \ \cdot \ v \ \cdot \ \tau. \tag{5.8}$$

5.2.6 User Throughput

The main performance metric of our NEWS framework is the average throughput of a passenger that exploits proposed HO techniques. Average throughput demonstrates the reciprocity between HO cost and capacity gain imposed by network densification. The average passenger throughput (bits/s (bps)) affected by HO rate and the impact of HO skipping techniques have been discussed in the following equation [48],

$$TP_{u,b_k} = W \cdot R_{u,b_k}(1 - \overrightarrow{HO_c}) \ , \tag{5.9}$$

where, W denotes the overall bandwidth and R_{u,b_k} is the ergodic spectral efficiency which can be defined by Shannon formula for capacity by using (5.3) as,

$$R_{u,b_k} = \mathbb{E}(\ln(1 + \mathrm{SINR})). \tag{5.10}$$

5.2.7 Context-Aware HO skipping

In regards to the traditional HO skipping techniques shown in Fig. 5.2 (schemes a to d), neither the alternate, nor the location or size-aware HO skipping alone accurately reflects the true cell dwell time obtained from passengers location, travel direction, most chosen path, train load and speed etc. In addition, hybrid HO skipping shown in Fig. 5.2 (scheme e), which is the combination of location and size-aware techniques is unable to address true challenges of HO skipping associated with mobility of passengers in the LUO network. Challenging and complex LUO train network dynamics overburden traditional HO schemes to drive smooth and seamless HOs. Situation gets more complex when passengers location, travel direction, most chosen path, train load, and train speed are added as the key parameters to warrant real-time LUO train environment. This is where, context-aware methodology comes into play which has the ability to harvest LUO train network information about its environment at any given time and adapt behaviors accordingly. This intelligently acquires the best methodology according to the changing scenario with the accountability of real-time environment and radio parameters to develop the responses with best possible strategy. Context-aware methodology relies on complex LUO train network to automatically build load-aware dataset based on passengers location, their travel direction, most chosen path, train load, and train speed. Alternatively, context-aware cultivates its response by intelligently adapting to the transitional environment.

5.3 Proposed Method

We first present an analytical model development of NEWS framework to optimise the passenger traffic flows in LUO train network, followed by blockchain to optimise HO skipping for train passengers using PPP [294]. Following are the proposed elements;

- ML driven mobility predictions for future location estimation and planning.
- Context-aware HO skipping.
- Privacy preserved context-aware HO skipping using blockchain technology.

Our proposed NEWS framework is based on the integration of ML [37, 39, 40, 85, 117, 261, 272–275] into PPP [294] mobility prediction model. Where, data is first trained into ML in order to classify North, East, West, and South directions along with LUO train lines. The output of ML is then fed into the PPP simulation model for HO skipping examination using passenger's trajectory, velocity, path, load, train lines, train directions, travelling time, etc. Both ML classification and PPP simulation are presented in the following subsections.

5.3.1 ML-Driven Mobility Prediction

The proposed NEWS framework adopts SL as a ML tool to predict the mobility prediction-based cardinal passenger traffic flows with the support of algorithms such as, LR, SVM, and MLP. In order to train the ML classifiers, we split the dataset into 70% training, 20% testing and 10% validation. In order to train the classifiers real dataset from TfL has been fed as inputs into three different ML classifiers after pre-processing. By using SL, dataset has been first classified into multiple binary labels in a NEWS fashion such as; Northbound, Eastbound, Westbound, Southbound. Followed by the TfL train line names and station codes/names along with passengers frequency and their entry/exits are further categorized into early, AM peak, midday, PM Peak, evening, and late travelers. In addition, 15 minute time intervals categorization have been introduced while further splitting the dataset in, (a) the number of passengers boarding onto train carriages called boarders and, (b) passengers who alight on the stations called alighters for classification purposes.

Historical traces of passengers mobility which include direction, path, load, time of travelling, associated cell IDs, and RSRP are assumed to be available for training the framework. It is worth mentioning that all LUO train lines in cardinal directions with a huge dataset have been analysed and normalized prior to ML model fitting as shown in Fig. 5.1. This normalization is being done with the help of minimum, maximum and average scaling using scikit-learn functions. By doing so, all features are transformed into the range $[0, 1]$ meaning that the minimum, maximum, and average value of a feature is going to be in the format of 0s and 1s, respectively. In addition, different features such as Kurtosis and skewness have been chosen for the different classifiers. Normalizing and using various features bring all the variables to contribute equally to the model fitting and model learned function without creating a bias. Below are the ML algorithms used to predict the mobility prediction-based cardinal passenger traffic flows;

- SVM in multi-class classification setting with a polynomial kernel.
- An MLP, which is a feed forward neutral network consisting of input, hidden and output layers. The classifier is trained for 100 iterations and it consists of one input layer three hidden layers (with 1500, 512, 1500 neurons, respectively) and an output layer, consisting of 4 nodes, which represent the cardinal directions (North, East, West, South).
- Logistic regression (LR) is type of machine learning algorithms which is used for binary classification. The LR is used to find the best fitting model to describe the relationship between characteristic of interest and set of independent features.

ML-driven results are exploited to model PPP for HO skipping evaluation. To generate comparative analysis in terms of coverage probability (number of users covered vs SINR), average throughput, and HO costs, multiple HO techniques are simulated. Passengers trajectory, velocity, path, train load, directions & lines, travelling time, etc., are used as the key parameters for HO skipping techniques model simulation.

5.3.2 Context-Aware HO Skipping

Considering that the speed and trajectory of the trains are known beforehand, the proposed algorithm is able to calculate the time that the users spend in each cell traversed in the users' path. As such, given the time in each cell as t_{b_k}, and a given time-based threshold, defined as t_{thresh}, for a user to skip a cell according to the context-aware approach, the following conditions must be met,

$$\Omega_1 = \begin{cases} 1, & \text{if } t_i \leq t_{thresh}, \\ 0, & \text{otherwise,} \end{cases} \tag{5.11}$$

where, t_{thresh} is half the average time in cell spent through the trains entire journey. Since the train follows a specific path with a predefined maximum speed, it is natural to know the average time spent in cells throughout the entire route.

Condition 1 (Ω_1) states that if the time spent inside a cell is lower than a threshold, users opt to skip the cell. However, in the context-aware approach, the load and the quality of the signal (in terms of SINR) are also considered. Thus, another condition needs to be checked in order to decide who is going to skip the cell. Given $\mathbb{S} = \{s_{1,b_k}, s_{2,b_k}, ..., s_{u,b_k}\}$ as the set of measured SINRs of all passengers $\mathbb{U} = 1, 2, ..., u$ at base-station b_k, $\mathbb{SS}$ as the sorted set of measured SINRs, $\mathbb{SS} = \{ss_j, ss_{j+1}, ..., ss_{|j|}\} \mid ss_j < ss_{j+1}$, where $|j| = |u|$ and RB_{rem,b_k} as the available resource blocks at base-station i, condition 2 can be expressed as:

$$\Omega_2 = \begin{cases} 1, & \text{if } \Omega_1 = 1 \ \& \ j > \text{RB}_{rem,b_k}, \\ 0, & \text{otherwise.} \end{cases} \tag{5.12}$$

Condition 2 states that a user skips a base-station if condition 1 (Ω_1) is satisfied and if the index occupied by the user's sorted SINR is larger than the number of resource blocks available at the target BS. In other words, if the user has a good enough SINR when compared to other users and the number of resource blocks available at the target base-station can support at most $j-1$ users, user j should skip the target base-station. Algorithm 3 shows an algorithm of the proposed context-aware skipping scheme.

5.3.3 Privacy Preserved Context-Aware HO Skipping

Fig. 5.3a shows the proposed architecture of the framework, where the train path and stations along the mobile network are represented by the black line and black dots, respectively. Additionally, green cells determine BSs that a certain

Algorithm 3: Context Aware HO Skipping Algorithm

Initialize area sizes L_1 and L_2;
Initialize train path, size, speed, initial position and stations' positions;
Initialize network parameters $W, N_o, N_s, N_{active,}$RB;
Initialize all thresholds;
for *counter = 1:*N_{runs} **do**
    Generate user positions inside train;
    Generate BS positions according to PPP and λ;
    while *Train is not in final station* **do**
        if *Train is in station* **then**
            SVM model predicts total number of users;
            Update number of users and positions;
        else
            Keep same number of users and positions;
        end
        Calculate RSRP via (5.2);
        Calculate SINR via (5.3);
        Determine user's cell association via (5.5);
        if *HO occurs* **then**
            Evaluate conditions Ω_1 and Ω_2;
            Update HO cost via (5.6);
        end
        Measure user throughput with (5.9);
        Update train and user positions;
    end
end
Calculate average coverage probability via (5.4);
Calculate average throughput;
Calculate average HO cost;

user has connected to, red cells denote skipped cells, while orange cells denote non-participating cells. As seen from Fig. 5.3a, it is assumed that whenever a user enters or exits a train station it interacts with the station's hotspot (either via Wi-Fi or cellular) in order to record the inbound/outbound station and the user's pseudonymous address in the blockchain. Since in this framework it is considered that each BS can be run by different operators that do not trust each other, therefore, each BS acts as a node in the blockchain. Thus, the blockchain can provide a trusted platform for data exchange and sharing among different providers. By leveraging the historic information collected in Steps (1) and (2), the mobile network can then make HO skipping decisions for each individual user, in Step (3). From a more technical perspective, Fig. 5.3b shows the data structure and data flow of the proposed framework. It is expected that whenever a user enters/leaves a train station the user, through a mobile application, sends a

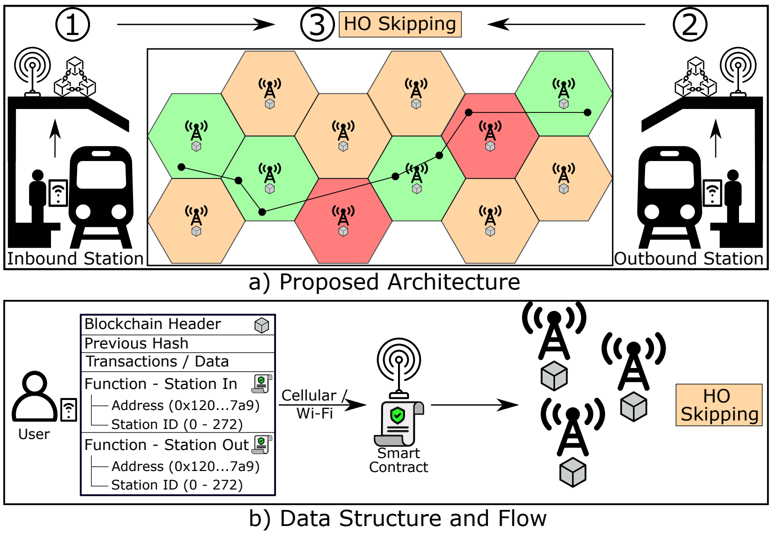


Figure 5.3: Proposed blockchain HO skipping architecture, data structure and flow. A specific train line in Westbound direction is considered as a use-case.

transaction to a smart contract at the blockchain, which is responsible for recording the station entries/exits. These user entries/exits are recorded as station IDs, together with the pseudonymous address of the user. This transaction is then mined by the nodes in the blockchain, which are at the train stations as well as the BSs. After validation, this information is then available at the BSs, which can then use this information, together with other previously collected data, to determine a user history and utilise it on algorithms outside the blockchain to perform HO skipping.

For this work we have considered a hybrid HO skipping algorithm, as in [48], which utilises mainly two criterion to define if a BS is going to be skipped or not. The two criterion for making a skipping decision are: i) if the size of a cell is lower than a threshold; ii) if the distance when the user enters the cell and the BS is larger than a threshold. These criterion are dependant on: the recorded information in the blockchain which holds user in/out station movements; train's path & direction; velocity of the train; and limited sojourn time of every user in a cell. Thus, with all this information combined, an individual user skipping can be performed.

5.4 HO Skipping Simulation and Results

5.4.1 Simulation Scenario

In order to validate the proposed scheme, a simulation scenario is performed in MATLAB. Several BSs are positioned according to a random PPP in a rectan-

Table 5.1: Simulation parameters

Parameter	**Value**
PPP rate (λ)	0.0001
Side of simulated area (L_1)	2,000 meters
Height of simulated area (L_2)	1,000 meters
Number of operators (N_o)	4
Bandwidth (W)	10MHz
Noise spectral density (N_0)	-204 dBW
Active users (N_{active})	90%
Path loss exponent (α)	4 [48]
BS transmit power (T_x)	0dBW [48]
Train speed (v)	64 km/h
RB per BS (RB)	150
Coverage probability threshold (T)	[-15, ..., 15] dB [48]
Minimum SINR (SINR$_{min}$)	0 dB
User offset X position (x_o)	±5 meters
User offset Y position (y_o)	±2 meters
HO delay (d)	1 second [48]
Size Threshold (s)	9 km^2
Location Threshold (L)	85 meters
Hybrid Thresholds (s, L)	9 km^2, 100 meters

gular area. It is also assumed that coverage is provided by 4 different operators, each having 20 bands of 10 MHz, each BS has 3 sectors and each sector has 50 resource blocks, resulting in a total of 150 resource blocks per BS. In this area, a total of 10 train stations, according to the underground map of London are positioned[2]. In addition, it is assumed that the train is moving west-bound with a fixed speed of 64 km/h and that at each station a certain number of users leave/board the trains. All simulation parameters are listed in Table 5.1.

For blockchain part, a rectangular area of sides $L_1 = 2,000$ meters, and $L_2 = 1,000$ meters is considered. In this area, $S = 11$ train stations are positioned according to the LUO map, more specifically a segment of the Piccadilly line (in a 1:10 scale). BSs are positioned according to a random PPP with rate of $\lambda = 0.0001$, each with a bandwidth of $W = 10$ MHz, corresponding to $R = 50$ RBs, and $T_x = 0$ dBW. The Rayleigh path loss exponent, $\alpha = 4$, noise spectral density, $N_0 = -204$ dBW, train speed is fixed at $v = 64$km/h, and the thresholds for the hybrid skipping are of 8.5km^2 for the cell area and 88 meters for the BS distance. A total of $u = 10$ users are considered, all starting from station 1 and ending at station 9. A simulation scenario is performed in MATLAB, and results are averaged over 10 random runs. The proposed framework is compared against

[2] In this work a 1:10 scale is adopted, meaning that the distance between train stations are scaled to a tenth of the actual distance.

no skipping, and hybrid skipping [48] in terms of HO cost, average throughput, and last-hop signal strength & delay. Also, how much storage and transactions per second (TPS) are needed considering just the simulated path, the whole Piccadilly line, and the whole LUO network is examined.

5.4.2 Metrics

In this scenario the different HO skipping techniques are compared, mainly: No skipping (best connected), alternate skipping, location-aware, size-aware, hybrid, and the proposed context-aware approach. Depending on the technique adopted, different types of HO skipping are performed. For instance, the no skipping approach never skips any BSs, whereas the alternate skipping skips every other BS. The location-aware skipping [48] skips BSs if at the time the train enters the cell, the distance between the BS and the train is larger than a threshold. In other words,

$$\Omega_{b_k} = \begin{cases} 1, & \text{if } L > \mathrm{d}_{train,b_k}, \\ 0, & \text{otherwise}, \end{cases} \tag{5.13}$$

where, Ω_{b_k} indicates if BS b_k will be skipped or not. In the case of the size-aware skipping [48], a BS is skipped whenever the size of a cell area is smaller than a threshold, or in other words,

$$\Omega_{b_k} = \begin{cases} 1, & \text{if } s_{b_k} < s, \\ 0, & \text{otherwise}. \end{cases} \tag{5.14}$$

Lastly, in the case of hybrid-skipping [48], the two metrics are combined, meaning that a BS is skipped if either the distance between the BS and the train is larger than a threshold or if the cell area is smaller than a threshold. In other words,

$$\Omega_{b_k} = \begin{cases} 1, & \text{if } s_{b_k} < s \vee L > \mathrm{d}_{train,b_k}, \\ 0, & \text{otherwise}. \end{cases} \tag{5.15}$$

A total of 100 runs of each technique are performed in order to average out the results. The 6 techniques are compared in terms of:

- Coverage probability: the probability that the average SINR of the users are above a certain threshold;
- Handover cost: the total average cost to handover users to all BSs from the starting train station to the last one;

Table 5.2: Mobility Prediction Classification

Classifier	Accuracy	Precision	Recall	F-Score
LR	91.76	0.91	0.90	0.91
MLP	92.57	0.92	0.91	0.92
SVM	94.51	0.94	0.93	0.94

- Throughput: the total average throughput of users weighted by the HO cost;
- SINR CDF: the cumulative density function of the average SINR of all users, which represents the percentage of users that have an average SINR above a certain value.

5.5 Results Discussion

5.5.1 Machine Learning Classifiers

The experimental results in the Table 5.2 are based on all ML features in scikit Python package that shows link load of one train line flowing in only one direction, i.e., East to West. Since the SVM classifier presents the best performance among all other classifiers, the remainder of the simulations and evaluations are completed with the SVM model only. According to our empirical testing, it can be seen that the SVM achieved better results due its effectiveness on high dimensional spaces. In addition, SVM can performs better where the number of dimensions are greater than the number of samples. Also, SVM performs well when there is a clear margin to separate between data inputs according to their different attributes. Likewise, in our framework, the number of classes which supported SVM were; link direction, train trajectory, passengers movement, travelling time and frequency, carriage load, network load, etc.

5.5.2 Context-Aware HO Skipping Network Analysis

From Fig. 5.4, it can be seen that the best connected case offers the highest coverage probability, as expected, followed closely by the proposed context-aware scheme. This shows the robustness of the proposed scheme, as even by skipping certain cells, the context-aware approach is able to achieve a very similar performance in terms of coverage probability. These 2 solutions are followed by the location-aware, size-aware and hybrid, which all have a very similar performance, and lastly the one with the worst performance is the alternate skipping

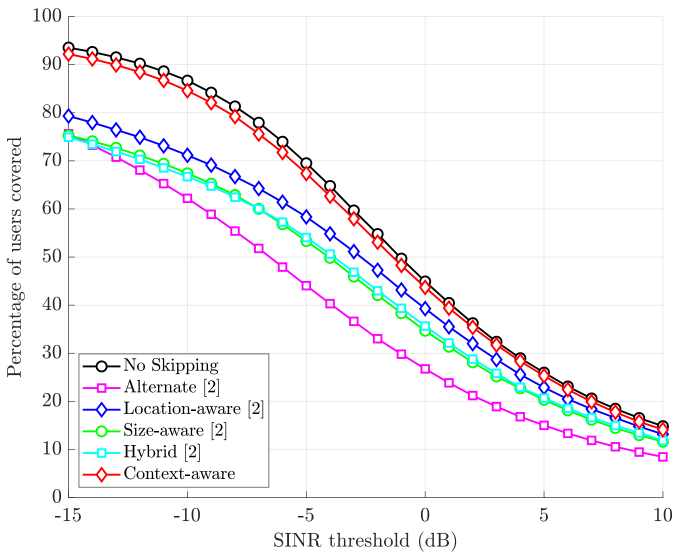


Figure 5.4: Coverage probability comparison of different HO skipping techniques vs SINR threshold.

method that skips every other cell. In addition we can also see that the gap between the no skipping, the proposed context-aware and the other solutions is larger when the SINR threshold is lower. This result suggests that both no skipping and context-aware approaches are able to find good enough BSs for the users to connect to, whereas the other approaches cannot. This happens since the location-aware, size-aware, hybrid and alternate schemes have a hard threshold in terms of skipping BSs, in which if that condition is met the target BS is skipped. This results in BSs that could potentially be the first or second best BS for users to connect to being skipped, resulting in a very poor SINR. In case of the context-aware approach, since both load and SINR information of the users are taken into account, this effect is mitigated, as users that have very poor SINR are forced to connect to these BSs, whereas users that have a good enough SINR can skip it. Lastly, the no skipping case is expected to be the best, as users always connect to the best available BS.

The average throughput results using (5.9) are extrapolated by SINR dependant spectral efficiencies as shown in Fig. 5.5. The HO cost impact on average throughput is directly proportional i.e., when velocity increases, due to the frequent HOs, cost increases as well. From Fig. 5.5, it can be seen that NEWS framework employed context-aware HO skipping outperforms with the minimum difference benchmarked against the no skipping case. Our proposed scheme has the best average throughput compared to other PPP HO skipping techniques.

In terms of HO cost and average throughput, it can be seen from Fig. 5.5 and

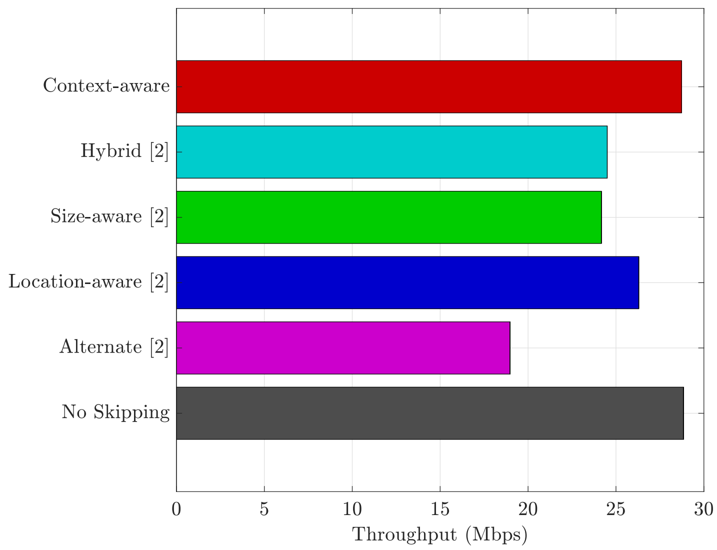


Figure 5.5: Average throughput comparison of different HO skipping techniques.

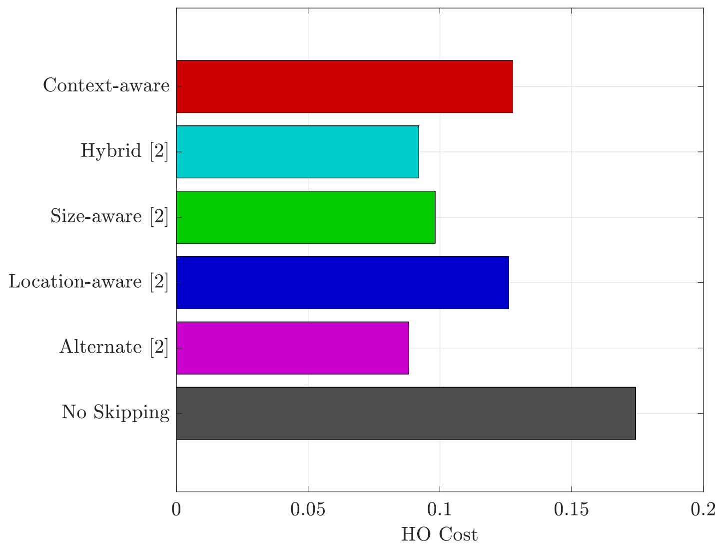


Figure 5.6: Average HO cost comparison of different HO skipping techniques.

Fig. 5.6 that the no skipping approach has the highest cost among all schemes and the best average throughput. This occurs as expected, since users do not skip any BSs in this scheme, thus users are always connected to the best BSs available. However, despite producing the highest throughput of all schemes, this also result in the highest cost. When comparing the alternate skipping approach, we can also see that its performance work as expected, as in this scheme every other BS is skipped, resulting in a percentage difference of around 50% when compared to the no skipping case. However, despite reducing the cost by almost 50%, the difference in terms of throughput is not as big, resulting in a loss of

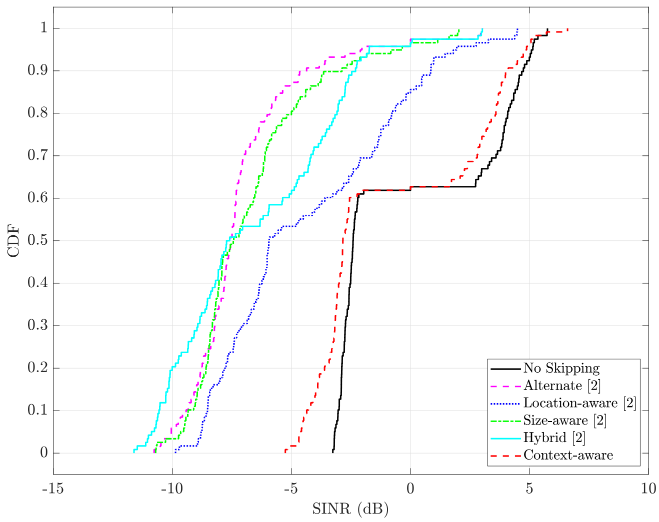


Figure 5.7: CDF of SINR for different HO skipping techniques.

around 34% when compared to the no skipping case. Next, the location-aware approach is the one that performs best in terms of throughput when compared to other conventional skipping schemes, with a throughput degradation of only around 9% when compared to the no skipping case. However, this comes at a price, as the location-aware needs to connect to more cells, thus reducing the HO costs by only around 28%. The other approaches, such as size-aware and hybrid have very similar performance, in which they are able to significantly reduce the HO cost by around 44% and 47%, respectively, achieving a cost reduction similar to the one seen in the alternate scheme. However, their performance in terms of throughput is not as bad as the alternate, having a throughput degradation of around 16% and 15% for the size-aware and hybrid approaches, respectively. Lastly, the context-aware approach is the one that achieves the best average throughput among all other skipping techniques, being worse only than the no skipping base by only around 0.4% and with a HO cost similar to the one of the location-aware approach. These results really demonstrate the benefits of skipping techniques, as all of them are able to significantly reduce HO costs (by more than 1/4) with different levels of throughput reduction. In addition, when load and SINR information from users are taken into account, the benefits are even greater, as it can be seen from the proposed context-aware approach, which is able to reduce HO costs by around 27% with a minimal throughput reduction.

Lastly, Fig. 5.7 shows results in terms of the CDF of the average SINR of the users. This figure follows a similar pattern to the one from coverage probability, with the no skipping approach yielding the best results, as expected, followed closely by the proposed context-aware approach. In addition, when observing these two curves we can clearly see two regions where the SINR of users was concentrated: from -5 to -2dB and from around 0 to 7dB. This can be explained as in the proposed scenario, sometimes BSs would be overloaded, not being able to accommodate all users. As such, these regions show two groups of users, the ones that were able to connect to the best available BS, and another group of users, which had to connect to other BSs. Since in the context-aware approach some users are able to connect to the best available BS while others skip that BS, the SINR of the users are far greater than the ones from the other skipping methods. As previously explained, since the other methods have a hard threshold in terms of skipping and do not consider the load or the SINR information in their decision, all users are forced to skip their preferred BSs at some point, thus drastically reducing the users' SINR. In terms of the other methods, we can see that the performance of the location-aware is slightly better than the other schemes and that the performance of both size-aware and hybrid are very similar. Lastly, the alternate approach presents the worst results in terms of SINR. It is important to note that our framework has been assessed with multiple velocities and different time thresholds and performed some empirical experiments where we have chosen their values based on the best trade-off in terms of HO cost and user throughput.

5.5.3 Privacy Preserved Context-Aware Analysis

Table 5.3 shows a comparison in terms of HO cost, weighted average throughput (according to (5.9)) as well as the average SINR and delay at the last hop (LH) for all techniques (according to (5.10)). As expected, the no skipping technique performs the best in terms of throughput, since in this scheme no BSs are skipped. However, this comes at a price of the highest HO cost. On the other hand, the hybrid technique [48] has the lowest HO cost, followed closely by the proposed blockchain-enabled skipping. In terms of throughput, it can also be seen that the proposed framework achieves a slightly higher throughput, as by considering the historic information from users (in and out stations) as well as the train's path, better results can be achieved. In addition, since users require to be connected whenever they leave a station, as users are more prone to making calls, or utilizing their data, it is also important to measure the quality of the signal at the last hop (LH). Based on Table 5.4 we can see that the proposed technique achieves similar levels of average SINR and delay as the no skipping case. By utilizing the historical information from the users, we can determine which BS the user should connect to when leaving the train, greatly improving the quality of its signal when comparing to the hybrid case. In addition, since the hybrid technique does not

Table 5.3: Average HO Cost, and throughput comparison

-	HO Cost	Avg TP (Mbps)
No Skipping	0.231 (0%)	42.37 (0%)
Hybrid [48]	0.099 (57.14%)	40.62 (4.13%)
Proposed	0.115 (50.21%)	41.61 (1.79%)

Table 5.4: Last hop metrics comparison

-	LH SINR (dB)	LH Delay (ns)
No Skipping	5.94dB = 3.92W (0%)	85 (0%)
Hybrid [48]	-33.6dB = 0.000437W (99.98%)	553 (-550.5%)
Proposed	5.79dB = 3.79W (3.31%)	85 (100%)

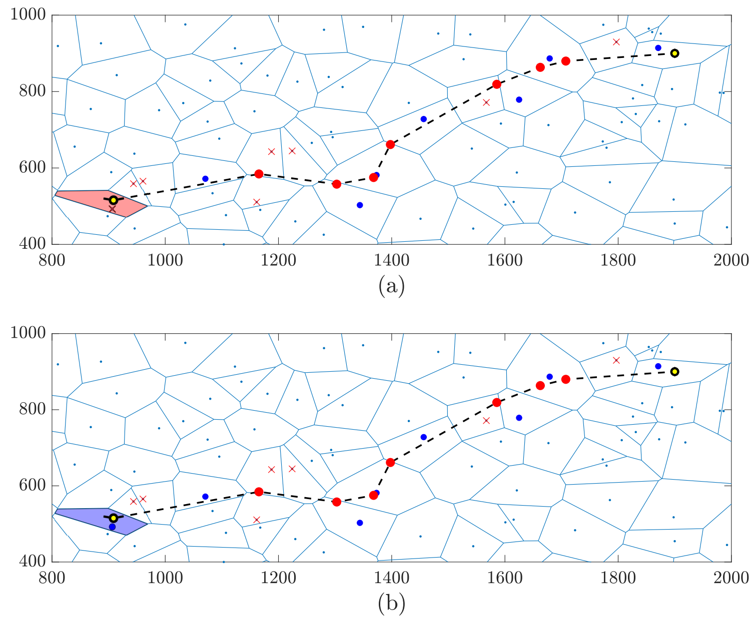


Figure 5.8: Simulated scenario shows the set of BSs skipped and connected for (a) the hybrid approach, and (b) the proposed approach.

have information about a user outbound station, it does not handover to the best possible cell, thus it achieves the lowest possible average SINR and the highest delay, albeit at the lowest HO cost.

Fig. 5.8 shows a comparison of the simulated scenario for the hybrid and proposed frameworks in (a) and (b), respectively. In this figure, the train path is represented by a dotted black line, with the starting and end stations represented by yellow circles, while intermediate stations are represented by red circles. BSs are represented by blue dots, while larger dots represent BSs that have been connected to and red crosses denote BSs that have been skipped. As we can

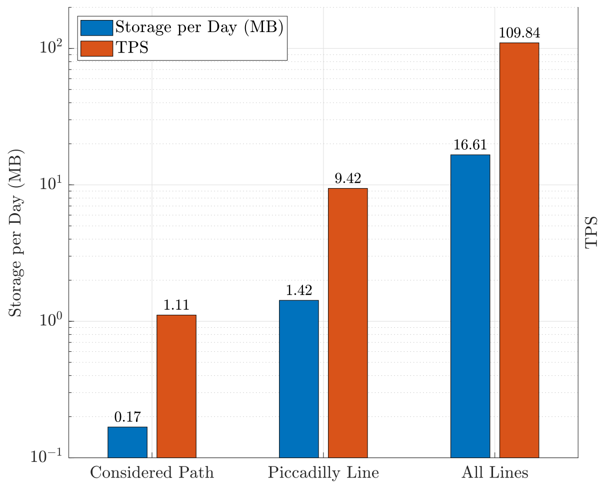


Figure 5.9: Estimated blockchain storage and transactions per second needed.

see, since the proposed approach builds upon the hybrid framework their mode of operation is quite similar, with the proposed approach being able to connect to the last hop BS (highlighted in blue color in Fig. 5.8), whereas the hybrid approach skips it (highlighted in red color in Fig. 5.8). As such, the proposed scheme is able to operate on top of any other HO skipping technique, and by leveraging this information from users, a better connection can be achieved, as seen by the other results.

Lastly, Fig. 5.9 shows key blockchain performance metrics in terms of storage needed per day and TPS. By considering the average number of passengers over a week for the pre-defined path, the Piccadilly line and the whole LUO network, we can see that both the storage needed at the blockchain and the number of TPS increases linearly with the number of users. In terms of blockchain storage, it can be seen that for the whole LUO network only 17 MB per day would be needed (around 6 GB per year), which is reasonable for today's standards. Whereas in terms of TPS, in the worst case scenario, a total of around 110 TPS would be necessary. Since traditional proof-of-stake based blockchain are able to achieve more than 100 TPS, neither the number of transactions nor storage should be a bottleneck in the system.

5.6 Summary

This chapter discussed a concept of NEWS framework that exploits an intelligent HO skipping scheme, context-aware HO skipping. The proposed technique allows train passengers to dynamically skip HOs by considering challenging and complex LUO train network dynamics over-burden traditional HO schemes to drive smooth and seamless HOs. To this end, NEWS framework first analyzes mobility prediction and future passenger directions for maximizing futuristic optimisation by using ML. Secondly, through ML classification results, PPP-based HO skipping model is trained and simulated, where topology-aware multiple HO skipping schemes for effective HO management are simulated. HO schemes take passenger location, cell-size, velocities, path, travel direction, and cell-loads into account to make HO decisions, for the avoidance of unnecessary HOs along the passengers trajectory. Context-aware HO skipping technique outperformed among all traditionally equipped HO schemes in terms of coverage probability, average throughput, and HO costs when assessed and simulated. In addition, context-aware HO skipping is analysed by blockchain-enabled privacy preservation that provides a secure platform for train passengers mobility predictions and future directions. The HO schemes take passenger locations, cell-sizes, velocities, and travelling paths into account to make HO decisions using blockchain approach, applying maximum privacy while observing passengers trajectory. Privacy preserved context-aware HO skipping scheme outperforms among traditionally equipped Hybrid HO scheme in terms of average throughput over the passenger velocity while significantly reducing the HO costs, and providing better last-hop signal quality and less transmission delay. For future works, intelligent schemes can be modelled/designed in such a way that they may consider passengers' smarter HO skipping in a multi-tier network for different train velocities.

Chapter 6

Conclusions, Future Trends and Open Issues

In this section, conclusions and future trends of the thesis are mentioned, where conclusions are drawn for each use-case investigated. Future trends, cover number of use-cases in the field of mobility management and NGRS which have become popular due to the technological advancements in the recent years.

6.1 Conclusion

In order to assess, observe, and providing state-of-the-art in mobility management, future networks need a shift from existing deployments to AI-driven solutions more specifically, ML algorithms. This will in turn, shifts the way of approaching the network paradigms and archetypes. As the capacity is keep on growing, thousands of parameters will need to be configured and managed for parametric optimisation not only from humans, but also from machines forming a HetNet environment. With the fact of increasing demands, manual handling is nearly impossible to deal with this amount of tasks, data, and users mobility operations. Thus, ML solutions are required to play a vital role in learning models in a relative short amount of time ensuring an autonomous and intelligent environment. In this context, ML-driven users mobility is considered to be highly suitable for future mobile and train networks because of their intelligence in learning complex and real time environment with their interactive nature. Furthermore, ML algorithms with their ability inherited to learn directly from raw data that drives several complex patterns and play an important role in next generation mobile and train networks. This can be done by enabling autonomous designs with a higher level of interactions in dynamic environments.

Based on this, this thesis covers some applications of ML algorithms providing mobility prediction use-cases. First, a literature review covering the areas of ML enabling users mobility using SON were presented supported by self-configuration, self-optimisation and self-healing. In the context of mobility driven-optimisation, the focus remained on the analysis of AI-driven techniques to exploit mobile and train network to self-optimise by using different ML techniques and use-cases were presented. After that, the use-cases of mobility management in dense mobile networks involving the smart cities, energy efficiency, encryption, optimisation, and mobility profiling were investigated. Future mobile networks will observe backhaul problems due to the network bottleneck. This would require breathing space by establishing cells association procedures through network intelligence. This is where ML-driven solutions come into place and are proposed to, first proactively support traditional mobility prediction based optimisation, and then, optimize SC parameters according to the network intelligence and requirements. Within that, a distributed solution based on Q-Learning was also proposed and compared to three other schemes for energy efficiency coupled with CO_2 emissions reduction and mobility optimisation. For all mobility scenarios discussed, results have shown that our proposed approaches outperforms highlighting the optimisation for both mobile and train networks. This eventually enhances performance of smart cities, energy efficiency, encryption, etc, leading to better throughput, latency and reliability. However, it is difficult to maintain or keep the cost lower when finding optimal results. Thus, as the results have indicated, the proposed solution, mobility management in dense mobile networks, is flexible enough to maintain a balanced trade-off between these metrics, as well as to adapt to changes in the network, while still converging promptly.

After that, this thesis investigates the use-cases of mobility management in next generation networks to discuss existing and future mobile and train network trends. In the context of mobility management in next generation networks, intelligent context-aware scenario was presented by using PPP, in which multiple HO skipping techniques were exploited and compared to benchmark coverage probability, throughput, HO cost, etc. Furthermore, blockchain-enabled HO skipping for high mobility train passengers were discussed in order to provide blockchain-enabled secure platform for a better trade-off in terms of network HO cost, user QoS, and last-hop signal quality. Results have shown that given enough time the BSs in underground and overground train network ere capable of learning user mobility and tracking users that were not associated to any BS through intelligence of load-awareness, thus, adapting to daily/new mobility requirements. Furthermore, when comparing the the proposed approach to the other schemes, the PPP-driven context-aware proposed solution achieved a better performance in terms of all considered metrics, mainly: coverage probability, user throughput satisfaction, a trade-off and balance on HO skipping cost, as well as better network resource utilisation (in terms of the backhaul).

Lastly, the integration of PMNs with edge intelligence was presented as a future trend and development in realizing the next generation of industry applications. In this context, IPN within the scope of transportation industry that can unlock several use-cases and critical applications were discussed. Due to the importance of the IPN, it is vital to understand the perspective of intelligence with three main angles, such as, user-centric edge intelligence, network-centric edge intelligence, and application-centric edge intelligence.

6.2 Future Trends In Mobility Management

The integration of Private Mobile Networks (PMN) with edge intelligence is expected to play an instrumental role in realizing the next generation of industry applications. This combination collectively termed as IPN deployed within the scope of specific industries such as transport systems can unlock several use-cases and critical applications that in turn can address rising business demands. This article presents a conceptual IPN that hosts intelligence at the network edge employing emerging technologies that satisfy a number of Next Generation Railway System (NGRS) applications. NGRS use-cases along with their applications and respective B5G enabling technologies have been discussed along with possible future research and development directions that will allow these promising technologies to be used and implemented widely.

In order for the current mobility setup to integrate with the future trends, it is envisaged to implement optimisation metrics such as, incorporation of underground specific tap-in tap-out individual offsets, energy efficiency coupled with carbon emissions, edge intelligence-driven mobility and connectivity, SON-driven mobility, etc. Furthermore, user-specific behaviours to maintain QoS requirements, would be able to provide reliable encryption and cellular cell constraints to effectively serve traffic flow in complex LUO environment.

Therefore, IPN for the NGRS and outlining the enabling technologies is a vast area to have research on. NGRS framework and its use-cases, under 5G and B5G networks, will be the key enabler in the scope of intelligent mobility.

6.2.1 Edge Intelligence in Mobile Networks

The exponential increase in computing resources and substantial improvements in AI algorithms over the past decade has paved the way for intelligence to be integrated into the day to day operations of mobile networks. Several studies [124, 244, 258, 295, 296] have presented the use of AI-based frameworks to enable the imminent and future demands of ever-expanding mobile networks. For instance, in [295], AI-based applications and services and their challenges in a comprehensive overview have been provided. It also highlights, AI services and their mechanism as to how they are being applied to the network edge near the data sources, and demonstrates how AI and edge computing can be mutually beneficial. To do so, it introduces and discusses: edge intelligence and intelligent edge; and their implementation methods and enabling technologies, namely AI training and inference in the customized edge computing framework. In [244], the standardisation of 5G cellular networks is being expedited to provide insight into the candidate techniques as a whole and examine the design philosophy behind them. It highlights one of the most fundamental features among the revolutionary techniques in the 5G era, i.e., there emerges initial intelligence in nearly every important aspect of cellular networks, including radio resource management, mobility management, service provisioning management, and so on. In [258], several IoT and 5G sensors networks in railway communication have been exploited along with the previous industry challenges and their forthcoming resolutions. In [124], a summary of self-healing block in self-organizing 5G networks that present a framework for autonomous outage detection and coverage optimisation in an LTE have been presented. In [296], presented a split in the 5G network into several 100-cell regions each monitored by an edge server; and propose a framework that preprocesses raw call detail records having user activities to create an image-like volume, fed to a ML model. In [297], the application of tactile Internet in healthcare by considering the diabetic ketoacidosis (DKA) as a 5G use case to monitor life-threatening complication of diabetes mellitus by using the C-Band sensing technique. Reducing the computational distribution and load in a dense deployment will require edge intelligence. With edge intelligence and dense deployment of base stations, the applications will be numerous. To explain the intelligence presented in future IPN for NGRS, we classify these operations into user-centric, network-centric, and application-centric edge intelligence. Although these will operate hand in hand in utter harmony, it is important to understand the perspective of intelligence from these different angles.

User-Centric Edge Intelligence

The QoS of any network is a key metric in evaluating its performance as it correlates to the users' level of satisfaction. In a similar pursuit, added intelligence in the network make them more user-centric by including users' experience in the feedback loop. B5G networks will be able to assess the users' demands by running various distributed federated learning algorithms at the edge of the network. With the inference capability derived from federated learning in hand, the edge nodes performing user sentiment analysis, can subsequently inform the network of required changes [298].

Network-Centric Edge Intelligence

The efficient utilization of network resources can make the network more sustainable in terms of lower operational and capital expenditure (OPEX/CAPEX). With that in mind, self-organizing and self-optimizing algorithms deployed at the network edge can enable timely inference and quick decisions for effective radio resource management, user mobility management, network orchestration, and service provisioning.

Application-Centric Edge Intelligence

In B5G networks, several applications are expected to be hosted at the edge of the network. This will require virtualization of application containers and related computational resources at the base station. Since applications have varying demands, the application intelligence employed along with the deployment strategy will vary from case to case, for example, AI algorithms used in train automation will have a different deployment strategy compared to AI campaigns that elevate passenger travel experience.

A number of mobility management use-cases, as well as highlighting their applications, enabling technologies, and potential research challenges can be found in Appendix A.

6.3 Future Trends in SON-driven Mobility

It is vibrant that current network limitations to be resolved by using 5G and B5G for new paradigms to work. Therefore, a shift is needed to accept different solutions to common problems. However, despite current work being done in the area of SON-driven mobility, the increase in the robustness of different ML algorithms, there will be more open issues and challenges to be resolved. This will in turn, enable a fully intelligent network in the near future with less human intervention. As such, in the next paragraphs a brief overview of future trends and open issues in the context of ML applied in SON is presented.

6.3.1 ML in SONs

More intelligence needs to be added to mobile networks for emerging SONs and mobility management. With the existing data collection and careful network monitoring, ML algorithms have an unimaginable potential to integrate intelligence into future mobile networks by enabling applications and services. For this fact, many new ML concepts and solutions have must be explored in the realm of users mobility to drive SONs. As the amount of data collected and generated by future networks are going to be enormous, providing virtually an infinite dataset for algorithms to train. ML algorithms have a great opportunity to excel in the field of railway networks, blockchain technology-based passengers movements, synchronisation of backhaul networks into passenger mobility, passengers HO management by intelligent decision protocol, etc. Below, a brief overview on how supervised, unsupervised learning, and deep learning can play an essential role in the mobility management of future networks is presented.

Supervised Learning: Due to the natural characteristic of supervised learning being driven by learning based on the output feedback, their limitations need a focus to resolve. The limitation is due to the difficulty in generating labelled data for certain network use-cases. Their model to be trained in such a way that information both from input and output data make predictions about the future networks in an improved manner. For instance, MNOs may not have the information of complete network status or a failure that may have happened due to some reason and where, etc, in case of self-healing. There could be another case where, labelled data is available and real-time information is not necessary. Future applications for supervised learning are envisioned in the area of mobility management, and mobility-driven applications such as self-healing (in terms of fault detection and classification), energy savings, resource allocation, privacy-mechanism, user patterns in the challenging environment, etc.

Deep Learning: Deep learning a powerful algorithms strategy in the recent times that is able to improve state-of-the-art solutions, for example, in object detection, speech recognition, and genomics [50]. In the context of mobile networks and mobility predictions, deep learning has seen an increased attention in recent years, more notably in its application at the physical layer [299], security [300], mm-Wave communications [301], and resource allocation [11]. As such, due to its ability to learn features directly from raw input data and its performance above human level, deep learning is expected to play an important role in future mobile networks and to solve an even larger number of applications and use-cases.

Unsupervised Learning: Unsupervised learning on the other hand needs improvement in order to deal with unlabelled data very well. As such, grouping or clustering applications of unsupervised learning algorithms, such as in fault management [302, 303] or resource optimisation [195, 201], needs a better shift. However, like supervised learning, unsupervised techniques still to be further developed in different network scenarios, such as, massive MIMO, UDN, 5G Radio, cMTC, etc

6.3.2 RL in SON

Besides ML-techniques, RL plays/will play a vital role in future mobile networks in order to support mobility prediction and applications. RL being a goal-oriented approach algorithm which interacts with the environment to generate samples from it and learn from previous conditions. RL algorithms are capable of online learning without any human intervention. As such, they are best fit to solve dynamic problems in a LUO environment, HetNet environment, and other complex changing environments, such as mobile networks in underground ecology, specially in the use-cases of self-optimisation and self-healing. However, despite RL being extensively used and preferred algorithm [61], it still needs improvement to deal with a great number of applications in mobile networks. Alongside, it is envisioned that, mobility management of users in future mobile networks is crucial and to be solved by RL optimisation approaches due to their innate ability to learn online and by constant interaction with the environment. As such, RL solutions, specially those based on value function approximation and deep RL, are expected to see an increased number of applications in future mobile networks.

Appendix A

Summary of NGRS Use-Cases and Applications

Table A.1: Summary of NGRS Use-Cases and Applications

Use-Cases	**Applications**	**Enabling Technologies**	**Research Challenges**
Intelligent Train to Train (IT2T) Communication	Train signalling, train to train communication, etc.	5G NR, mmWave, URLLC	High bandwidth and low latency.
Contact-Tracing System (CTS)	Passengers who tested positive against the COVID-19 are tracked by using 5G network/enabled devices.	5G UWB monitoring short range devices.	Data security and privacy, and low power communication.
Intelligent Drones System (IDS)	Overcrowding stations monitoring.	5G Drones	Real-time low latency communication and high resolution image processing.
Transport Hub Crowd Management (THCM)	Positioning, resource allocation and management.	RTLS, IPS, cMTC, ICCTV, and 5G cellular and 5G private network.	Diverse bandwidth and low latency.
Disaster Scenario Response (DSR)	Remote monitor, detect and provide suggestions for onsite incidents team equipped with visualisation cameras.	5G Intelligent Extended Reality (IXR) portable devices with HD cameras.	High bandwidth, latency and reliability.
Intelligent Monitoring Services (IMS)	Underground tunnels gas and water metering, pressurised fuel and smoke alarms detection, fire alarms monitoring, etc.	Sensor based cMTC, gadget monitoring application and LPWAN technology such as NB-IoT. Laser-based 5G technology to monitor toxic gases.	Longer battery life and low latency for critical alarms.
Intelligent Wireless Audio (IWA)	Emergency departments such as police, detectives, special forces, and Accident and Emergency (A&E).	5G handsets with URLLC connectivity.	Low latency and reliability.
Emergency Services (ES)	Ambulance, fire-fighters, first-aid staff, mission-critical fault detection teams, paramedic services etc.	5G handsets with MCPTT	Diverse bandwidth, low latency and reliability.
Intelligent Depots 4.0 (ID 4.0)	Depot services	Sensor based cMTC, gadget monitoring application, CAI and LPWAN technology such as NB-IoT.	Diverse bandwidth and wireless automation.

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