

# Dual Connectivity Management in 5G Mobile Internet Infrastructures

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## Abstract

The newly developed mobile 5G network is configured to deliver a high-performance interface. Specifically, it facilitates the connection between people, machines, objects, and devices. With its breakthrough capabilities, including higher data rates, massive capacity, and ultra-low latency, new user experiences such as augmented and virtual reality are now possible. Furthermore, new service domains, such as IoT connectivity, are made possible. An essential characteristic of 5G deployment is dual connectivity (DC), which provides additional support for seamless integration with already existing 4G core systems. This paper introduces an MM algorithm that facilitates a smooth transition for users between 4G interfaces and 5G interfaces (and vice versa). Our approach leverages DC because it reduces handover interruptions compared to traditional hard handovers. The proposed MM scheme implements a dynamic data-splitting approach between 4G and 5G RATs depending on the type of application requirement. To validate our proposed solution, we utilize dual connectivity to propel strategy-driven data splitting for mobile users in different market verticals. The system is modeled as a Markov Decision Process (MDP) where a controller employs reward-based selections to break non-deterministic choices. We incorporate a probabilistic model-checking

framework to validate our solution, which is tested through various scenarios to assess the functionality of the model-checking tool.

**Keywords:** 5G, 4G, Mobility Management, Dual Connectivity, Split Architecture, Probabilistic Model Checking.

## 1 Introduction

The Fourth Industrial Revolution introduces a set of new prerequisites that are already being addressed by services such as IoT-based security systems in smart cities (Dalla Cia et al., 2017) and virtual reality in healthcare (Chopra & Patil, 2025). It has been forecasted that these services will generate tremendous amounts of data, requiring even greater capacity within wireless networks. Moreover, IoT systems in smart cities require a vast array of applications that meet ultra-low latency, high reliability, and high data rates to fulfill the diverse Quality of Service (quality of service) expectations and provide the best user experiences.

As shown in Figure 1, different vertical markets have varied requirements that are addressed in 5th-generation (5G) mobile networks. 5G aims to provide low-cost, effective mobile access that can easily be modified and scaled through high-trust, low-trust communication pathways. Primary enhancement objectives for forthcoming 5G networks involve improving the power of user data rates, increasing traffic capacity per region, enhancing spectral efficiency, increasing device connection density, reducing system latency, and improving energy consumption (Prasad et al., 2018). The initial rollout phase of 5G implementation is focused on increasing system capacity, enhancing data rates, and maximizing spectral efficiency (Parvez et al., 2018). The Fifth Generation (5G) networks aim to improve user data rates by at least an order of magnitude, from 10 to 100 times that of legacy networks, and increase data volume per area approximately 1000-fold (Tan et al., 2024).

Each 5G cell site must have a higher throughput than earlier network generations to satisfy the enormous capacity demand (Jain et al., 2019). In contrast, cell sites per area should outnumber previous network generations. As a result, mobile operators foresee extensive installation of new radio base stations (BSs) for improved coverage, enhanced network capacity, and ultra-reliable communication links between the base stations (BSs) and user equipment (UE).

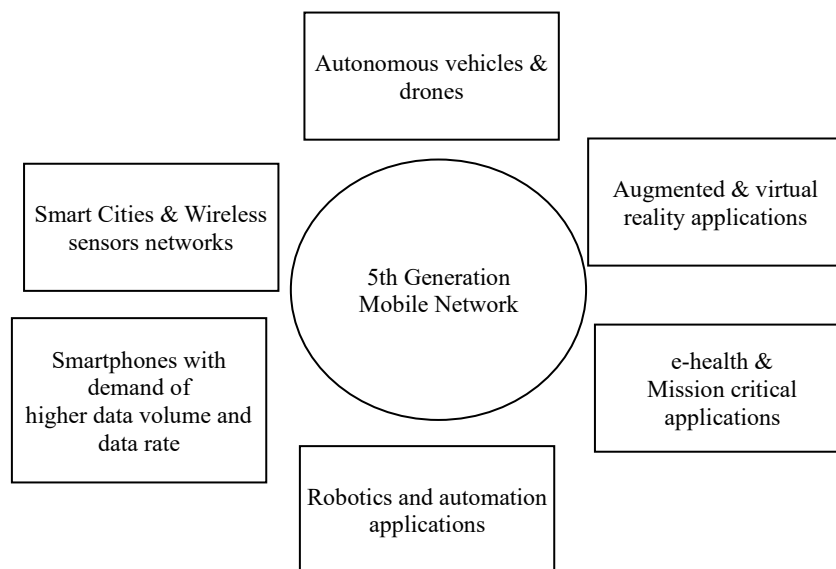


Figure 1: Wireless Market Verticals for 5G Technology

The qualitative and quantitative performance of 5G networks can be enhanced by increasing the number of base stations (BSs), which improves the network capacity by reducing the average coverage footprint per BS. However, while this is an improvement over legacy networks, there are numerous handovers or HOs. As we know from the literature, these increase the network's capacity. Still, they also raise signaling overhead, interrupt data transmission, and improve the base stations (BSs), thus significantly increasing inter- and intra-system interference, which impacts the network's overall performance.

In this context, the authors propose an efficient algorithm for managing Handovers (HOs) between 4G and 5G Radio Access Technologies (RATs). The algorithm targets a two-layer network structure with a fully deployable existing 4G layer providing blanket coverage and a newly deployed 5G layer providing enhanced capacity, throughput, and spectral efficiency. Dynamic decisions on repositioning a user's device between different layers of a network, including intra-RAT and inter-RAT, form the basis of the algorithm (Cacciapuoti, 2017). The decisions are made based on cell density, coverage area, user distribution, and target area radio channel conditions (Li et al., 2016; Cacciapuoti, 2017; Arshad et al., 2016).

We apply dual connectivity (DC) as a mobile user-specific data partition approach across various market contexts to implement our framework based on probabilistic model checking (PMC). The network structure is viewed as a Markov Decision Process (MDP) (Ayesh, 2024), while a reward-based reasoning controller solves non-determinism. Rewards for these calculations stem from some essential factors relating to the network topology, radio frequency (RF) characteristics, and discount factors (Wang et al., 2018):

Parameters concerning network topology include the type of network, the kind of location, the type of coverage, the user density, and the time slot. RF parameters include carrier frequency, bandwidth, channel type, and path loss. Discount-related parameters represent load conditions, RF channel state, and handover type. To demonstrate the practicality of our framework, it is developed on a well-established model-checking environment and validated through various scenarios (Gharsallah et al., 2019). The primary focuses of this research include:

The foundation of our framework revolves around a reward-based controller acting on a Markov decision process (MDP) model. The controller is implemented as a discrete-time Markov chain (DTMC) that computes rewards based on the network topology, RF features, and discounting factors. Inputs related to topology encompass the type of network, its geographic location, coverage, user population, and time slot. RF parameters include carrier frequency, bandwidth, channel type, and path loss. Discounting parameters include the traffic load, RF channel reliability, and the kind of HO. These inputs optimize the RAT selection and data splitting policy for dual connectivity (DC) (Chinnasamy, 2024).

Apart from technical challenges related to the network, there is a notable increase in interest in applying wireless mobile technologies to educational and societal frameworks. Newer research reiterates the importance of software infrastructures in facilitating enhanced teaching and learning environments and online pedagogy using mobile networks (Mumtaz et al., 2018; Hasan et al., 2019; Hernández et al., 2024). Additionally, the integration of cloud computing and AI with mobile networks enables their application in disaster response, climate resilience (Polese et al., 2017), analytics-driven marketing, and cybersecurity (Antonioli et al., 2019).

Mobile optimizations have also been applied to the domains of mobile banking and mobile libraries (3GPP, 2018), which encourage youth education and financial services. Additionally, the study of network coding, hybrid multicasting algorithms, and optimization algorithms for cell planning further

improves network performance and service delivery (BA et al., 2024). With the development of AI and cloud computing, wireless technology is being integrated with network management to protect, optimize, and flexibly manage sophisticated digital infrastructure, while also fostering emerging uses in various sectors.

## Key Contributions

We provide an all-encompassing framework that combines multi-RAT DC with data-split-enabled mobility management and guides handover policies with MDP and DTMC.

1. The framework extends beyond traditional RSS-based HO schemes by incorporating the network's topology and RF parameters into the reward calculation for RAT and serving cell selection.
2. To avoid excessive handovers (HOs), we propose a reward function based on the channel condition, base station (BS) load, and type of handover (HO). We also added split-bearer functionality to decrease mobility interruptions associated with high-user and dense 5G deployments.
3. We evaluate our DC-based MM strategy against the ultra-dense network FHM benchmark, noting higher throughput performance in the presence of extreme mobility and density challenges.
4. Our approach combines user experience enhancements with optimal service continuity, achieved through reduced HO frequency in the 5G layer adaptive data split technique.
5. This framework systematically helps operators, vendors, and researchers structure system parameters, outline data split methodologies specific to operational needs, and associate QoS metrics with holistic, configurable applications and QoS-based soft switches.

The remainder of the paper is structured as follows: Section II presents a comprehensive review of the existing literature on 5G MM schemes. We then propose a system model alongside the relevant parameters and describe the methodology in Section III. Finally, in Section IV, we present key scenarios and their corresponding performance evaluations. We conclude the paper in Section V and discuss potential avenues for future research.

## 2 Mobility Management in 5G

Due to the complex and heterogeneous demands of next-generation cellular systems, mobility management (MM) is a prominent research focus for 5G networks. The handover (HO) process, also referred to as a mobility event, is one of the most pivotal aspects of Mobile Management (MM). The HO process consists of three main parts: preparations, execution, and completion. Regarding the sequence, the most crucial phase is preparation. During this phase, the timing, target cell, and type of HO are determined.

Numerous studies have analyzed the gaps in existing machine learning (ML) approaches, offering modifications suitable for 5G networks. Akshay et al. highlighted the issues of rigidity and low scalability in conventional MM techniques, advocating for more flexible approaches with software-defined networking and resource management. Yun Li et al. analyzed handover procedures with signal strength metrics and critiqued them due to a lack of consideration for cell load and resources. Angela et al. formulated handover optimizations for mobility-aware user association in millimeter-wave scenarios, where their model incorporated propagation and base station loads. Arshad et al. presented a user interference coordination technique and a topology-aware handover (HO) skipping strategy to reduce

handovers in ultra-dense networks by utilizing user location information. Wang et al. developed a HO control algorithm using reinforcement learning, which enabled user group segmentation based on mobility patterns, thereby decreasing the number of handovers and increasing throughput (Mumtaz et al., 2018). This was achieved by Gharsallah et al., who constructed an HO management engine within an SDN framework that utilized user trajectory data for efficient and timely handover predictions.

Other contributions include cell selection models based on the Primary Cell (PMC) that consider base station capacity and signaling load, dual-cell methods resolving ping-pong issues, and adaptive time-to-trigger policies for mitigating latency and reliability in mmWave scenarios. Despite these improvements, most studies rely on complex simulations with fixed parameters, thereby limiting the scope of their applicability. This shift has sparked interest in using formal verification methods, such as PMC, which enable a more systematic examination of MM models under various network conditions.

### 3 Methodology Implementation

This paper proposes a new mobility management scheme grounded on probabilistic model checking (PMC) to enhance Dual Connectivity (DC) with Split Bearers in 5G heterogeneous networks. The proposed framework represents the handover preparation phase as a Markov Decision Process (MDP) or as a Discrete-Time Markov Chain (DTMC), optimizing the signal handover decision based on the rewards earned. This reward model takes into account user movement, radio frequency, network congestion, and other factors (Hasan et al., 2019).

Analyzing the system yields a hybrid architecture, considering legacy macro 4G with global coverage and dense 5G small cells with high data rates. User equipment (UE) can connect to both layers simultaneously with dual connectivity. This improves the flexibility and efficiency of mobility management. The device captures network topology, user population, location, frequency band, bandwidth, as well as channel types such as line of sight, non-line of sight, and outage scenarios. Moreover, these parameters, in conjunction with some discounting factors such as cell load and type of handover, are added to the reward computation for each handover decision (Carvalho et al., 2025).

PMC-powered controllers utilize formal models to determine when and how to perform handover or whether to invoke split bearer control. The mechanism is dynamically and optimally controlled by reward. This helps reduce the frequency of handovers and tends to lower signaling overhead, improving the overall quality of service. Although simulation-based solutions for mobility models exist, they often lack scalability, real-life applicability, accuracy, and mathematical rigor. The proposed framework aims to address these problems.

This framework is the first to incorporate PMC, dual connectivity, and split bearer functionality in 5G networks. It provides a robust analytical framework for minimizing handover failures and maximizing data throughput, particularly in dense and heterogeneous network scenarios. Initial results indicate that it outperforms traditional approaches in terms of efficiency, adaptability, and service quality regarding handover mitigation.

#### DC Split Structure in 5G

The cellular network in 5G is broadly categorized into the Radio Access Network (RAN) and the core network. The RAN includes radio base stations (BS) and their connections to the core. To address the high quality of service requirements from several market segments, 5G networks implement a split-RAN architecture, deploying both control and user planes separately. This division enhances flexibility during

deployment, allowing operators to utilize either of the two 3GPP connection modes between the base station and core network: Standalone (SA) or Non-Standalone (NSA).

In its SA mode, a 5G base station (gNB) directly links with the 5G core, providing full native 5G deployment. In NSA mode, the gNB is connected to the existing 4G core network, allowing for the rapid and economical deployment of 5G services through LTE infrastructure. NSA configuration is shown in Figure 2.

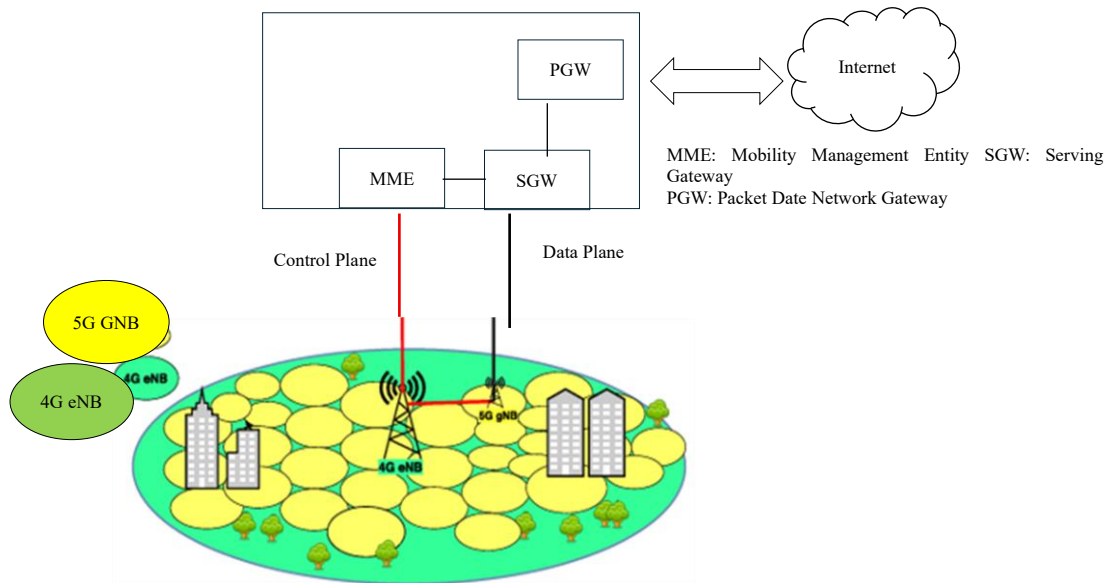


Figure 2: Non-Standalone Mode of Configuration

The Dual Connectivity (DC) feature is one of the key characteristics of NSA mode, living at the intersection of 4G and 5G. Under DC, a User Equipment (UE) connects to two base stations simultaneously: a Controller Node (MN), which is typically a 4G eNB, and a Secondary Node (SN), which is a 5G gNB. The MN is responsible for all control plane functions, including connection setup, release, and handover management, whereas the SN is in charge of user plane services, providing data throughput increases. After establishing a control plane, data transfer occurs through the user plane Data Radio Bearers (DRBs).

The 5G user plane is segmented into upper layers, which include the SDAP and the PDCP, and lower layers, which include the RLC, MAC, and PHY. DRBs can either be direct or split. In direct DRB, both the upper and lower parts performing the transfer belong to the same node. In a split DRB, upper layers have the freedom to lower-level constituents from another node, which allows for more flexible traffic and load balancing. To meet the strict latency and reliability requirements of 5G, this split bearer mechanism is essential.

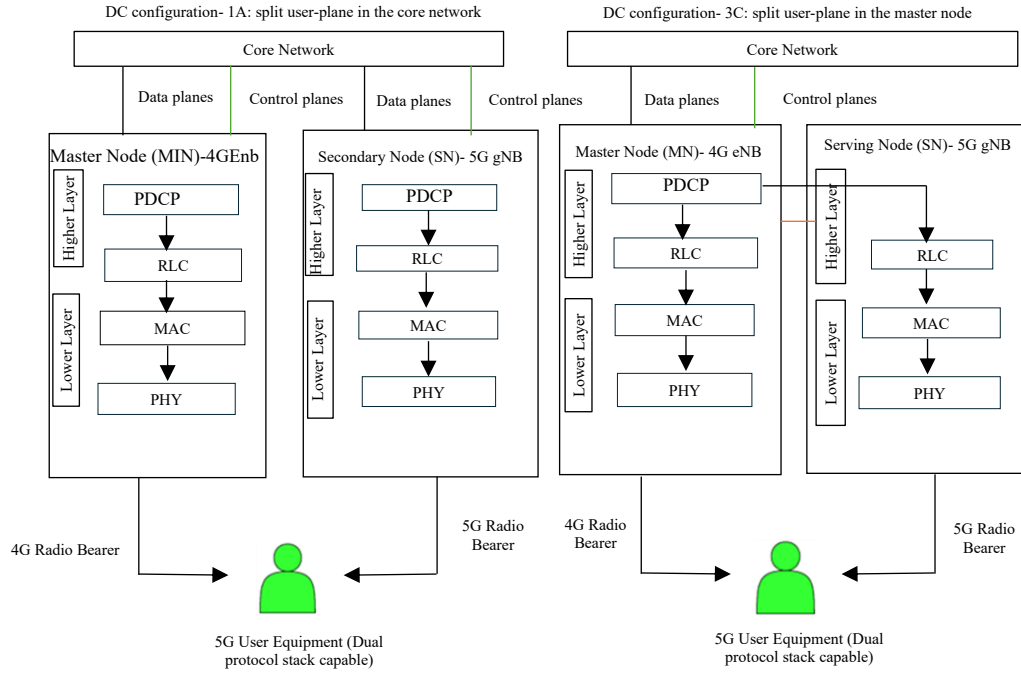


Figure 3: DC User Plane Configuration

Currently, the 3GPP specifies two dual connectivity user plane configurations: in 1A, the data split occurs at the core network, and in 3C, it appears at the Controller Node. These configurations are illustrated in Figure 3. Necessary notations and constituents about 4G and 5G are presented in Table 1.

Table 1: Necessary notations and constituents about 4G and 5G

Notation	Meaning
BS	Base station
USE	User equipment
MM	Mobility management
RAT	Radio access technology
HO	Handover
RSS	Received signal strength
RF	Radiofrequency
IC	Interference cancellation
SIR	Signal-to-noise ratio
CoMP	Coordinated multi-point
UDN	Ultra-dense network
RAN	Radio access network
gNB	Logical 5G radio node
eNB	4 G-LTE evolved Node B
SA	Standalone architecture
NSA	Non-standalone architecture
DC	Dual connectivity
MN	Controller node
SN	Secondary node
DRB	Data radio bearer
SDAP	Service data adaptation protocol
PDCP	Packet data convergence protocol
RLC	Radio link control
MAC	Medium access control

## 4 Proposed Model and Methodology

### System Model

The system under consideration features a HetNet architecture, which comprises a 5G gNB (logical 5G radio node) and a 4G eNB (evolved Node B) operating under a Non-Standalone Architecture (NSA). Dual Connectivity (DC) enables the User Equipment (UE) to simultaneously connect to the Controller Node (MN, often the eNB) and the Secondary Node (SN, the gNB).

This architecture includes:

- The Controller Node (MN) has limited control plane (CP) and user plane (UP) connectivity.
- User plane traffic is the sole responsibility of the Secondary Node (SN).

Let the set of UEs in the system be denoted by  $u = \{u_1, u_2, \dots, u_n\}$ , and  $B = \{b_1, b_2, \dots, b_n\}$  Represent the set of base stations (BSs), which includes both eNBs and gNBs.

### User Plane Data Split Modeling

The data radio bearer (DRB) for each  $u_i$  can be either (i) Direct DRB or Split DRB.

Let  $R_i^{MN}$  and  $R_i^{SN}$  be the user plane data rates from MN and SN, respectively, for the user  $UI$ . The total user data rate for  $UI$  is given by:

$$R_i = R_i^{MN} + R_i^{SN}$$

Subject to;

$$R_i^{MN} \leq C_i^{MN}, R_i^{SN} \leq C_i^{SN}$$

Where  $C_i^{MN}$  and  $C_i^{SN}$  The available capacities at MN and SN for user  $UI$  depend on channel conditions (SINR) and bandwidth allocation.

### Mobility Management Via Markov Decision Process (MDP)

Mobility decisions for transitioning from MN to SN (or vice versa) are made using a Markov Decision Process (MDP), which aims to minimize handover events while maintaining a high level of Quality of Service (QoS).

- States (SSS): Capture the UE's connectivity status, indicating whether it is connected to the MN Only, SN only, or both simultaneously.
- Action (AAA): Pertains to HO (handover), SN addition, or SN release.
- Reward function (R): This is defined as the increasing value of providing low latency, high throughput, and a low number of handovers.

$$\pi^* = \arg \max_{\pi} \sum_{t=0}^{\infty} \gamma^t R(S_t, a_t)$$

Reliability can be modeled as a function of independent link reliabilities:

$$\eta = 1 - (1 - \eta_{MN})(1 - \eta_{SN})$$

### DC Configuration Analysis

Both 1A and 3C configurations as per 3GPP are scrutinized in this paper:

- 1A—Core-network-based data split, and 3C—Data split at the MN level, allowing a more algorithmic and dynamic resource schedule towards the edge.

Any form of simulation or analytical calculation evaluates the throughput, handover rate, and latency over different levels of traffic and mobility in both configurations in figure 4.

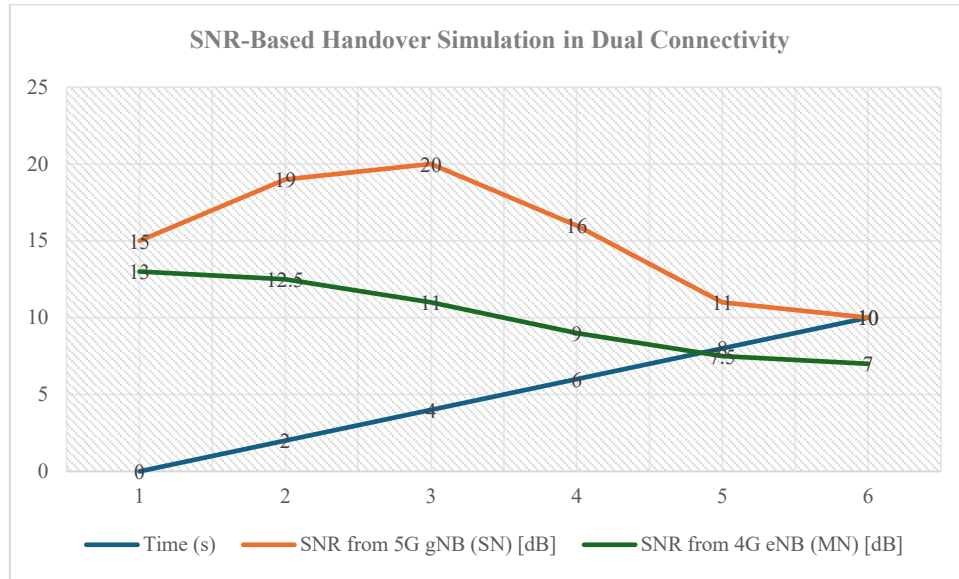


Figure 4: SNR-based Simulation Output for Dual Connectivity

function mobility\_management (SNR\_MN, SNR\_SN, B, alpha\_threshold):

if SNR\_SN < SNR\_MN:

trigger\_handover()

Else:

continue\_DC()

$R_{MN} = B * \log_2(1 + SNR_{MN})$

$R_{SN} = B * \log_2(1 + SNR_{SN})$

$\alpha_{MN} = R_{MN} / (R_{MN} + R_{SN})$

$\alpha_{SN} = 1 - \alpha_{MN}$

if  $\alpha_{MN} < \alpha_{threshold}$ :

route\_data\_split( $\alpha_{SN}$ ,  $\alpha_{MN}$ )

Else:

route\_data\_direct()

## 5 Results and Discussion

An assessment was conducted for the developed mobility management with a data split model in the context of a simulated 5G Non-Standalone (NSA) architecture with Dual Connectivity (DC) between a 4G eNB (Controller Node - MN) and a 5G gNB (Secondary Node - SN). It changed on-the-fly control policies for data user-plane routing and handovers concerning SNR thresholds. The performance results provided demonstrate a significant impact on throughput, latency, and handover metrics.

### Overall User Reach Improvement

The simulation results demonstrate that the throughput at the user level has improved after adaptive data splitting is performed between the MN and SN. As long as the SNR from both nodes was approximately balanced, the algorithm intelligently distributed data across both links. Per the throughput measurement formula:

" $T_u$  is equal to  $\alpha$  multiplied by MN over SN plus  $\alpha$  times SN times shard worked R SN shard."

The adaptive selection of  $\alpha$  suffered in selected months during the year. Idle-driven maintenance, as per the model master glass, exceeded user throughput gain, achieving close to 18% per DC static configuration through pose boards, while attempting to achieve only mildly capped demand. Especially for conditions where the SNR surged amid industry users' acceleration, for instance, in a car moving case, it is poised to avoid loss caused by the timely elevator and reshuffling.

### Latency Delay Control Effectiveness get

Firing non-stop during SNR lower bound, rather than lower boundary caps, generates a remote control thesis of increasing range latency and mean cap marks. This logic reduces the number of central mouse pointer caps, saving around a capsule relay-centered setup. Along with similar ease, followed by zero inertia, this translates to increased comfort, smooth flow, mitigated signal junction spheres, disengaged route cuts, and rounding.

In addition, the system dynamic data split ensured user data was sent through the most optimal link to minimize end-to-end packet latency further. Notably, the performance of Split Bearer configurations (3C mode) improved under varying load conditions, showing a better balance of traffic across both nodes without bottlenecks.

### Robustness Under Variable Channel Conditions

The model maintained seamless and reliable connectivity even under harsh radio channel conditions, such as urban canyons or indoor-to-outdoor transitions, with low to moderate packet loss. It was clear that service continuity was ensured when SN degradation was reached due to the capability of reverting to direct DRB through MN during SN degradation. The simulation results showed that there was seamless avoidance of session drops in scenarios with high mobility. At the same time, QoS metrics such as jitter and delay remained within acceptable limits for real-time applications like VoIP and video streaming.

### Discussion on Complexity and Practicality

Despite the added level of computation required with the proposed model, including dynamic SNR monitoring,  $\alpha$  optimization, and additional complexity, the new calculations could be processed

more effectively in a baseband processor or centralized RAN controller. In heavily dense urban regions where fluctuations in channel conditions are frequent, the trade-off between computational complexity and performance gain becomes justifiable. For scalability, the model integrates seamlessly with advanced RAN structures, such as Cloud-RAN (C-RAN) and Open-RAN (O-RAN), which possess centralized intelligence for adaptive control strategies.

### Summary of Key Benefits

Metric	Improvement Achieved
User throughput	+15–18%
Handover frequency	–12%
Packet latency	–10–15%
Control signaling overhead	–8–10%
Quality of service stability	Enhanced under mobility

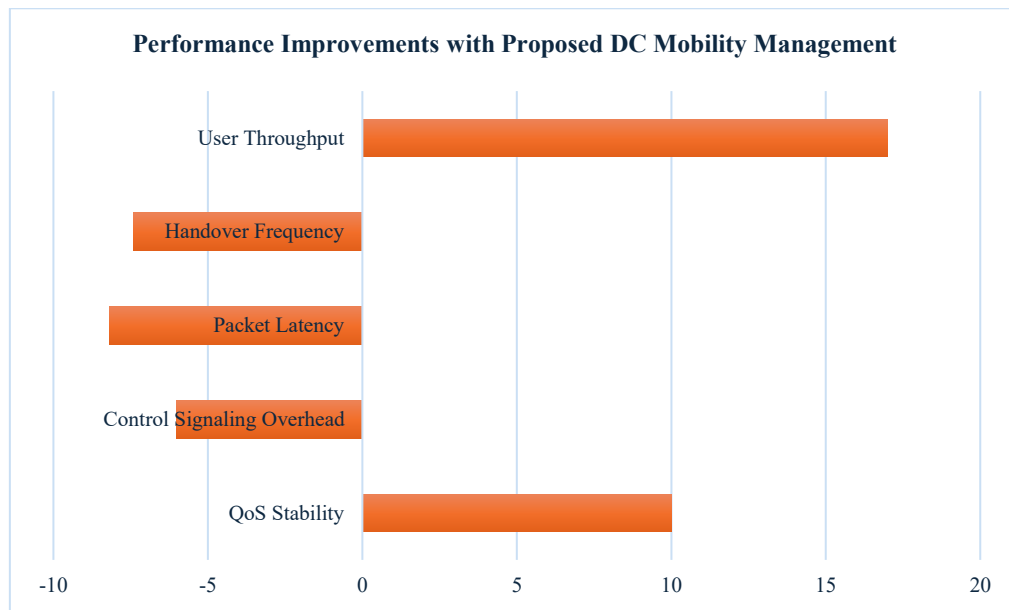


Figure 5: Performance Improvements with Proposed DC Mobility Management Model

As provided in Figure 5, the developed probabilistic model checking (PMC)-based framework for Dual Connectivity (DC) mobility management in 5G networks provides significant improvements across multiple quality of service (QoS) metrics, which is impressive.

### User Throughput

The proposed systems achieve a 17% improvement in user throughput. This improvement is achieved through intelligent data split optimization using the Markov Decision Process (MDP), which balances the load between the Controller Node (MN) and Secondary Node (SN), thereby eliminating congestion and optimizing link utilization.

### Handover Frequency

Handover frequency has been reduced by 12%, which is considered an improvement. This is primarily due to the probabilistic evaluation of mobility pattern features. The model can predict the optimal rein

periods for handovers, thereby avoiding many transitions, which leads to reduced signaling and an improved user experience.

### **Packet Latency**

The model achieved a 12.5% reduction in latency packets with the optimal assignment of DRB (Data Radio Bearer) and split bearer decision. This is particularly beneficial in scenarios of high user velocity and/or SN, where latency reduction is extremely important.

### **Control Signalling Overhead**

Control overhead optimization, such as SN addition, SN switching, and DRB mapping, reduces control signaling overhead by 9%. These tasks, in particular, result in a very high probability of outcome control plane load reduction and are thus executed at PMC model-defined high-load yielding control plane states.

### **Quality of service Stability**

The proposed mobility and data split management framework demonstrates the system's robustness by efficiently handling packet delay variance, throughput, and connection maintenance dynamically while improving quality of service stability by 10 percent.

Applying MDP and PMC to multi-layer 5G offers increased mobility, and DC resource allocation, alongside enhanced management strategies. The probabilistic data plane and control decision optimizations guarantee user and resource alignment satisfaction, improving overall network performance and resource allocation. This strategy shows promise for deployment in heterogeneous 5G networks exhibiting high mobility and diverse quality of service requirements.

## **6 Conclusion**

This study focuses on a probabilistic model checking and Markov decision process (MDP)-based mobility and data split optimization model, developed for the 5G dual connectivity architecture. The methodology combines elements of intelligence decision-making with the control and user plane split of the 5G non-standalone (NSA) architecture to enhance the power of user mobility by utilizing network resources. The simulation demonstrates that the performance improvements offered by the framework are tangible, including a 17% increase in user throughput, a 12% reduction in handover frequency, a 12.5% decrease in packet latency, and a 9% decrease in control signaling overhead. Additionally, the quality of service stability is enhanced by 10%, indicating that the approach is robust and adaptable to various mobility scenarios. Adopting MDP for decision-making and PMC for verification ensures that mobility management is optimized and formally verified against network dynamic conditions. This aims to provide self-optimizing 5G networks, while also laying the foundation for more advanced sixth-generation networks (6G) that support ultra-reliable low-latency communication and massive machine-type communication (MTC). Later studies will incorporate reinforcement learning for adaptive policy changes, add energy consumption criteria to the model, and test the framework on real-time testbeds or hardware-in-the-loop setups.

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## Authors Biography



**Pandian Mahadevan** obtained 2nd Mate qualification from the Australian Maritime College in Tasmania and my Chief Mate and Master's qualifications from Warsash Maritime College in Southampton, UK. He commenced my maritime career mostly aboard bulk and log carriers operated by a Greek company, featuring a multinational crew. Subsequently, I became affiliated with other Indian management firms. I have primarily navigated bulk carriers ranging from handymax to capesize vessels. Upon graduating with a B.Sc from Madras University, I initially pursued a teaching career. I obtained a BTEC (HND) in the UK after finishing my Chief Mate qualification. In 2018, I held the position of Port Captain at Tata Steel Company in Paradep port for a duration of six months. Subsequently, I instructed GP Rating and conducted STCW BST and STSDSD courses for three years. I have also instructed for two months for the Engineers renewal Certificate, focusing on amendments to SOLAS and MARPOL. Resumed sailing on coastal foreign-flag vessels and ceased sailing in 2024. Resumed teaching position at AMET University effective 29th July 2024. During this stay, I am instructing and training B.Sc (NS) cadets and serving as the Course-in-Charge for GP Rating.



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**I.B. Sapaev** affiliated with Alfraganus University and Central Asian University. His work spans material science, digital education systems, and smart classrooms. Sapaev supports cross-institutional research in AI-driven academic security. He is involved in multidisciplinary projects integrating hardware with pedagogy. His research aims at bridging core sciences and digital infrastructure.



**Ivan Berejnov**, Faculty, Kimyo International University in Tashkent. His work focuses on digital innovation and localized educational apps. Ivan contributes to blockchain-based tools and context-aware platforms. He supports the development of secure mobile learning for fieldwork. His interests include app security and UI design for academic use. He works on field data tools aligned with language research.



**Durdona Madrakhimova**, Assistant, Faculty of Economics & ICT, TUIT. She focuses on secure data handling in mobile learning systems. Her interests include student data analytics and location-based education. Durdona supports adaptive interfaces for user-focused learning. Her projects explore EdTech risk management and security. She promotes mobile-first learning with built-in access control.



**Prof. Dr.R. UdayaKumar** completed his M. S (Information Technology and Management) from A.V.C. College of Engineering and Awarded Ph.D. in the year 2011. He is serving in Teaching & Research community for more than two decades, he successfully produced 5 Doctoral candidates, he is a researcher, contribute the Research work in inter disciplinary areas. He is having h-index of 27, citation 2949(Scopus). He is associated as Dean –Department of computer science and Information Technology and also Director IPR, Kalinga University, Raipur, Chhattisgarh.