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AI-driven 5G Networks for Autonomous Positioning System Platform

Faculty of Engineering and Applied Sciences

PhD in Aerospace
Academic Year: 2021–2025

Supervisors: Professor Saba Al-Rubaye
Professor Gokhan Inalhan
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Abstract

Unmanned Aerial Vehicles (UAVs) are becoming essential for various urban applications, such as surveillance, delivery, logistics, disaster management, and traffic monitoring. However, their positioning performance in urban environments can be limited due to challenges such as non-line-of-sight (NLOS) propagation, multipath interference, and signal blockage caused by tall buildings, trees, and other obstacles. These factors lead to reduced positioning accuracy and unreliable communication. To address these issues, this thesis introduces three key and novel contributions. First, it presents one of the first real-world evaluations of the 5G network performance for UAV operations at altitudes between 50 and 110 meters, using XCAL-based field trials. This provides new insights into the altitude-dependent Quality of Service (QoS) parameters such as latency, throughput, and handover (HO) efficiency and provides practical recommendations for UAV-specific connectivity protocols. Second, a novel hybrid positioning framework is proposed that integrates the observed time difference of arrival (OTDOA) of the new 5G radio (NR) with the fusion of sensor and barometric pressure sensor through an Extended Kalman Filter (EK). This combination significantly improves positioning accuracy (2.8–7 m) in GNSS GNSS-challenged urban environment, which has not been demonstrated in prior UAV studies. Third, the thesis introduces a lightweight feedforward neural network (FNN) for mitigating NLOS errors in 5G-based UAV positioning. Trained on simulated MATLAB data, the model corrects time-of-arrival (TOA) measurements in real time, reducing positioning error to 1.3 m in LOS and 1.7 m in NLOS, outperforming conventional methods. Unlike existing solutions, this model is designed for real-time deployment on UAV

platforms with limited resources. Overall, this research strengthens UAV navigation and connectivity in urban airspace by combining 5G advancements, sensor fusion, and AI-powered error correction. The novelty lies in the integration of real-world 5G performance analysis, a hybrid OTDOA sensor fusion framework, and an AI-based NLOS correction model into a unified solution for reliable, accurate, and scalable Urban Air Mobility (UAM), opening the door to future improvements in AI-driven 5G networks for autonomous system platforms.

Keywords:

Unmanned Aerial Vehicles (UAV), Fifth Generation (5G), Observed Time Difference of Arrival (OTDOA), Artificial Intelligence (AI), Neural Networks (NN), Sensor Fusion, Urban Air Mobility (UAM), Positioning, Non-Line-of-Sight (NLOS), Quality of Service (QoS)

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List of Abbreviations

3D	Three-Dimensional
3GPP	Third Generation Partnership Project
4G	Fourth-Generation
5G	Fifth-Generation
6G	Sixth-Generation
AoA	Angle of Arrival
AI	Artificial Intelligence
BAP	Barometric Air Pressure
BS	Base Station
BVLoS	Beyond Visual Line of Sight
CAA	Civil Aviation Authority
CEP	Circular Error Probable
CNN	Convolutional Neural Network
NN	Neural Network
CSI	Channel State Information
CQI	Channel Quality Indicator
GRU	Gated Recurrent Unit
SDN	Network Function Virtualisation

CFO	Carrier Frequency Offset
RFR	Random Forest Regression (RFR
EU	Uropean Union
CSMA	Carrier Sense Multiple Acces
CA	Collision Avoidance
UTM	Unmanned Traffic Managemen
DAA	Detection and Avoidance
RHC	Receding Horizon Control
MILP	Mixed-Integer Linear Programming
MIMO	Multiple Input Multiple Output
KPIs	Key Performance Indicators
D2D	Device-to-Device
DL	Deep Learning
DQL	Deep Q-Learning
EKF	Extended Kalman Filter
ENDC	Evolved-Universal Terrestrial Radio Access NR Dual Connectivity
EPS	Evolved Packet System
FEAS	Faculty of Engineering and Applied Sciences
ReLU	Rectified Linear Unit
FNN	Feedforward Neural Network
BPSs	Barometric Pressure Sensors
GA	Genetic Algorithm
GEO	Geostationary Earth Orbit
gNB	Next Generation Node B

GNSS	Global Navigation Satellite System
GM	Graph Model
GPS	Global Positioning System
SDN	Software Defined Networks
NSA	non-standalone
GSMA	Global System for Mobile Communications
GSM	Global System for Mobile Communications
HD	High Definition
HO	Handover
HTTP	Hypertext Transfer Protocol
iPerf	Internet Performance Measurement Tool
IMU	Inertial Measurement Unit
IoT	Internet of Things
INS	Inertial Navigation System
ISM	Industrial, Scientific, and Medical
KNN	K-Nearest Neighbors
KPI	Key Performance Indicators
LEO	Low Earth Orbit
LoS	Line of Sight
LTE	Long Term Evolution
MAE	Mean Absolute Error
Mbps	Megabits Per Second
ML	Machine Learning
mmWave	Millimetre Wave

MSE	Mean Square Error
NCA	Non-Contiguous Carrier Aggregation
NG-RAN	Next Generation Radio Access Network
NLoS	Non Line of Sight
NR	New Radio
OFDM	Orthogonal Frequency Division Multiplexing
OTDOA	Observed Time Difference of Arrival
PDF	Probability Density Function
PDSCH	Physical Downlink Shared Channel
PRS	Positioning Reference Signal
PSO	Particle Swarm Optimization
QoE	Quality of Experience
QoS	Quality of Service
RAB	Radio Access Bearer
RACH	Random Access Channel
RF	Radio Frequency
RNN	Recurrent Neural Network
RMSE	Root Mean Square Error
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
LeGNSS	LEO constellation augmented GNSS
NFV	Network function virtualisation

EPS	Evolved Packet System
MMTC	Massive Machine-Type Communications
eMBB	Enhanced Mobile Broadband
SDK	Software Development Kit
SNR	Signal to Noise Ratio
SINR	Signal to Interference plus Noise Ratio
SMS	Short Message Service
SS-RSRP	Synchronisation Signal - Reference Signal Received Power
SS-RSRQ	Synchronisation Signal - Reference Signal Received Quality
SS-SINR	Synchronisation Signal - Signal to Interference Plus Noise Ratio
TCP	Transmission Control Protocol
TDOA	Time Difference of Arrival
TOA	Time of Arrival
eNodeB	evolved Node-B
UAM	Urban Air Mobility
UAV	Unmanned Aerial Vehicle
UK	United Kingdom
UL	Uplink
URLLC	Ultra Reliable Low Latency Communication
VLoS	Visual Line of Sight
VoLTE	Voice Over LTE
XCAL	Accuver's Network Measurement Tool
XCAP	Accuver's Network Analysis Tool

Publications

Conferences and Journal

1. Mousa, Morad, Saba Al-Rubaye, and Gokhan Inalhan. "Unmanned Aerial Vehicle Positioning using 5G New Radio Technology in Urban Environment." 2023 IEEE/AIAA 42nd Digital Avionics Systems Conference (DASC). IEEE, 2023.

2. Mousa, Morad, et al. "Performing QoS measurements in UAV field trials with 5G-advanced communications at various altitudes." IET 6G and Future Networks Conference (IET 6G 2024). Vol. 2024. IET, 2024.

3. Mousa, M., Al-Rubaye, S. (2025). Intelligent 5G-Aided UAV Positioning in High-Density Environments Using Neural Networks for NLOS Mitigation. Aerospace, 12(6), 543. https://doi.org/10.3390/aerospace12060543.

Chapter 1

Introduction

1.1 Unmanned Aerial Vehicles Overview

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become an important technology that is changing many areas. Their use has rapidly increased in recent years, from transportation and agriculture to surveillance and environmental monitoring, the use of UAVs has increased rapidly in recent years. For example, in precision agriculture, UAVs improve efficiency by increasing crop yields by 15 to 20%, reducing water use by 30% and cutting operational costs by 10 to 15% versus traditional methods. In military applications, UAVs equipped with artificial intelligence (AI) have transformed operations through autonomous navigation and swarm tactics. Using computational techniques such as Machine Learning (ML) has advanced UAV capabilities, improving predictive maintenance and decision-making for logistics and surveillance [1]. This growth highlights the importance of understanding their definitions, classifications, and global development trends. Fundamentally, a UAV operates without an onboard human pilot. These vehicles are autonomously controlled by computers on board or remotely controlled by human operators at ground stations. UAVS are categorised by size, range, purpose, and design.

As shown in Figure 1.1 (adapted from [2]), UAVs can be classified based on both their design and operational functions. There are three main types of design; fixed-wing UAVS are optimised for long-range missions due to their aerodynamic efficiency, making them suitable for applications like surveillance and environmental monitoring. Rotary-wing UAVs, including quadcopters, are preferred for short-range tasks that require vertical take-off and landing, such as search and rescue operations and infrastructure inspections. Hybrid UAVs combine the advantages of fixed-wing and rotary-wing designs, allowing vertical take-off while maintaining extended endurance, offering greater flexibility for various applications [2],[3],[4],[5],[6],[7]. UAVs can also be classified based on their operational roles into commercial, military, and recre-

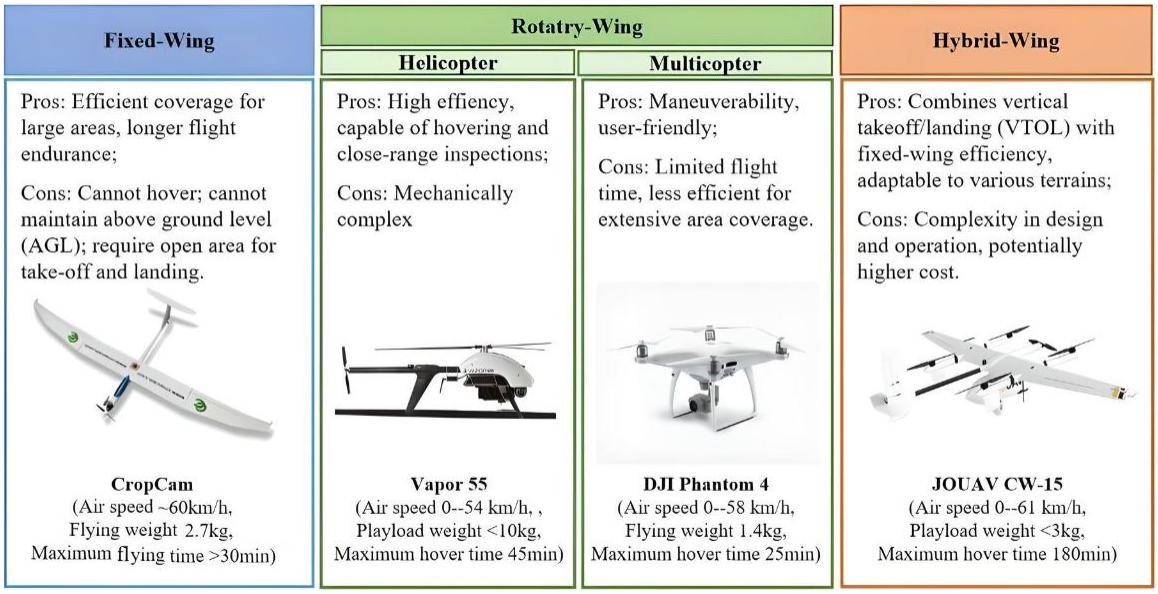


Figure 1.1: UAV Classification [2].

ational categories. Commercial UAVs are widely used in agriculture, logistics, and environmental monitoring, assisting in crop analysis, last-mile delivery, and climate data collection. Military UAVs serve strategic purposes, including surveillance, reconnaissance, and combat, enhancing operational efficiency while reducing human involvement. Recreational UAVs, on the other hand, cater to hobbyists and enthusiasts for personal enjoyment, featuring user-friendly designs. A significant emerging trend in UAV applications is Urban Air Mobility (UAM), where UAVs are expected to facilitate air taxi services, transforming urban transportation by reducing traffic congestion [8–11].

1.1.1 Global Trends in UAV Technology

The evolution of UAV technology has seen rapid improvements in automation, AI, and connectivity. There has been a shift from large, remotely controlled UAVs to smaller, autonomous UAVs that can work together to perform complex tasks. This transformation is driven by the growing demand for improved sensing, communication, and control algorithms that can adapt to dynamic environments [12]. Regulatory compliance and safety improvements remain critical in the development of UAVs. Improved regulatory frameworks have contributed to reducing safety incidents and strengthening the importance of reliability in UAV operations. In addition, integrating cutting-edge technologies such as ML and multisensor fusion has enhanced UAV capabilities, enabling autonomous navigation and real-time data processing [13],[14]. Another critical aspect shaping UAV advancements is their environmental impact. There is a growing trend toward the development of electric UAVs, which offer advantages in terms of safety, flexibility, and reduced operational costs. This transition

aligns with global sustainability objectives, as UAVs are increasingly used in environmental monitoring and resource management applications [8],[15]. In summary, UAVs are a rapidly evolving technology with diverse applications in multiple industries. UAVs are a rapidly changing technology with diverse applications in various industries. Their structural and operational classifications offer helpful insight into their functionalities. Global trends in automation, regulatory advancements, and sustainability efforts shape the future of UAV technology, ensuring continued innovation and integration into modern technological landscapes. As UAVs become more essential to the logistics, agriculture and defence sectors, their potential to revolutionise industries and improve efficiency is unmatched.

1.1.2 Commercial and Applications

Unmanned Aerial Vehicles (UAVs) are now widely used in commercial sectors such as agriculture, logistics, infrastructure inspection, and emergency response (see Figure 1.2). In agriculture, UAVs enable precision farming by applying fertilisers and pesticides in a targeted manner, reducing costs and environmental impact [16]. In infrastructure, UAVs equipped with imaging and 3D mapping tools support efficient inspections of bridges, pipelines, and power lines [17]. In emergency response, UAVs provide real-time aerial images during natural disasters or search-and-rescue operations, improving situational awareness for decision-making. Logistics companies are also testing UAVs for last-mile delivery, offering faster and more cost-effective services compared to traditional transport methods [18],[19]. These applications show the growing role of UAVs in critical and commercial services. However, they also emphasise the need for reliable connectivity and accurate positioning, particularly in densely populated urban environments where GNSS performance is degraded. This motivates the focus of this thesis on 5G- and AI-enabled positioning solutions for UAVs

1.1.3 Technological Improvements in UAVs

Recent advances in UAV technology have significantly improved their functionality, primarily through innovations in AI, battery life, and autonomy. AI plays a critical role in the advancement of UAV applications, enabling tasks such as object recognition, tracking, and classification using neural networks (NN) and digital radar twins, which are vital for safety and security in industries. The integration of ML and Internet of Things (IoT) has improved UAV autonomy, especially in agriculture, where autonomous UAV fleets use deep reinforcement learning and ant colony optimisation for efficient task scheduling and synchronisation, leading to optimised farming practices[19–21]. Battery life, a key factor in UAV performance, has improved through energy-efficient frameworks applying adaptive deep reinforcement learning to optimise energy consumption and extend operational time, thus improving wireless coverage and reducing interference in UAV networks [22]. In addition, predictive control

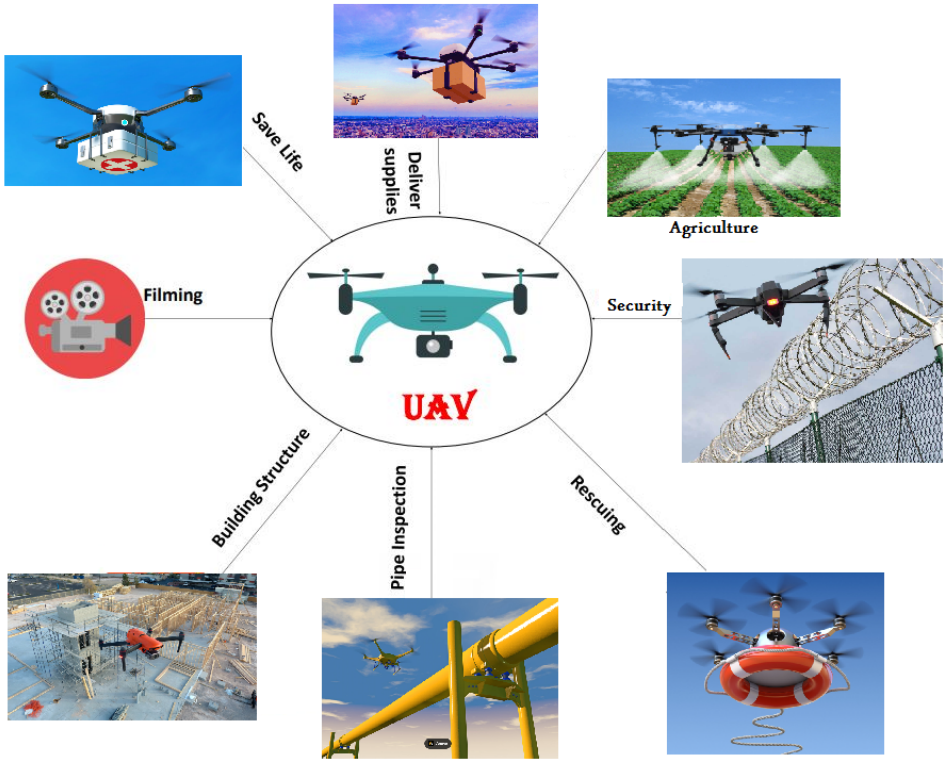


Figure 1.2: UAV Application Scenario

techniques for models have been developed to improve flight time by minimising trajectory errors, improving UAV efficiency, and setting the foundation for the integration of intelligent algorithms into UAV control systems. Together, these technological advances enhance the versatility and effectiveness of UAVs in various applications, from environmental monitoring to disaster response, thus driving innovation and efficiency across industries [19],[18].

1.1.4 Challenges and Regulations

The regulation of UAVs is adapted to ensure safety and effective traffic management, especially within the European Union (EU). The EU has established a legal framework that classifies UAV operations based on risk levels, prioritising safety over liability to support UAV integration into European airspace [23]. This framework is supported by the general AI regulations of the EU, which apply to autonomous UAV operations, highlighting the need for cohesive rules that address aviation safety and AI ethics [23]. Advanced communication protocols, such as carrier sense multiple access/collision avoidance (CSMA/CA), improve safety by preventing data transmission collisions, a key factor in public safety communications and unmanned traffic management (UTM) systems [24]. Beyond regulations, UAVs play a vital role in environmental applications, including wildlife conservation and disaster monitoring. They offer superior adaptability in data collection and analysis, supporting tasks such

as assessing disaster damage and aerial surveillance for conservation efforts [18]. As UAV technology progresses, regulators need to evolve policies to balance innovation and safety, ensuring that UAVs provide social and environmental benefits [25],[23]. The growing use of UAVs demands improved integration into crowded airspace. The main challenges involve cybersecurity, privacy, infrastructure, and technical standards. Inconsistent regulations across countries slow down global UAV adoption and innovation. International collaboration is essential to establish standardised rules and enable the effective deployment of UAVs. Integrating UAVs into crowded airspace poses multiple challenges, including cybersecurity, privacy, infrastructure, and technical standards, exacerbated by regulatory inconsistencies between countries [26],[27]. Cybersecurity is a critical issue, as UAVs are vulnerable to attacks such as Global Navigation Satellite System (GNSS) spoofing, signal jamming, and interception of data links, which jeopardise operations and threaten critical infrastructure [28–32]. To address these risks, suggested measures include robust encryption protocols and ML-based intrusion detection systems, in line with the EU's NIS2 directive to improve UAV security in regions like Albania [26]. In Europe, the regulatory landscape for UAVs is diverse, with national rules often exceeding EU frameworks (e.g., Regulation (EU) 2018/1139), resulting in a fragmented system that complicates airspace integration [25],[33]. Germany demonstrates the shift from national to EU regulations, highlighting the need for ongoing legal updates to support the evolving UAV industry. Globally, the rapid development of UAV technology challenges existing air law, requiring updates to conventions such as the Paris and Chicago agreements to reflect the unique legal status of UAVs and their role in international conflicts [34]. These challenges highlight the urgency of international cooperation to create unified regulations that enable the secure and efficient use of UAVs worldwide.

1.1.5 Categories of UAV Operations

Operations for UAVs require pilots to maintain direct visual contact with the UAV to avoid collisions, usually limited to 500 metres horizontally and 120 meters vertically as outlined in Figure 1.3. This operational category faces challenges such as difficulty tracking small UAVs, a higher pilot workload, and poor weather conditions that hinder visibility [35]. Operators use technologies such as GNSS-based planning tools and collision avoidance systems to improve safety in Visual Line of Sight (VLoS) operations. These technologies are critical in reducing the risks associated with UAV operations, as they offer automated solutions to detect and avoid obstacles, thus decreasing the reliance on human visual acuity and high-pressure decision-making. The adoption of such technologies reflects a growing trend toward greater automation and safety in UAV operations, seen in Beyond Visual Line of Sight (BVLoS) missions, where sophisticated risk management and path planning strategies address similar safety challenges [35]. Additionally, advancements such as geofencing and operational limits tracked during flight help ensure that UAVs stay within safe limits, preventing unauthorised airspace incursions and improving overall safety. As UAVs expand into sec-

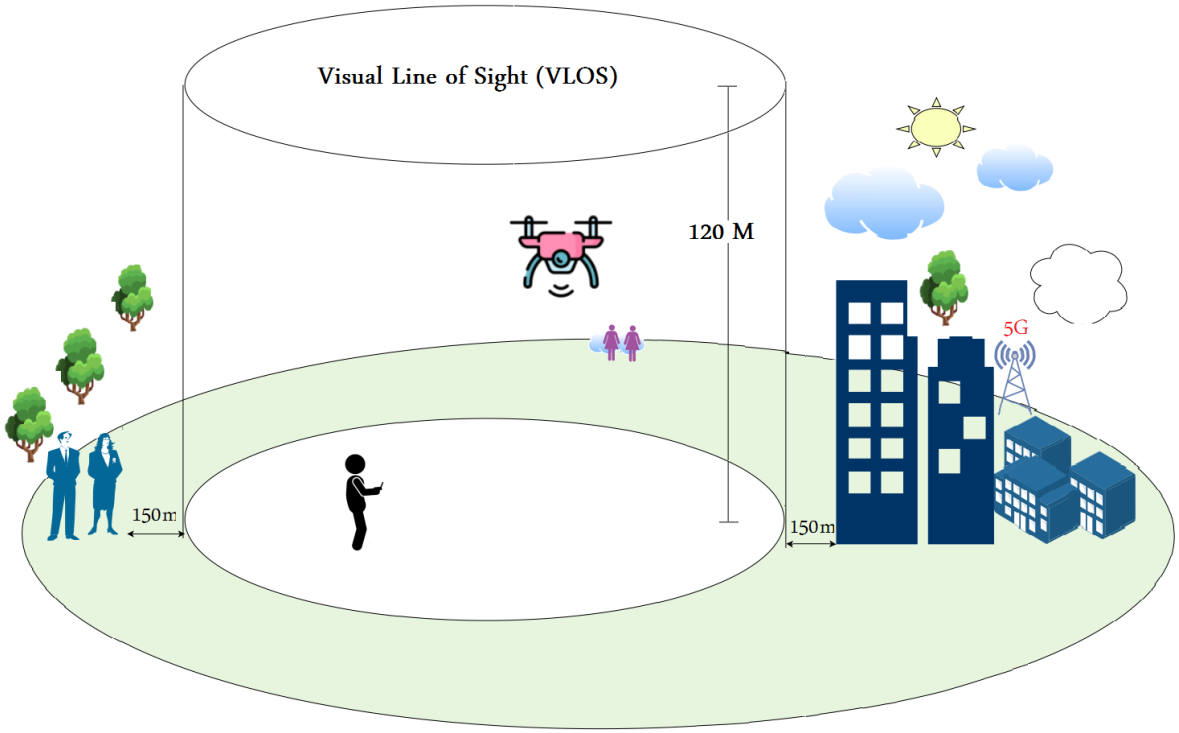


Figure 1.3: Maximum Allowed Altitude for VLoS operations

tors such as UAM, public perception and regulatory frameworks will shape the future of UAV operations, emphasising the need for ongoing innovation in safety technologies [35]. Operations for UAVs greatly enhance efficiency by allowing UAVs to fly beyond the pilot's visual range, vital for long-distance missions [11]. This capability relies on advanced detection and avoidance (DAA) systems or segregated airspace to reduce collision risks. To optimise routes, navigation strategies such as energy efficient 3D path planning employ receding horizon control (RHC) and mixed-integer linear programming (MILP), minimising energy use and avoiding collisions in challenging environments [11]. The D * algorithm, for instance, improves path planning efficiency by 92% and reduces collision rates by 5% , offering a reliable solution for dynamic or unknown settings [36]. Training programs, such as NASA's initiatives, are critical for preparing remote ground control station operators to handle BVLoS complexities, focusing on integrating human factors and advanced simulations [37]. Risk assessment frameworks classify risks into ground and air categories, providing strategies to manage them effectively in BVLoS scenarios [35]. Innovative path planning methods, such as the two-layer ant colony and Dung Beetle algorithms, enhance the quality of the path in large airspaces, ensuring safe BVLoS operations. These advancements highlight the need for sophisticated route planning, risk management, and operator training to fully unlock the potential of BVLoS [38].

The future of UAV adoption will likely be shaped by advances in AI-driven autonomy, stronger cybersecurity, and improved economic models, increasing their usefulness in agriculture, infrastructure, and logistics. In agriculture, UAVs are already revolutionising precision farming through efficient crop monitoring, disease detec-

tion, and targeted spraying, reducing pesticide use by up to 30% [29]. Equipped with AI and sensors, they enable better resource management and yield predictions. For infrastructure, UAVs provide cost-effective solutions for long-range inspections and environmental monitoring, driven by advances in imaging and remote sensing technologies. However, increasing the use of UAVs increases cybersecurity risks, as attacks could threaten data integrity and system functionality. To address this, technologies such as Blockchain and ML are being tested to improve UAV cybersecurity [39],[40]. Additionally, integrating ML algorithms is the key to stopping unauthorised access and ensuring public safety [18]. Standardised global regulations and effective airspace management are vital to enabling safe integration of UAVs into civilian airspace [29]. These developments show the potential of UAVs to tackle global challenges if regulatory, technological, and socioeconomic barriers are appropriately addressed. Precision navigation and positioning greatly enhance the safety, efficiency, and versatility of UAVs across industries by enabling more accurate operations [41]. In power inspections, high-precision positioning allows intelligent trajectory planning, optimising flight paths, and maintaining safe distances from infrastructure, increasing both safety and efficiency in inspection tasks. In industrial settings where GNSS is unavailable, reliable navigation systems allow UAVs to autonomously manoeuvre complex environments such as tanks and pipelines, reducing reliance on manual inspections and improving safety and cost efficiency [42]. Combining visual-inertial odometry with algorithms like Cartographer enhances positioning accuracy, allowing UAVs to navigate narrow spaces and avoid obstacles in challenging conditions [43]. For photogrammetry, attached UAVs show how precise positioning improves stability and data accuracy, supporting high-quality 3D modelling [44]. Multisensor systems, such as LEO constellation augmented GNSS (LeGNSS) / inertial navigation system (INS), offer reliable and uninterrupted positioning even in areas with interference, gaining benefits for sectors such as aviation and defense [45]. These advancements highlight the critical role of precise navigation in expanding UAV capabilities and safety across applications [45].

1.2 5G Technology Overview

5G technology marks the next evolution in mobile communication networks, following fourth generation (4G). It uses small cells to improve connectivity and performance, supporting innovations such as the IoT, smart cities, and augmented/virtual reality. Features such as multiple Input multiple output (MIMO), beamforming, and network signalisation position it as a transformative leap in wireless telecommunications, offering faster speeds, higher capacity, and lower latency [40],[46],[47]. By 2024, 5G is projected to reach 1.9 billion global subscribers, driven by its ability to enable new applications and business opportunities in all industries [48],[49]. Mobile providers are investing heavily in 5G infrastructure, opening the way for wireless virtual reality, smart city systems, and industrial automation. The willingness of

operators to explore new business models accelerates adoption, enabling innovative applications that strengthen global connectivity [50]. 5G technology boasts download speeds of up to 10 Gbit/s, supports 1,000 times current traffic volumes, and connects up to 100 billion devices, making it ideal for smart cities, healthcare, industrial automation, and autonomous vehicles. These capabilities meet critical needs such as low latency, high reliability, and better battery efficiency [51–53]. The integration of 5G with the IoT uses technologies such as network slicing, edge computing, and massive MIMO to make IoT systems more efficient and scalable. As mobile data traffic is expected to exceed 1 zettabyte per month by 2028 due to the growth of the IoT, the ability of 5G to handle massive data volumes and provide ultra-reliable, low-latency communication (URLLC) becomes increasingly critical [54].

1.2.1 Frequency Bands and Deployment

Deploying 5G networks across various frequency bands leads to different performance characteristics and challenges. Low-band frequencies (600–900 MHz) offer wide coverage and data rates between 30 and 250 Mbit/s, making them well-suited for broad-area applications similar to 4G [55],[56]. Mid-band frequencies (2.3–4.7 GHz) deliver higher speeds (100–900 Mbit/s) and cover several kilometres, balancing coverage and capacity [57]. High-band frequencies, especially millimetre wave (mmWave) bands (24–47 GHz) , enable gigabit speeds but suffer from limited range and sensitivity to obstacles like walls. This requires a dense small cell infrastructure for effective use [58]. High costs and infrastructure demands limit mmWave deployment to urban and high-density areas. Despite these hurdles, the mmWave bands are critical to achieving the promised high speeds and low latency of 5G, as seen in MIMO antenna systems that boost performance through multi-stream data transmission [59]. However, mmWave performance varies in real-world settings, such as outdoor to indoor environments, where significant throughput depends on optimal conditions like LOS to base stations (BSs). Thus, while mmWave holds promise for high-speed applications, its deployment demands careful environmental and infrastructure planning to overcome limitations [57].

1.2.2 5G-Enabled UAV Communications

5G-enabled UAV communications represent a major advancement in wireless technology, offering improved capabilities for applications such as emergency response and industrial automation. UAVs are increasingly being used as aerial BSs to extend 5G coverage, support emergency operations, and collect IoT data, as shown in Figure 1.4 [18],[19],[60],[61]. Innovations such as 300-meter aerial 5G networks and advanced onboard terminals tackle challenges such as flight distance, bandwidth, and latency, improving communication stability [62]. However, in dense urban areas, UAV communication faces obstacles due to poor planning and aerial coverage interference,

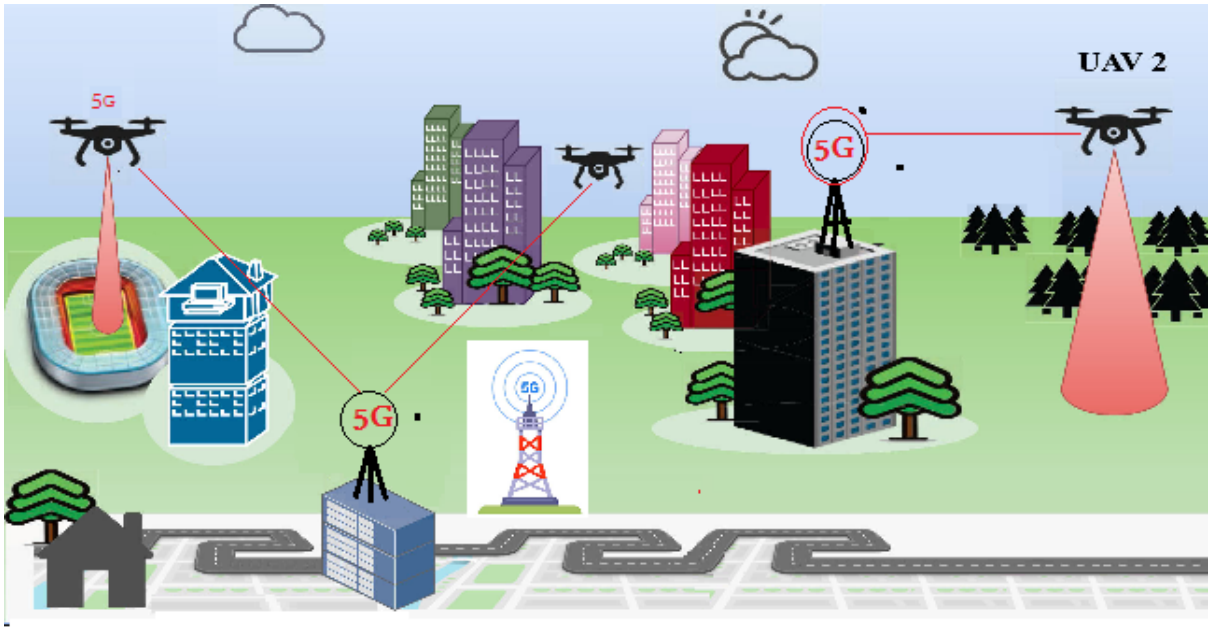


Figure 1.4: 5G-Enabled UAV Communications

requiring network upgrades for reliability. In traffic monitoring, UAVS enhance data collection via cooperative device-to-device (D2D) communications, boosting throughput and reducing latency compared to traditional methods [63]. Additionally, gated recurrent unit (GRU)-based modulation and coding schemes optimise transmission speed by predicting signal-to-noise ratios, surpassing traditional approaches [60],[64], [65]. These advancements highlight the potential of 5G-enabled UAVs to revolutionise applications such as disaster recovery and industrial automation. 5G standards form a dynamic framework to meet the demands of the modern wireless network, prioritising faster speeds, low latency, and wide connectivity. The 3rd generation partnership project (3GPP) leads global standardisation, releases such as release 15 to release 17 guiding advances towards 6G [66],[67],[68],[69]. The 5G architecture takes advantage of innovations such as software-defined networking (SDN) and network function virtualisation (NFV), improving the flexibility of radio access and core networks [67]. These standards support various applications, from the mobile Internet to IoT in Industry 4.0 and healthcare, which require reliable data transmission as illustrated in Figure 1.5 [70]. Security is critical, with encryption and authentication systems needed to address vulnerabilities and supply chain risks [71]. The EU and other regions actively shape standards to balance economic, security, and innovation goals [66]. As 5G evolves, backward compatibility and 5G-Advanced advancements driven by SDN will boost the capabilities of the mobile network [72]. These efforts highlight the role of 5G in defining the future of global telecommunications.

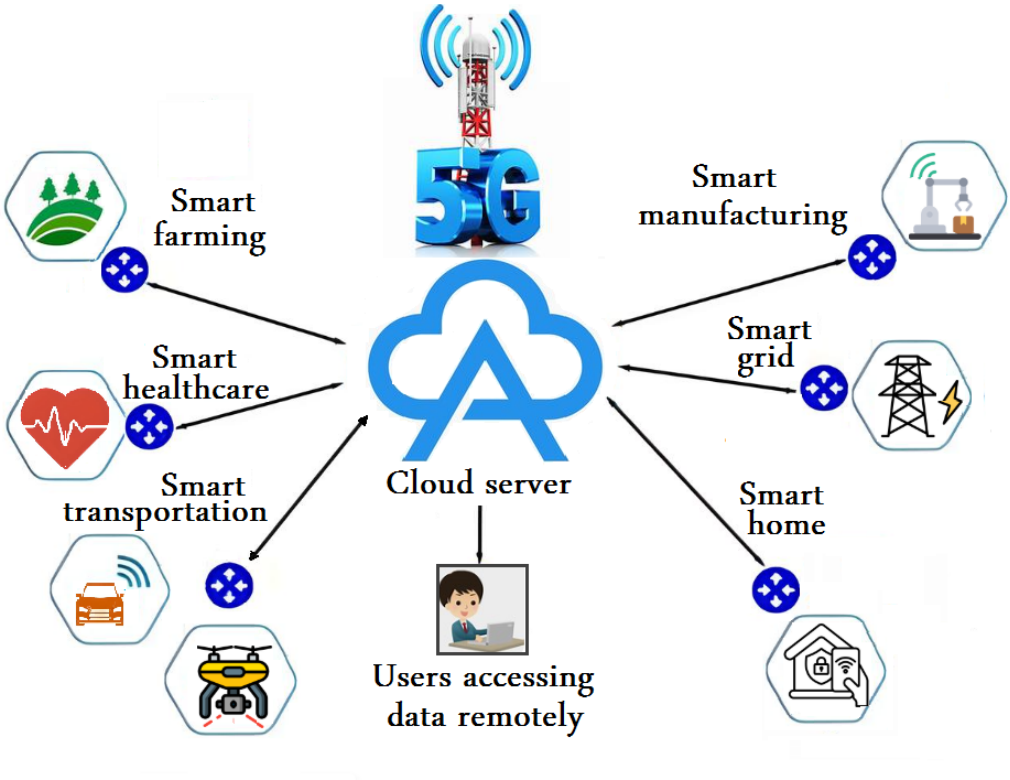


Figure 1.5: 5G- enabled IoT communications environment

1.3 UAV Quality of Service Performance

The use of UAVs in 5G-Advanced networks opens up exciting possibilities for aerial communication, but also presents challenges when it comes to maintaining quality of service (QoS). Ensuring reliable communication between UAVs and ground stations requires a close look at key performance indicators (KPIs), such as latency, data throughput, and how smoothly handovers between BSs occur [73],[74]. This study conducted real-world trials to assess QoS at different altitudes, providing insight into optimising network performance. Key factors affecting QoS include mobility and altitude, as UAVs at higher altitudes experience weaker signals and more delay, making adaptive network strategies essential for maintaining performance. Handover (HO) efficiency is also crucial since smooth transitions between BSs prevent connection drops. Latency and throughput play an essential role, especially in real-time applications such as surveillance, which require fast response times and high data speeds [75]. Additionally, interference and congestion in urban areas can cause signal problems, making effective spectrum management necessary for reliable connectivity. Improving QoS will enable reliable UAV connectivity, disaster recovery, and logistics in smart cities [76]. These results provide a foundation for advancing autonomous UAV operations and next-generation 5G services, transforming aerial mobility and communication.

1.4 5G Positioning for UAVs

Using 5G technology in UAV positioning systems introduces a promising new approach to urban aerial navigation. However, applying 5G NR for accurate positioning in complex urban environments brings several challenges, primarily due to signal propagation characteristics and the complexities of sensor fusion. While 5G NR offers low-latency communication and high-frequency signals that can significantly improve positioning accuracy, especially where GNSS often struggles under NLOS conditions, it also introduces new technical demands [40],[46],[47]. Urban environments pose further challenges to UAV positioning due to several interrelated factors. NLOS conditions and multipath interference are common, as high-rise buildings and reflective surfaces obstruct direct signal paths, causing reflected signals to reach the UAV receiver with varied delays. This leads to distorted positioning data and complicates time-based measurement techniques. Furthermore, on-board sensors such as IMUs and barometric altimeters, while essential for maintaining orientation and altitude, are prone to noise, drift, and environmental variability [47]. These errors can accumulate without periodic correction from external references, severely degrading positioning accuracy. The complexity increases when integrating data from multiple heterogeneous sources such as 5G NR base stations, IMUs, and barometric sensors. This data fusion process, often managed through an EKF, demands precise algorithmic tuning and synchronisation across diverse inputs to ensure reliable real-time performance [77],[78]. Moreover, the requirement for instantaneous updates during dynamic urban flights imposes high computational demands, challenging systems to deliver timely and robust positional data despite noise and latency. Addressing these multifaceted challenges is critical for UAV deployment in applications ranging from precision deliveries to emergency response operations. Using 5G NR technology with advanced sensor analytics greatly improves situational awareness and navigational reliability for UAVs, reducing dependence on satellite-based systems and enabling more autonomous and resilient UAV operations in GNSS-challenged urban environments [69],[62]. Ultimately, resolving these positioning issues is not only fundamental to improving UAV operational efficiency but also key to realising intelligent, scalable, and interconnected aerial networks within future smart cities.

1.5 AI Enabling 5G Positioning

Navigating complex urban environments presents significant challenges for UAVs, where tall structures and dense infrastructure often disrupt GNSS signals. This degradation in signal quality severely limits the precision of traditional positioning systems. As an alternative, 5G networks have emerged as a robust solution using positioning reference signals (PRS) to estimate location based on signal timing and other channel features. These capabilities offer improved reliability and spatial resolution, especially in GNSS-denied environments.

Beyond standalone positioning, AI enables more advanced forms of cooperative localisation. Techniques such as reinforcement learning allow multiple UAVs or autonomous agents to share and evaluate range measurements dynamically, optimising the selection of the most accurate positioning data based on real-time 5G signal conditions [79] . Hybrid systems that integrate 5G with inertial navigation systems (INS), supported by models like the recurrent NN-based fuzzy inference system (RNNFIS), have also shown promise. These systems maintain positioning accuracy even in situations where 5G signal strength is compromised [80]. Moreover, deep learning approaches have been instrumental in optimising positioning under various signal constraints. By merging data sources such as received signal strength (RSS), carrier frequency offset (CFO), and occasional GNSS input, AI models can create robust and adaptable localisation frameworks that maintain low error margins in varied environments [81]. These advancements are critical in enabling precise, autonomous UAV navigation in real-time applications such as smart city logistics, infrastructure inspection, traffic monitoring, and emergency response. The integration of AI with 5G positioning enhances accuracy and resilience and facilitates the seamless operation of UAVs in dynamic and challenging scenarios. As 5G infrastructure expands and AI models continue to improve in efficiency and generalisability, this synergy is set to become a cornerstone of next-generation autonomous aerial mobility. AI, particularly ML techniques, have been used to further enhance the accuracy of 5G-based localisation. NNs trained on simulated datasets have shown strong potential in improving real-time UAV positioning by learning from discrepancies between predicted and actual locations. In practical tests, this AI-enhanced system achieved an average error of only 1.3 metres in open areas and 1.7 metres in dense urban environments, demonstrating its viability as a reliable alternative to GNSS.

1.6 Problem Formulation

UAVs face significant challenges in urban environments due to signal reflections, tall buildings, and non line of sight (NLOS) conditions [82],[83]. These factors interfere with GNSS, causing frequent signal blockages and reduced positioning accuracy. Various navigation techniques, such as multisensor fusion, AI-driven models, and hybrid systems, have been explored to address these issues. However, existing solutions still struggle with real-time adaptability and accuracy in dense urban environments. Although UAV positioning has been widely explored, current methods do not thoroughly combine 5G NR OTDOA with AI-based neural networks to improve positioning accuracy. Furthermore, 5G OTDOA is limitedly implemented, as most studies focus on ground-based applications rather than aerial mobility. Poor multipath error correction and NLOS effects further impact real-time positioning accuracy [84],[85]. In addition, there is a lack of real-world field tests that assess UAV connectivity, positioning accuracy, and QoS parameters at various altitudes in urban environments. These limitations restrict the advancement of reliable UAV operations

in innovative urban environments, where precise navigation is crucial for autonomous delivery, emergency response, and UAM applications [74],[86]. Therefore, there is an urgent need for innovative solutions that use AI, 5G, and advanced sensor fusion to improve the accuracy and reliability of UAV positioning in urban environments.

1.7 Research Gap

While previous studies [82],[83],[84],[85],[86] have made significant contributions to UAV connectivity and 5G networks, there remains a critical gap in research that explores the integration of 5G NR technology with advanced OTDOA techniques and NNs to enhance UAV positioning accuracy. The integration of these technologies is essential for enabling real-time tracking and navigation, both of which are crucial for the safe and reliable operation of UAM. Existing positioning methods face substantial challenges in urban environments, where multipath interference and NLOS conditions significantly degrade the accuracy and reliability of real-time positioning systems. These limitations are particularly pronounced in UAM applications, where high precision and low latency are non-negotiable. To address this gap, our research introduces an innovative framework that seamlessly integrates 5G NR, OTDOA, and NNs, offering a holistic solution to improve UAV positioning accuracy, UAV-to-ground communication, and overall safety and operational efficiency. This framework represents a novel advancement in UAV navigation by combining cutting-edge 5G technologies with AI-driven models, which have not been sufficiently explored in real-time UAV operations.

1.8 Aim and Objectives

This thesis aims to develop a novel UAV positioning technique for BVLOS operations by combining 5G NR technology with AI algorithms to enhance real-time navigation accuracy in urban environments. The primary objectives of this research are:

- Conduct a comprehensive review of existing literature, market trends, industry reports, and economic factors to critically evaluate the state-of-the-art and untapped potential of 5G NR and AI technologies for improving UAV positioning in complex urban environments.
- Investigate the field of 5G NR networks in UAV operations at varied altitudes, focusing on key QoS parameters, such as latency, throughput, and signal reliability.
- Develop an advanced positioning mechanism utilising the OTDOA technique to address specific challenges in urban UAV positioning, with the aim of improving accuracy and robustness in dense, multipath environments.

- Design a novel AI-based algorithm that integrates 5G PRS with NN architectures, aimed at mitigating NLOS and multipath interference to significantly enhance positioning accuracy in urban environments.
- Validate the proposed positioning system through comprehensive simulations, and validate 5G network performance through field trials by testing QoS parameters such as latency, throughput, and signal quality at various altitudes. Positioning effectiveness is assessed in simulated urban environments, which are crucial for autonomous delivery and emergency response applications.

1.9 Thieses Contributions

This study introduces a groundbreaking AI-driven, 5G NR-based UAV positioning system that effectively addresses critical challenges in dense urban environments, where traditional systems often fail due to multipath interference and NLOS conditions. The main contributions of this work are:

- Develop a new UAV positioning mechanism to significantly improve positioning accuracy in urban environments. This approach integrates 5G NR positioning via the OTDOA technique with sensor fusion from IMUs and barometric pressure sensors, achieving positioning accuracy of 2.8–7 meters in simulated urban scenarios. Benchmark comparisons show that this represents a 26–31% improvement over baseline 5G TDOA methods (3.8–5.1 m error). Furthermore, while GNSS accuracy typically degrades to 10–50 meters in dense urban environments due to signal blockage and multipath interference, the proposed method maintains consistent 2.8–7 meter accuracy, making it 3–7 times more accurate than GNSS in challenging urban environments. This advancement provides a reliable alternative to GNSS-based positioning, enabling more dependable UAV operations in applications such as aerial surveillance, package delivery, urban planning, and emergency response scenarios like search and rescue.
- **5**G-Network QoS evaluation for UAV communications across different altitudes. By conducting structured flight trials and collecting real-time data with specialised measurement tools, this study quantifies the impact of altitude on key network performance metrics such as latency, throughput, and signal quality. The results reveal that while specific QoS parameters, such as latency and throughput, degrade with increasing altitude due to path loss and aerial radio conditions, others, such as transmission power, remain stable. These insights are critical for network design and aerial communication optimisation, contributing significantly to deploying reliable UAV-enabled services in real-world scenarios.
- Novel framework-based machine learning for enhancing UAV positioning accuracy in dense urban environments, specifically designed for 5G integration. This framework combines a fully connected feedforward neural network with

5G TOA measurements to mitigate errors caused by NLOS conditions one of the most challenging issues for GNSS systems in urban areas. The neural network model is trained and validated using simulated urban scenarios that closely mirror real-world signal propagation. The framework significantly reduces positioning errors, achieving an average Mean Absolute Error (MAE) of 1.5 meters and Root Mean Square Error (RMSE) of 2.3 meters. This work represents a significant advancement in UAV navigation, providing a scalable, real-time solution suitable for critical applications such as UAM, delivery, emergency response, and surveillance.

These contributions provide a significant leap forward in overcoming the critical limitations associated with UAV positioning and connectivity reliability. By addressing these issues, this work enables the broader deployment of UAV-based systems in sectors such as logistics, public safety, smart city infrastructure, and disaster management, with the potential to transform key urban services and applications.

1.10 Thesis Structure

This research explores how 5G and AI can enhance the positioning and connectivity of UAVs in urban areas, where GNSS signals may be limited. The following chapters are organised as follows:

- **Chapter 1: Introduction;** provides an overview of UAV technologies and 5G communication systems. It outlines the motivation behind this study, highlights the research gap in urban positioning, and introduces NN solutions for NLOS scenarios.
- **Chapter 2: Literature Review;** reviews current advancements in UAV positioning techniques, the integration of 5G in UAV systems, and AI-based methods for NLOS mitigation. This chapter forms the theoretical basis for the research.
- **Chapter 3: Field Trials and QoS Testing;** describes real-world field experiments to assess QoS metrics such as RSRP, SINR, and throughput at various UAV altitudes in urban environments. Challenges in communication reliability are analysed using data collected from simulation and field trials.
- **Chapter 4: Enhanced Positioning in Rural Areas;** introduces a hybrid positioning system using 5G OTDOA measurements and inertial sensors combined through an Extended Kalman Filter. The methodology is evaluated in rural environments where GNSS is limited.
- **Chapter 5: Neural Network for NLOS Mitigation;** addresses positioning errors due to NLOS conditions in urban environments. Proposes a machine learning framework using feedforward neural networks trained on simulated TOA data to improve positioning accuracy.

- **Chapter 6: Conclusion and Future Work;** summarises the main findings of the study, evaluates the effectiveness of the proposed approaches, and outlines directions for future research in AI-5G integrated UAV systems.

Chapter 2

Related Works

This chapter comprehensively reviews existing research on UAV positioning challenges within 5G networks and the impact of altitude on QoS. The review sets the stage for identifying research gaps, defining the problem, and establishing the aim and objectives outlined in Chapter 1. The content supports the first research objective by addressing UAV positioning in urban environments.

2.1 QoS in UAV-5G Communication

Reliable UAV-terrestrial network connectivity is essential to enjoy safe BLoS UAV operations [87]. From the perspective of the telecommunication service provider, a UAV can either act as a user that needs to exchange data or as a relay providing coverage in urgent scenarios [88],[89],[90]. To explore UAV-terrestrial connections, previous work has addressed analysing the performance of UAVs in 4G networks, identifying the coverage area of 4G networks, and defining the associated issues. That encouraged 3GPP to examine the ability of the long-term evolution (LTE) network to support UAVs in the published technical report 36.777 [91]. That was followed by the technical specification 36.331, which proposed reporting two height thresholds to help the evolved Node-B (eNodeB) detect the UAV [92]. Before release 17, the 3GPP did not explicitly clarify how the new 5G NR will support low-altitude UAV communications. Several aspects of UAV-5G communications have been discussed, including coverage, power consumption, and UAV safety. Furthermore, recent studies have explored how 5G can overcome the limitations of LTE by using technologies such as massive MIMO, beamforming, and advanced network management to improve UAV communication. Although these advances improve link reliability and reduce latency, challenges persist, including optimising beamforming for aerial users and ensuring seamless HOs at high velocities [17],[93]. Investigating the capability of terrestrial 5G networks to provide

sufficient coverage for UAVs by conducting theoretical studies, simulations, and even field measurements was discussed in [86],[94],[95],[96]. Studies have shown that UAV altitude plays a crucial role in network performance. Although higher altitudes improve NLOS connectivity, they also lead to more significant intercell interference and weaker signal strength, especially near the edges of coverage areas [74]. To address these challenges, researchers have explored solutions such as dedicated UAV service cells and adaptive antenna tilt adjustments to strengthen coverage and network reliability [97],[98]. However, integrating UAVs into existing networks is not without difficulties. Deploying and managing these aerial systems effectively requires careful planning, particularly in balancing coverage, resource allocation, and minimising interference. Approaches such as dynamic programming and reinforcement learning have been used to improve UAV positioning, but ensuring scalability and network stability remains a challenge [99],[100]. Furthermore, factors such as power limitations and adapting to different network conditions further complicate their real-world implementation [101],[102]. Addressing these issues requires further study and refinements to make UAV-based communication systems more practical and widely applicable. In addition, standardisation efforts have progressed with 3GPP Release 17, introducing a dedicated UAV system architecture that includes identification, authorisation, and connectivity management within 5G networks Global System for Mobile Communications (GSMA), 2023. In parallel, studies on U-space integration highlight the role of 5G in supporting UAV traffic management through real-time telemetry, geofencing, and remote command-and-control functions [63]. This work aims to provide extensive field measurements of 5G performance as a function of UAV altitude by flying a customised quadcopter UAV, equipped with Accuver's Network Measurement Tool (XCAL), over a range of altitudes from 50 to 110 metres. By capturing key metrics, such as signal strength, throughput, and latency at different heights, we provide novel insights into altitude-dependent 5G connectivity for UAVs. These insights will shed light on the real-world factors that impact UAV performance that may not be captured in simulations. Building on previous studies, our analysis further examines the role of altitude in 5G connectivity, evaluates how current 5G infrastructures handle UAV mobility challenges, and explores potential network enhancements for optimised UAV operations.

2.2 Positioning in Urban Environment

One of the most widely used UAV navigation technologies is GNSS, which includes the Global Positioning System (GPS), GLONASS, and BeiDou. GNSS provides accurate global positioning for UAVs [82],[103],[104]. However, tall buildings often block the signals in urban environments, leading to obstruction, multipath interference, and positioning errors [83],[105]. GNSS typically achieves metre-level accuracy, which is insufficient for tasks requiring sub-metre precision, such as formation flying [106]. GNSS signals are frequently blocked in dense urban areas, making it dif-

ficult for UAVs to navigate reliably. Researchers [107],[108] have explored cooperative navigation where UAVs share positioning data to overcome this issue. Nevertheless, such methods can introduce communication synchronisation problems and network congestion. In restricted indoor environments, GNSS limitations become even more severe. UAVs require precise localisation systems, which leads to hybrid positioning methods that combine inertial navigation systems (INS) with visual sensing [109],[110]. Passive azimuth-based techniques have also been proposed to reduce GNSS reliance in densely built-up areas [111],[112]. Although GNSS remains essential for UAV positioning, its shortcomings highlight the need for multi-source fusion strategies that combine sensors and wireless networks to improve accuracy in urban settings [113],[114]. High-rise buildings block satellite signals, resulting in poor visibility and compromised positioning. Studies show that GNSS errors can reach tens or even hundreds of metres without adequate satellite coverage, making it unreliable for UAV applications [115],[116]. Multipath interference happens when GNSS signals reflect off buildings before reaching the receiver, leading to positioning errors [117],[118]. These errors occur because the receiver mistakes the reflected signals for direct transmissions [119]. To address these issues, researchers have used techniques like dual-polarisation antennas and advanced signal processing algorithms [120]. Beyond physical obstructions, electronic interference and jamming can also disrupt GNSS signals.IIMU and other sensors help UAVS remain resilient to these problems [109],[121]. Wireless network-based positioning provides another option. Common approaches include ToA, TDoA, angle of arrival (AoA), RSS, and combinations of these methods. ToA measures distance by timing the signal's travel between transmitter and receiver. TDoA compares time differences across multiple receivers for triangulation, yielding high precision in controlled environments, but it is prone to synchronisation issues and multipath effects in urban areas [122],[123]. AoA locates UAVs based on the angle at which the signal arrives at an antenna array. It works well in line-of-sight conditions but suffers inaccuracies if there are obstacles and requires careful antenna calibration [124],[125]. RSS-based methods estimate distance through signal attenuation models, although they are sensitive to changing urban conditions [126],[127]. Hybrid techniques combine multiple approaches, such as ToA with AoA or RSS, to boost accuracy but increase computational complexity and demand sophisticated sensor fusion [126],[128]. The emergence of 5G networks presents new possibilities for UAV positioning, offering low latency, high throughput, and network slicing capabilities. Network slicing enables UAVs to utilise dedicated virtual networks, ensuring reliable communication [129],[130]. However, most research on 5G and UAVs has focused on communication reliability rather than highly accurate localisation. While OTDOA relies on signal timing differences for positioning, it has been studied mainly for mobile networks instead of UAVs [84],[85]. Despite recent progress, applying 5G-based positioning techniques directly to UAVs in complex urban settings remains underexplored. This work addresses that gap by integrating 5G OTDOA with multisensor fusion to enhance UAV positioning accuracy. Sensor fusion that combines IMUs, EKF, and barometric sensors has already shown promise for improving navigation by providing motion data and refining altitude estimates [131].

The table 4.1 provides a comparison of key UAV positioning techniques from previous studies, highlighting their strengths, limitations, and how this research improves upon them.

Table 2.1: Comparison of UAV Positioning Techniques

Study	**Method Used**	**Technology**	**Key Findings**	**Limitations**	**How This Work Improves**
Sheridan (2020) [103]	GPS, Glonass, Galileo, BeiDou	GNSS-based UAV positioning	Standard navigation accuracy for open areas	Poor performance in urban environments (NLOS & multipath effects)	Uses 5G PRS signals instead of GNSS for better urban coverage
Zhang & Hsu (2019) [132]	GNSS, Error Maps	Path planning using GNSS error maps	Improves UAV navigation by compensating for GNSS errors	Still relies on GPS signals and doesn't work in full GNSS-denied environments	This work eliminates dependency on GPS by using 5G networks
Roth et al. (2018) [133]	Long Term Evolution (LTE), 4G Networks	Cellular network-based UAV positioning	Uses cellular tower signals for UAV localization	Limited by LTE's high latency and low bandwidth	This work uses 5G's ultra-low latency and high accuracy
Bandelier et al. (2023) [134]	5G, V2V communication	Multi-connectivity for UAVs	UAVs use multiple networks for seamless connectivity	Does not focus on UAV positioning accuracy	This work specifically focuses on precise UAV localization using 5G NR
Khan et al. (2017) [135]	5G RSSI measurements	RSS-based localization	Uses signal strength for rough UAV positioning	High errors in urban areas due to multipath fading	This work combines RSS with OTDOA and sensor fusion for higher accuracy
Markovic et al. (2022) [78]	IMU, Lidar, GPS	Multi-sensor fusion for UAV navigation	Improves UAV indoor localization without GPS	Limited to indoor environments	This approach extends sensor fusion to urban outdoor UAV navigation with 5G PRS signals

GNSS remains the foundational technology for UAV positioning, but it faces significant challenges in obstructed and interference-prone settings. Wireless network-based positioning, especially within 5G, has potential for more robust and accurate localisation, but practical, UAV-oriented deployments are still limited. The opportunity to combine 5G positioning signals with multisensor fusion methods such as IMU, barometric sensors, and optical flow represents a critical gap in the literature and an avenue for delivering high-precision positioning in complex environments.

2.3 Neural Networks for NLOS Mitigation

The integration of ML and DL into 5G-based positioning systems, particularly using PRS, has been extensively studied in recent years due to the increasing demand for high-precision UAV localisation, especially in challenging urban and indoor environments. These environments introduce significant complexities, including NLOS conditions, multipath propagation, and signal degradation, which traditional positioning systems struggle to overcome [136]. The following sections provide a detailed overview of recent advances and highlight key challenges that ML and DL methodologies address for 5G positioning. The adoption of 5G PRS for UAV positioning has gained significant attention due to its potential to achieve high accuracy and robustness in various environments. Studies have shown that 5G PRS can achieve centimetre level precision through advanced carrier phase measurements and time-based techniques [137]. For example, recent research demonstrated that carrier phase-based methods could achieve centimetre-level precision in LOS conditions, significantly surpassing traditional time-of-arrival techniques. Carrier phase measurements have successfully achieved sub-meter accuracy with minimal BS infrastructure [137]. Similarly, a multifrequency carrier phase range method was proposed using 5G NR signals based on orthogonal frequency division multiplexing (OFDM), effectively mitigating antenna reference point errors and improving positioning accuracy in complex urban environments [138]. Furthermore, the effectiveness of 5G PRS for UAV applications in diverse environments, particularly urban and indoor areas, has been extensively explored. Studies have shown that 5G PRS can achieve submeter accuracy with minimal BS deployments. For example, a study in LOS environment achieved centimetre-level precision by using advanced carrier-phase measurements with only a few BSs, thus demonstrating the feasibility and practicality of implementing precise positioning systems without extensive infrastructure deployment [137]. Similarly, innovative methods using NR signals based on OFDM-based NR signals for multi-frequency carrier phase ranging have been proposed to mitigate antenna reference point position errors and improve accuracy effectively [138].

However, these solutions predominantly rely on ideal LOS conditions, leaving substantial gaps in robustness under realistic urban conditions characterised by severe multipath propagation and NLOS. To address these NLOS challenges, innovative methods using ML and DL have been developed. Recent approaches have utilised NLOS detection techniques by exploiting the differences between Received Signal Strength Indicator (RSSI)-based and time-based measurements, successfully filtering out erroneous signals that cause significant positioning inaccuracies. For instance, a method was introduced that combines RSSI and time-based measurements with a Kalman Filter-based estimator, achieving sub-meter accuracy in 95% of cases [139]. Similarly, location fingerprinting methods that employ RSSI-based weighted K-nearest neighbour algorithms demonstrated substantial improvements in accuracy by effectively managing multipath interference [140]. Nevertheless, fingerprinting methods require extensive initial data collection and periodic updates, which limit scalability and flexibility in dynamic UAV deployments. In [141], ML-based methods, including

random forest regression (RFR) and NNs, were used with signal beam power measurements to mitigate NLOS effects, achieving sub-10-metre accuracy in urban scenarios. Specifically, the authors investigated ML-based approaches such as random forest regression (RFR) and NNs, using signal beam power measurements to mitigate NLOS effects, achieving sub-10-meter accuracy in urban scenarios. DL architectures have enhanced precision, such as temporal convolutional networks (TCNs) and fully connected neural networks (FCNNs). For example, temporal convolutional networks achieved sub-2 meter accuracy in mmWave positioning scenarios with severe multipath and NLOS effects by extracting complex temporal and spatial signal features [140],[142]. Deep learning-based Radio Frequency (RF) fingerprinting methods have also been shown to extract complex signal patterns, achieving sub-meter positioning accuracy in urban environments [143]. Hybrid positioning approaches, combining 5G signals with other technologies such as GNSS, have also shown promise. A GNSS-5G hybrid approach was demonstrated in [144], achieving sub-metre accuracy in most urban scenarios by integrating GNSS data with 5G PRS measurements. Despite these promising results, such hybrid methods remain constrained by their reliance on GNSS, which limits their effectiveness in GNSS-denied environments, such as urban canyons and indoor areas with poor satellite visibility.

Kalman Filter-based positioning methods have also been widely explored, notably the entropy adaptive kalman filter integrated with recurrent neural networks (RNNs), effectively managing non-linear UAV dynamics and non-Gaussian noise scenarios [142]. Despite their effectiveness in stable environments, these filters often struggle under highly dynamic multipath interference and non-linear signal conditions common in urban UAV scenarios. Furthermore, the application of long short-term memory (LSTM) networks in UAV positioning systems has been explored to exploit temporal dependencies in positioning data. Recent studies employing LSTM networks have shown improved positioning accuracy through real-time error correction of GNSS-based positioning solutions [145]. However, the computational complexity and resource demands of LSTM limit their deployment in resource-constrained UAV systems, necessitating more straightforward yet effective alternatives. Despite significant advancements, current UAV positioning solutions using 5G PRS, ML, and DL techniques face several notable limitations.

- Current high-precision positioning methods often depend on dense deployments of 5G base stations, which limits their practicality in rural or remote areas with sparse infrastructure.
- Urban environments continue to pose significant challenges due to multipath interference and signal degradation, despite technological advancements.
- Techniques that rely on complex algorithms, such as carrier phase measurements or deep learning models like LSTMs, require substantial computational resources and advanced implementation strategies.
- Hybrid systems that integrate GNSS and 5G Positioning Reference Signals (PRS)

remain limited in effectiveness within GNSS-denied environments, reducing their applicability in urban areas where satellite signals are frequently obstructed.

Our research directly addresses these challenges by using advanced ML techniques, specifically fully connected NN trained on comprehensive datasets encompassing diverse LOS and NLOS scenarios. This approach reduces infrastructure dependency, robustly manages dynamic multipath interference, and effectively captures non-linear signal interactions, offering improved scalability and real-time adaptability. Thus, our method provides a more feasible, scalable, and precise UAV positioning solution, particularly suitable for challenging dense urban environments.

Chapter 3

Field Trials and QoS Evaluation

This chapter comprehensively reviews existing research on UAV positioning challenges within 5G networks and the impact of altitude on QoS. The review sets the stage for identifying research gaps, defining the problem, and establishing the aim and objectives outlined in Chapter 1. The content supports the second research objective by addressing UAV positioning in urban environments.

3.1 Introduction

The use of UAVs in 5G-Advanced communication systems is a big step forward for wireless connectivity, especially in places where traditional ground networks struggle. UAVs are highly versatile and can act as flying BSs, relays, or data collectors. This makes them perfect for increasing coverage in remote areas, difficult-to-reach locations, or crowded urban environments. However, maintaining reliable communication links between UAVs and ground networks remains a significant challenge. Challenges like altitude changes, signal loss, and environmental interference can all affect performance. To address these issues, evaluating the QoS during real-world UAV flights is essential. By measuring key performance metrics such as latency, throughput, signal stability, and HO efficiency, it becomes possible to identify weaknesses in the network and optimise its configuration for improved performance. In this study, we conducted trials at different altitudes (50 m, 72 m, 88 m, and 110 m) to see how height impacts network performance, as displayed in Figure 3.1. To gather accurate data, we equipped the UAV with the XCAL measurement tool, allowing us to assess network conditions in real time.

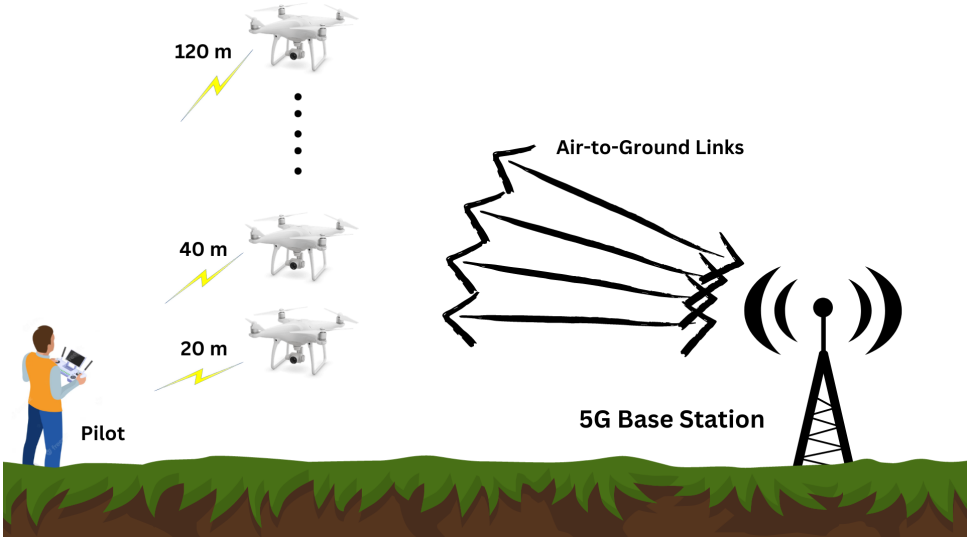


Figure 3.1: Outdoor measurement scenario

This research takes a two-pronged approach, combining field measurements with simulation-based evaluations. By analysing how UAV-to-ground communication performs at various heights, we aim to improve deployment strategies and optimise network configurations. These efforts will help integrate UAVs more seamlessly into next-generation wireless systems, supporting applications such as disaster response, smart city infrastructure, and space-air-ground networks. Ultimately, the insights gained from this work will play a crucial role in refining UAV communication protocols. By addressing current limitations, this work contributes to developing more efficient, adaptable, and scalable aerial networks, offering new possibilities for future connectivity. QoS differs between LTE and 5G technologies, where QoS in LTE is performed at the Evolved Packet Service (EPS) bearer level. Accordingly, a one-to-one mapping is implemented, ensuring that each EPS bearer is associated with an EPS Radio Access Bearer (RAB), an S1 bearer, and a Radio Bearer (RB). In contrast, 5G networks offer a more flexible QoS model, with QoS flow being the finest granularity at which QoS is applied. The abstraction of QoS flow allows us to decouple the roles of 5G Core and Next Generation Radio Access Network (NG-RAN). The access network independently decides the mapping of QoS flows to radio bearers. This flexible design allows the gNB to map multiple QoS flows to a single RB if such an RB can be configured to fulfill the requirements of those QoS flows.

3.2 QoS Challenges in UAV Networks

The integration of UAVs into 5G networks has emerged as a transformative advance for various applications, including surveillance, package delivery, and disaster response. 5G networks are designed to support three primary usage scenarios: enhanced mobile broadband (eMBB), URLLC, and massive machine-type communications (MMTC). These capabilities make 5G networks highly suitable for UAV opera-

tions that demand high throughput, low latency, and reliable communication links [146]. 5G technology improves UAV communications through key capabilities such as URLLC and eMBB. URLLC is crucial for mission critical applications such as remote UAV control and real-time video streaming, ensuring ultra-low latency for precise maneuvering in dynamic environments, particularly in search and rescue operations and autonomous navigation [147]. Meanwhile, eMBB supports high-throughput communication, enabling high definition (HD) video streaming, real-time surveillance, and large-scale sensor data transmission [146]. However, UAV-to-ground communication faces several challenges. Shared spectrum interference, caused by UAVs operating in both licensed and unlicensed bands, degrades performance due to congestion of terrestrial wireless devices. Mitigation strategies include beamforming, spectrum sharing, and AI-driven dynamic spectrum access [148]. The high mobility of UAVs complicates seamless handovers between BSs, necessitating solutions such as core-RAN colocation and predictive handover algorithms to maintain stable connections with minimal latency [149], [150]. Furthermore, signal attenuation at higher altitudes weakens transmission, increasing latency, and reducing throughput, which can be countered using phased array antennas, UAV-specific network slicing, and multihop relay architectures [148],[151]. Urban environments introduce additional obstacles, including signal blockage, multipath fading, and interference from tall buildings. Techniques like radio environment mapping can dynamically optimise UAV communications to effectively address these challenges [151]. QoS refers to the ability of a network to provide guaranteed performance for specific applications or services. In the context of UAV networks, QoS is crucial to ensure that communication links meet the requirements of various UAV applications, such as low latency, high throughput, and high reliability. QoS is particularly important for mission-critical applications, such as search and rescue operations, where reliable and low-latency communication is essential [74].

QoS has a direct impact on latency, throughput, and reliability in UAV networks. Low latency is essential for real-time applications, such as remote control of UAVs and real-time video streaming. High throughput is necessary for applications that require the transmission of large amounts of data, such as high-definition video streaming and data-intensive sensing tasks. Reliability is critical for mission-critical applications, where communication links must be maintained even in the presence of interference or other challenging conditions. By ensuring high QoS, UAV networks can provide the necessary performance for a wide range of applications. Unlike 4G's Evolved Packet System (EPS) bearer-based QoS, 5G introduces dynamic QoS flows, enabling UAV-specific priority adjustments [74],[147]. 5G networks offer several advantages over 4G networks for UAV applications. These advantages include lower latency, higher throughput, and greater reliability. 5G networks are designed to support URLLC and eMBB, which are essential for real-time communication and high-throughput applications. In contrast, 4G networks are limited in their ability to provide the low latency and high throughput required for many UAV applications. As a result, 5G networks are better suited to support the diverse needs of UAVs, including real-time control, high-definition video streaming, and data-intensive sensing tasks. Table 3.1 highlights the key differences [152],[148]: 5G networks are particularly advantageous for appli-

cations that require real-time data transmission, such as remote control of UAVs and streaming of real-time video. These applications require low latency and high reliability, which are provided by 5G networks through URLLC and eMBB. In contrast, 4G networks are not suitable for these applications due to their higher latency and lower throughput. As a result, 5G networks are essential for enabling the next generation of UAV applications that require real-time communication and high-throughput data transmission [148],[152],[153].

Table 3.1: Comparison of 4G and 5G performance for UAV communications.

Performance Metric	**4G LTE**	**5G NR**
Latency	20–50 ms	$<$1 ms
Throughput	$\sim$100 Mbps	1+ Gbps
HO Delay	$\sim$30 ms	$<$10 ms
Reliability	Moderate	High
Network Slicing	No	Yes

3.3 Flight Scenario and Measurement Setup

In the United Kingdom (UK), UAVs can operate at a spectrum of altitudes, depending on weight, ambient environment, and proximity to existing terrestrial infrastructure [154], from a few meters above ground to a couple of kilometres. Generally, increasing altitude can lead to a complex wireless communication environment, since it impacts signal strength, interference, handover, resource allocation, and deployment [155],[156]. Thus, QoS parameters should be customised to meet the needs of the UAV application. For example, a UAV conducting low-altitude surveillance operations will probably require lower latency and higher throughput to stream 4K videos. Meanwhile, a UAV deployed at high altitude is highly likely to suffer from atmospheric attenuation, which makes it difficult to maintain consistent services. Table 3.2 presents the end-to-end latency, data rate, and UAV speed, reported in the 3GPP specifications [157]. Hence, conducting a field trial to measure the parameters of the 5G-UAV connection can provide an opportunity to explore whether these values are accurate and also to enhance overall UAV communication performance and efficiency. These trials foster collaboration among academia, industry stakeholders, and regulatory bodies, driving the development and standardisation of 5G technologies for UAV applications. The UAV platform used in this study is a custom-built DJI F450 quadcopter, as illustrated in Figure 3.2 (a). It is equipped with advanced flight control and measurement tools to enable accurate data collection capabilities, as depicted in Figure 3.2 (b).

Table 3.2: 3GPP QoS parameters for UAV–5G BS links [157].

Parameter	Value
End-to-end latency	100 ms
Data rate	0.06 Mbps
Service area	Rural area
UAV speed	79 km/h
Altitudes	50, 72, 88, and 110 m

(a) (b)

Figure 3.2: Measurement hardware. (a) DJI F450, (b) XCAL tool.

The detailed specifications of the UAV hardware, including the flight controller, GPS module, communication system, and onboard measurement device, are presented in Table 3.3.

Table 3.3: F450 UAV Specifications

Item	Specification
UAV frame	DJI F450 (quad-copter)
Motor	Brushless 2213
Transmitter	FS-i6X (6 channels)
Receiver	FS-iA6B (6 channels)
Battery	LiPo (4200 mAh)
Maximum altitude	466 m

These components were carefully selected to ensure stable flight, precise positioning, and reliable monitoring of 5G network performance during the flight trials.

- Pixhawk 4 is used as an autopilot, which is an open-source flight control software that is capable of supporting various configurations, including multicopters, fixed

wings, rovers, and even unmanned underwater vehicles. In addition, it provides production-grade firmware and allows configuration, autonomous operation, and external control via an Software Development Kit (SDK) using a companion computer, telemetry link, or cloud connectivity. Additionally, it is equipped with two IMU modules.

- An external GPS sensor (M8N GPS module) is connected to the autopilot to enable a high positioning accuracy of up to 50 cm with the capability of searching 20 satellites per minute in open areas. This module guarantees low power consumption and enables dual compass backup.
- FlySky FS-i6 is utilised to control the proposed UAV. It operates in the Global Industrial, Scientific, and Medical (ISM) band at a frequency of 2.4 GHz with a bandwidth of 500 kHz and RF power of less than 20 dBm.
- An FS-iA6B transmitter of 6 channels was connected to the autopilot to increase the number of control commands using the FlySky remote controller.
- LiPo battery (4200 mAh, 11.1 V) with three cells powered the UAV platform to enable a flight time of up to 18 minutes.

3.3.1 Accuver XCAL Tool

The Accuver XCAL tool is a software solution designed for wireless network optimisation and performance measurement. It can be used for data collection since it interfaces with smartphones, modems, and network cards. Furthermore, it can be used to test QoS on voice and data services using embedded automated call scripts. It can support various mobile chipsets, including those from Qualcomm, Nokia, Samsung, Icera, and Infineon. Regarding 5G QoS, XCAL is able to assess QoS and quality of experience (QoE) and ensure seamless service integration with existing technologies ranging from 2G to 5G [158]. By automatically recording and interpreting messages from the air interface, XCAL detects any network bottlenecks and impediments that can affect the delivery of high-quality voice and data services, providing invaluable information for network enterprises.

Hence, the XCAL tool will be used for the measurement introduced to capture parameters such as latency, throughput, packet loss, and jitter. The XCAL tool will generate a unique log file for each measurement. In the proposed measurement, a 163 g Sony Xperia 5 II smartphone equipped with the XCAL tool is used and attached to the UAV, as shown in Figure 3.2 (b). This tool can support a variety of call types for capturing QoS parameters such as Internet Performance Measurement Tool (iPerf), voice call, email, Voice over LTE (VoLTE), FTP, Hypertext Transfer Protocol (HTTP), Short Message Service SMS, and other configurations. iPerf is an example of an open source tool for measuring network performance by generating Transmission Control Protocol (TCP) and User Datagram Protocol (UDP) streams between two endpoints.

It supports evaluating bandwidth, throughput, and various other metrics related to network performance. Before the measurements were conducted, key system characteristics were configured, as detailed in Table 3.4. These components collectively form the complete measurement setup, whose interaction is illustrated in Figure 3.3.

Table 3.4: iPerf Scenario-specific Parameters

Parameter	Definition	Value
Destination	Configures IP address or URL of destination	ATL, Speedtest, Cloudiver
iPerf version	Selects v3.1.3 or v2.0.5	v3.1.3
Mode Selects	TCP or UDP	UDP
Direction	Selects Up: Transfers packet from smartphones (client) to server or Down: Transfer packet from the server (client) to smartphone.	UP
Packet Size	Configures iPerf buffer size to be transferred.	500 bytes

3.3.2 Flight Planning

Figure 3.3 illustrates the overall measurement setup, while Figure 3.5 categorizes the equipment into ground and airborne segments. To comply with the regulations of the UK Civil Aviation Authority (CAA) [159], the experiment was conducted in a rural area, with the maximum flight altitude limited to 120 m. The ground equipment includes the FlySky remote controller, ambient 4G and 5G base stations, and a data processing unit. Prior to flight, several safety checks and procedures were performed:

1. Checking the regulations applicable to the designated flight area.
2. Checking the connection between the UAV and the remote controller.
3. Inspecting the batteries for charge level and physical condition.
4. Assessing weather conditions, including:
    - Precipitation probability (<10%)
    - Wind speed (<20 mph)
    - Visibility, particularly during dawn or dusk

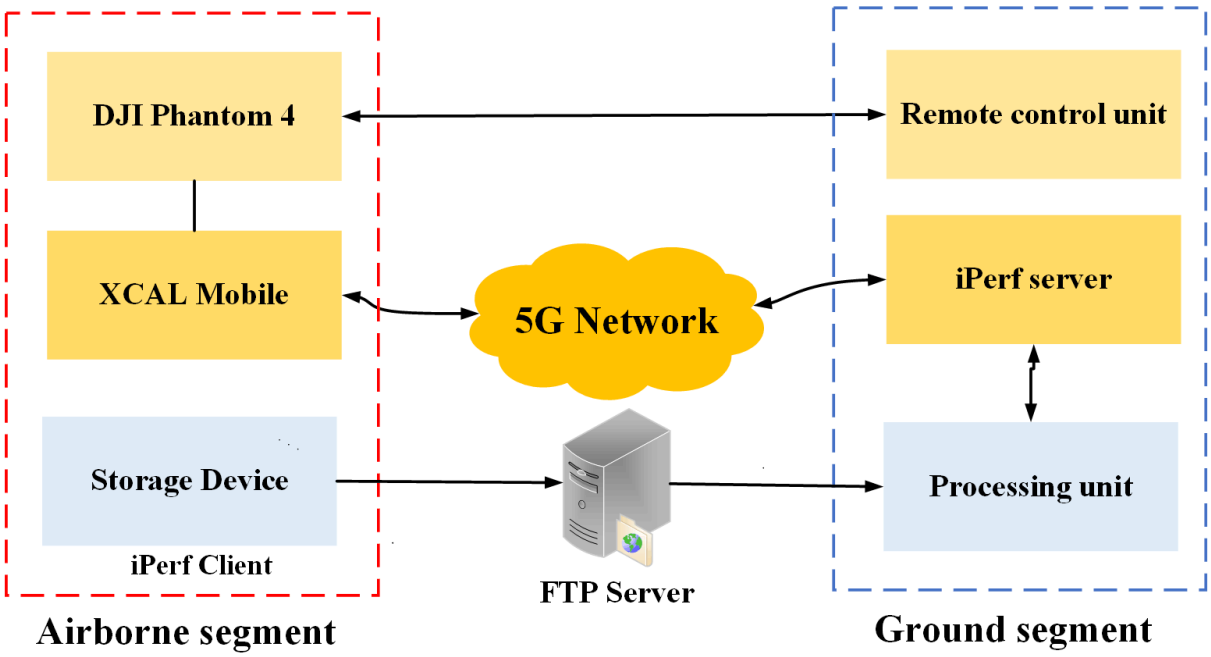


Figure 3.3: System design for Measurement

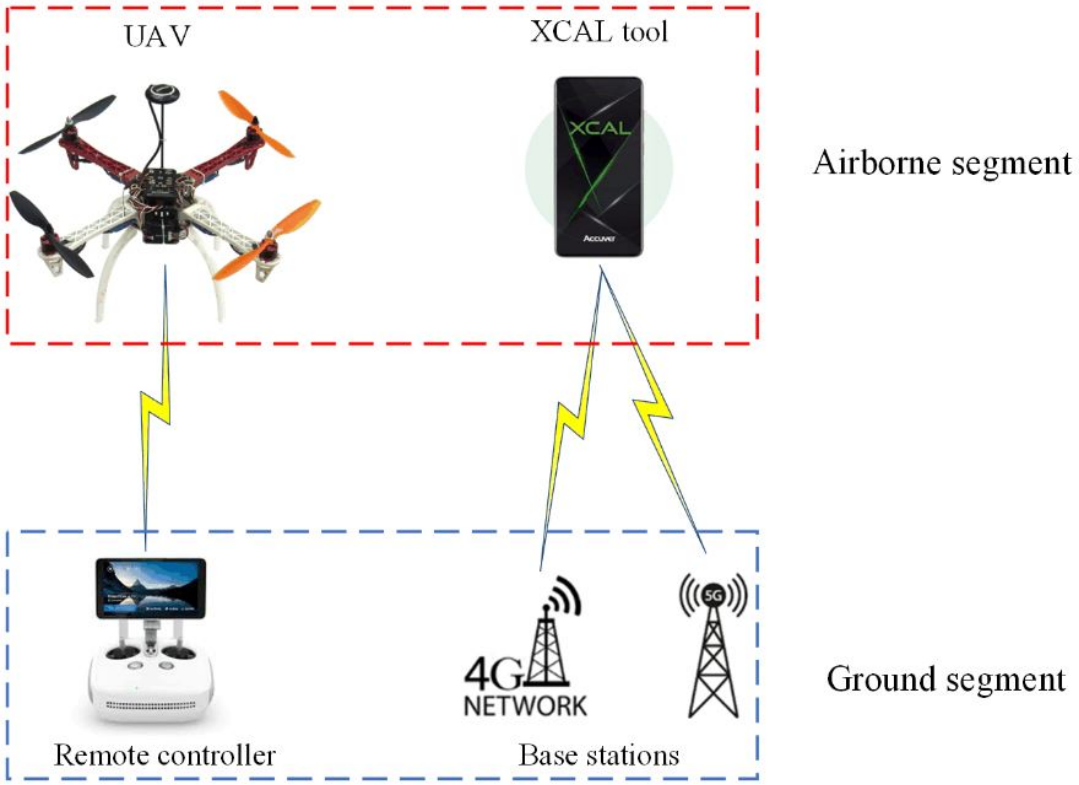


Figure 3.4: Overview of Measurement System Architecture

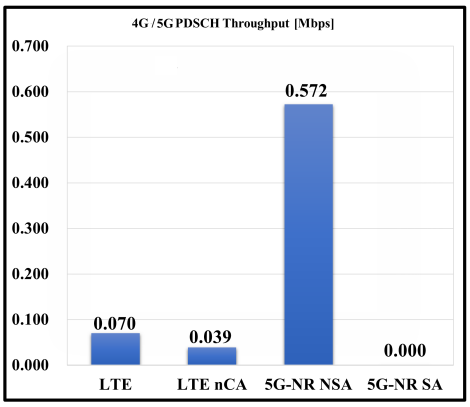
The experiment evaluated multiple operational scenarios, including voice communication, HD video calls, streaming HD videos, and running iPerf tests. The diagram, illustrated in Figure 3.3, highlights the measurement steps for an iPerf scenario. First, the iPerf scenario is configured on the XCAL tool in terms of time, mode (TCP/UDP),

traffic direction, and packet size before it is attached firmly to the UAV. The next step is taking off the UAV to the first altitude, which is controlled using the FlySky. During varying the altitude, the XCAL tool recorded the session and enjoyed a connection to a 4G or 5G network based on the signal strength. The data were recorded on a server and transferred later to the processing unit to be analysed and produced in a suitable format. The iPerf scenario was run during the entire UAV flight and increased the altitude between 50 and 110 m. Subsequently, the UAV moved in a square route to scan the area exhibited in Figure 3.5.

Figure 3.5: Flight Path of UAV in Measurement Scenario

3.4 Results and Discussion

Here, the impact of altitude on QoS of the UAV-5G links is evaluated, and whether signal strength will degrade at higher altitudes due to an increase in transmission distance. Figure 3.6 shows several KPIs of the UAV network links, such as throughput of the physical downlink shared channel (PDSCH), the success rate of the newly developed universal terrestrial radio access-new radio dual connectivity (ENDC), SS-RSRP, synchronisation signal-reference signal received quality (SS-RSRQ), synchronisation signal-signal to synchronisation signal-signal to interference plus noise ratio (SS-SINR). As is known, the PDSCH delivers user data from the base station (BS). Figure. 3.6 (a) illustrates the percentage distribution of each technology used for data exchange with users. The 5G non-standalone (NSA) provides 0.572 Mbps during the voice call scenario compared to 0.070 and 0.039 Mbps for LTE and LTE non-contiguous



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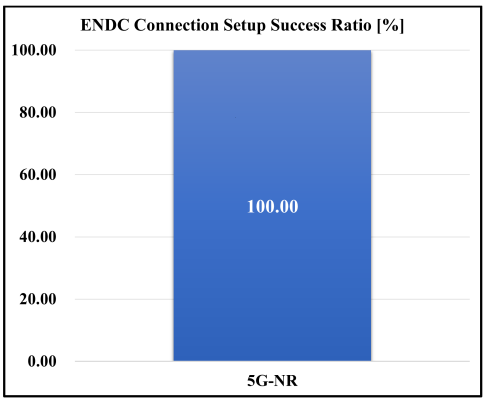

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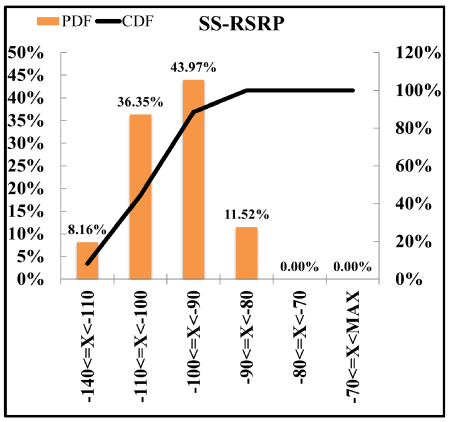

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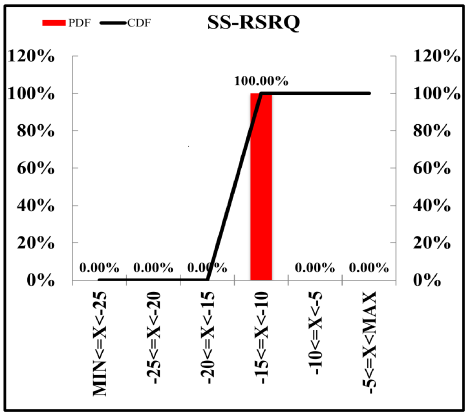

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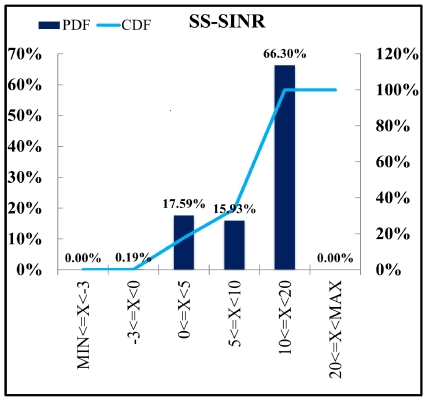

(e)

Figure 3.6: Measured KPI charts. (a) 4G/5G PDSCH throughput, (b) ENDC connection setup success ratio, (c) SS-RSRP, (d) SS-RSRQ, and (d) SS-SINR.

carrier aggregation (NCA), respectively. As a result, 5G was dominant during the measurement campaign. Whereas Figure 3.6 (b) shows a 100% successful ENDC dual connectivity rate, this parameter is crucial as it enables smartphones to exchange data simultaneously with NR and LTE base stations. Figures 3.6 (c),(d) and (e) demonstrate key parameters that help optimise network performance, improve user experience, and guide decisions related to network configuration and handover by computing the probability density function (PDF) and the cumulative distribution function (CDF) for each of them. First, SS-RSRP measurement is essential for assessing the downlink channel since it determines the path loss and the average channel quality. The majority is located in the good RF condition range for RSRP. The SS-RSRQ values are mainly within this range, which means that overall single health during measurement is considered good. The same applies to the SS-SINR. As illustrated in Figure 3.5, the movement of the UAV has scanned a square area, which, in turn, has led to several 4G and 5G handovers. Table 3.5 highlights the mobility factor, in which, during the measurement, there were 10 LTE and 8 5G handovers, respectively. All 5G handovers were successful, whereas the LTE connection experienced one failure. In addition, there were two LTE radio link failures. Considering the random access channel (RACH), used by customers to access the service, the total attempts were 14 LTE attempts with one failure and 11 successful 5G attempts. However, the correlation between RSRP and RSRQ is demonstrated in Figure 3.7. As RSRP increases, indicating better signal strength, RSRQ tends to improve and shift toward higher values. The minimum, maximum, average, median, and percentile values are represented by the yellow, aqua, blue, orange, and red lines, respectively. Knowing that the dispersed black points represent the serving RSRQ values.

Table 3.5: Key Performance Indicators (KPIs) during UAV communications

Factor	**LTE**	**NSA 5G**
Handover attempts	10	8
Handover success (failures)	9 (1)	8 (0)
Radio link failures	2	0
RACH attempts	14	11
RACH success (failures)	13 (1)	11 (0)

Figure 3.8 displays the impact of altitude on RSRP, RSRQ, CQI, and SINR for both smartphone antennas (0 and 1). The obtained results show that 5G performance degrades with increasing altitude, except for transmitted power (Tx), which remains nearly the same. That can return to the fact that standard commercial mobile SIMs and plans are typically designed for ground purposes. However, altitude, vibration,

and ambient temperature of the UAV can negatively affect performance [160]. Factors such as increased path loss with distance and lack of vibration resistance characteristics when using standard SIMs above the Earth level may explain the decline in the observed QoS parameters. Recently, BT has suggested the UAV SIM as an optimised solution for UAVs to withstand vibration and temperature [160].

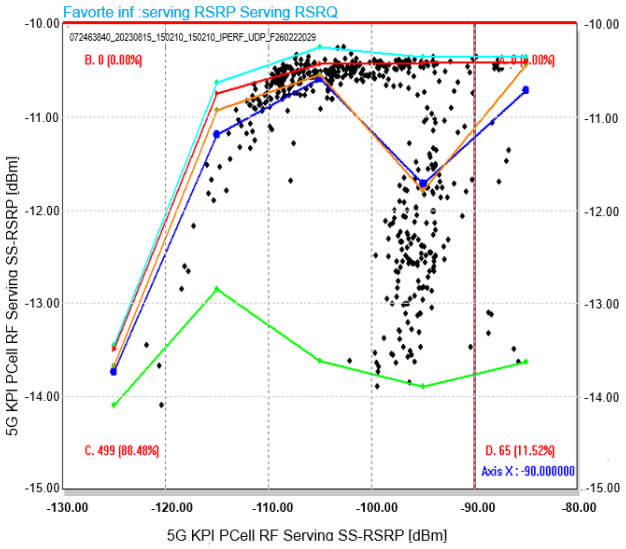

Figure 3.7: Correlation graph for RSRP/RSRQ.

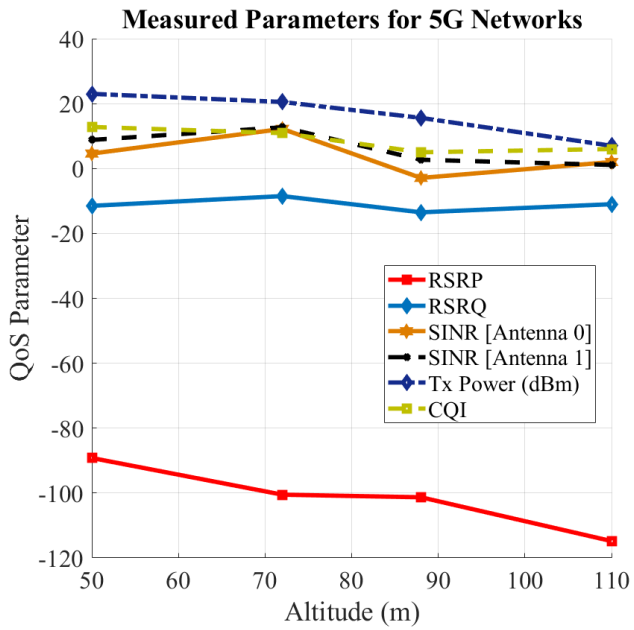

Figure 3.8: QoS parameters vs altitude for UAV-5G links.

3.5 Conclusion

This chapter investigated the impact of altitude on UAV–5G communication through field measurements. Several QoS parameters (RSRP, RSRQ, SINR, and CQI) were measured and analysed to examine the wireless communication system performance at different altitudes 50. 72, 88, and 110 m. Mobility and handover performance were also analysed, showing LTE handover failures at certain points. The specific altitudes were chosen because they fall within the 3GPP-defined operational range for UAV–5G communication, which supports flights up to 120 m above ground level. This research contributes to a deeper understanding of the characteristics of 5G networks at various altitudes, providing a foundation for the development of a robust network tailored to assist 5G-UAV communications. However, the analysis was limited to a rural environment, which may not fully reflect the complexity of urban network conditions. Future work should consider trials in urban areas where multipath, interference, and user density introduce additional challenges.

Chapter 4

5G NR-Enabled Urban UAV Positioning

This chapter explains how 5G improves UAV positioning by offering fast, reliable communication and advanced processing. It also covers different positioning methods and introduces a sensor fusion approach using EKF. This supports the second and fourth research objectives on improving accuracy.

4.1 Introduction

UAVs, also known as drones, have become increasingly popular in various industries, including logistics, agriculture, and surveillance. One commonly used UAV navigation technology is the GNSS, which includes the GPS, Glonass, Galileo, and BeiDou systems. GNSS provides accurate and global positioning information for the UAV navigation system [103], [104],[161]. However, their positioning capabilities in urban environments can be limited due to challenges such as NLOS propagation, multipath interference, and signal blockage caused by tall buildings, trees, and other obstacles, which can affect their positioning capabilities [65],[132]. As the demand for more precise and reliable UAV positioning increases, the emergence of 5G technology offers promising solutions. UAVs are becoming available and connected to cellular networks [47]. The 5G NR is the next generation in wireless communications technology, offering significant improvements over previous generations. 5G NR provides faster data transfer rates, reduced latency, and improved dependability, which makes it well-suited for various applications in diverse fields. This technology offers the necessary infrastructure for advancements in fields such as the IoT, UAVs and autonomous vehicles [162],[163]. This development will pave the way for novel UAV

applications, including self-governing flight, enhanced safety measures, and instantaneous data transmission. With the implementation of 5G NR, the UAV industry is poised for significant growth and innovation. The 5G NR technology will provide the infrastructure needed for UAVs to take advantage of the increased speed, reliability, and low latency offered by 5G networks [152],[164],[165].

Overall, the use of 5G NR technology and the OTDOA technique for UAV positioning in urban environments has the potential to improve the accuracy and reliability of UAVs, allowing for a wide range of applications and services. The results of the study have important implications for UAV positioning in urban environments using new 5G radio technology. One of the main advantages of using 5G for UAV positioning is that it can provide more accurate and reliable position information than GNSS systems, which can be obstructed by buildings and other structures in urban environments. When comparing and contrasting the results with the existing literature on UAV positioning and communication in urban environments, it can be seen that there have been several studies that have explored the use of different technologies for UAV positioning and communication, including GNSS, cellular networks, and Wi-Fi. However, using 5G NR technology and the OTDOA technique is a relatively new approach that has not been extensively studied in the literature. This study uses 5G NR technology and the OTDOA technique to improve UAV positioning in urban environments. While previous research mainly explored communication capabilities, this work aims to enhance the accuracy and reliability of UAV positioning, which is crucial for various real-world applications. To achieve better performance, the system integrates an IMU and an EKF, as part of the UAV platform architecture. In addition, barometric pressure measurements are incorporated to improve altitude estimation in 3D space. These measurements offer an independent source of altitude information, helping to correct potential errors from the IMU and TDOA data. The system can achieve more accurate and stable position estimates by fusing all three data sources TDOA, IMU, and barometric pressure through the EKF. This is especially beneficial when altitude precision is critical, such as UAV navigation in urban environments or vertical positioning in multi-story buildings. However, using barometric data also introduces challenges, such as sensitivity to weather conditions and pressure variations with altitude, which must be carefully managed.

4.2 5G-Enabled UAV Positioning Techniques

One significant benefit of 5G technology is its ultra-reliable and low-latency communication. This enables real-time positioning updates with minimal delay, enabling more precise control [104]. 5G networks offer much higher bandwidth compared to previous generations. This enhanced data transfer capability enables UAVs to transmit large volumes of positioning-related data, such as GNSS coordinates, altitude, and orientation, in real time. As a result, operators can obtain more precise and detailed information on the position and status of the UAV [166]. 5G networks support multicon-

nectivity and network segmentation features to ensure reliable and seamless UAV positioning. Multiconnectivity allows UAVs to connect to multiple BSs simultaneously, enhancing signal strength and reducing the risk of signal loss in areas with limited coverage. Network segmentation enables the creation of dedicated virtual networks, ensuring uninterrupted and prioritised communication for UAV positioning requirements [167]. 5G networks facilitate edge computing, enabling UAVs to offload specific processing tasks to edge servers closer to the deployment area. Using edge computing capabilities, UAVs can achieve faster processing of positioning data, reducing latency and improving overall positioning accuracy. This distributed processing approach also helps alleviate the computational burden on the UAV's onboard systems.

5G technology can be seamlessly integrated with other emerging technologies to enhance UAV positioning capabilities further. For example, combining 5G with AI and ML enables advanced positioning data analytics, leading to predictive positioning models and intelligent flight path planning. Furthermore, integrating 5G with satellite-based navigation systems, such as GNSS, ensures reliable and precise positioning in environments with limited coverage of GNSS [7],[134]. There are two main types of signal processing techniques for position estimation in wireless networks: range-based and range-free methods [133],[168]. Range-based methods are based on measuring specific parameters, such as ToA. It is a technique used to measure the time taken for a signal to travel between an anchor node and a target node [103]. Several techniques can be used for position estimation in 5G wireless networks. Here are some of them:

- Time of Arrival (ToA) measures the signal travel time between the transmitter and receiver. By using the known speed of the signal, the distance can be calculated and subsequently used to approximate the receiver's location [169].
- Angle of Arrival (AoA) estimates the position of the transmitter based on the angle at which the signal arrives at the receiver. This often involves using multiple antennas to determine the angle of incidence [170].
- Received Signal Strength (RSS) estimates the distance between the transmitter and receiver by analysing the signal's strength at the receiver. When data from multiple receivers is available, the transmitter's position can be inferred [171].
- Time Difference of Arrival (TDoA) calculates the position of the transmitter by measuring the difference in signal arrival times at multiple receivers [172].
- Hybrid techniques improve positioning accuracy by combining two or more of the above methods. For instance, combining ToA and RSS can enhance the precision of position estimation [173].

While range-based methods can provide accurate positioning, they often require specialised hardware and are sensitive to interference, multipath propagation, and environmental conditions. In contrast, range-free methods do not rely on distance or angle measurements; instead, they estimate positions using connectivity and network topology. These approaches are simpler and more robust but generally less accurate [44].

A summary comparison of UAV positioning techniques for urban environments is presented in Table 4.1.

Table 4.1: Comparison of UAV Positioning Techniques for Urban Environments

Method	Accuracy	Complexity	Environmental Suitability	Hardware Requirements	Implementation Restrictions	Ref
ToA	1–5 m	Medium	Good in LOS; poor in NLOS	Precise timing synchronization	Requires accurate atomic clocks	[166]
AoA	2–10 m	High	Good in open areas	Large antenna arrays	Limited by antenna size constraints	[167]
RSS	5–15 m	Low	Poor in multipath environments	Simple receivers	Highly environment-dependent	[168]
TDoA	1–3 m	Medium	Good overall	Multiple receivers	Requires base station synchronization	[169]
OTDOA (5G)	1–7 m	Medium	Good in urban environments	5G network infrastructure	Coverage dependent	[80, 81]
Proposed Hybrid	2.8–7 m	High	Excellent in all environments	5G + IMU + Barometric sensors	Increased complexity but robust	

4.2.1 Implementation Potential Analysis

The choice of positioning method directly affects deployment feasibility, scalability, and cost. Based on implementation restrictions, these methods can be grouped as follows:

- **High Restriction Methods:** Angle of Arrival (AoA) requires large antenna arrays, adding weight and power demands that reduce UAV flight endurance [174]. Standalone RSS-based methods are simple but highly sensitive to multipath and environmental variability, requiring extensive calibration and often producing poor accuracy in urban deployments [175].
- **Medium Restriction Methods:** Time of Arrival (ToA) requires precise timing using atomic clocks, increasing cost and maintenance complexity [176]. Time Difference of Arrival (TDoA) depends on tight synchronisation across receivers, which complicates scaling in large or urban networks [125].
- **Low Restriction Methods:** Hybrid approaches combine multiple techniques (e.g., ToA, RSS) with onboard sensor fusion (IMU and barometric sensors). These

methods use existing 5G infrastructure and reduce reliance on specialised hardware. While computationally more complex, they are scalable and robust across diverse environments [177].

These restrictions highlight the trade-off between accuracy, cost, and scalability. The proposed 5G OTDOA + sensor fusion method developed in this thesis falls within the low-restriction category. It introduces additional computational demand but achieves a practical balance of accuracy, robustness, and deployment feasibility, making it suitable for large-scale UAV operations in dense urban environments.

4.3 System Design and Implementation

The system was developed to integrate 5G, IMU, BPSs, and EKF to enhance UAV positioning as illustrated in Figure 4.1. The system consists of five main components: 5G receiver, Barometric Air Pressure (BAP), an IMU, and EKF.

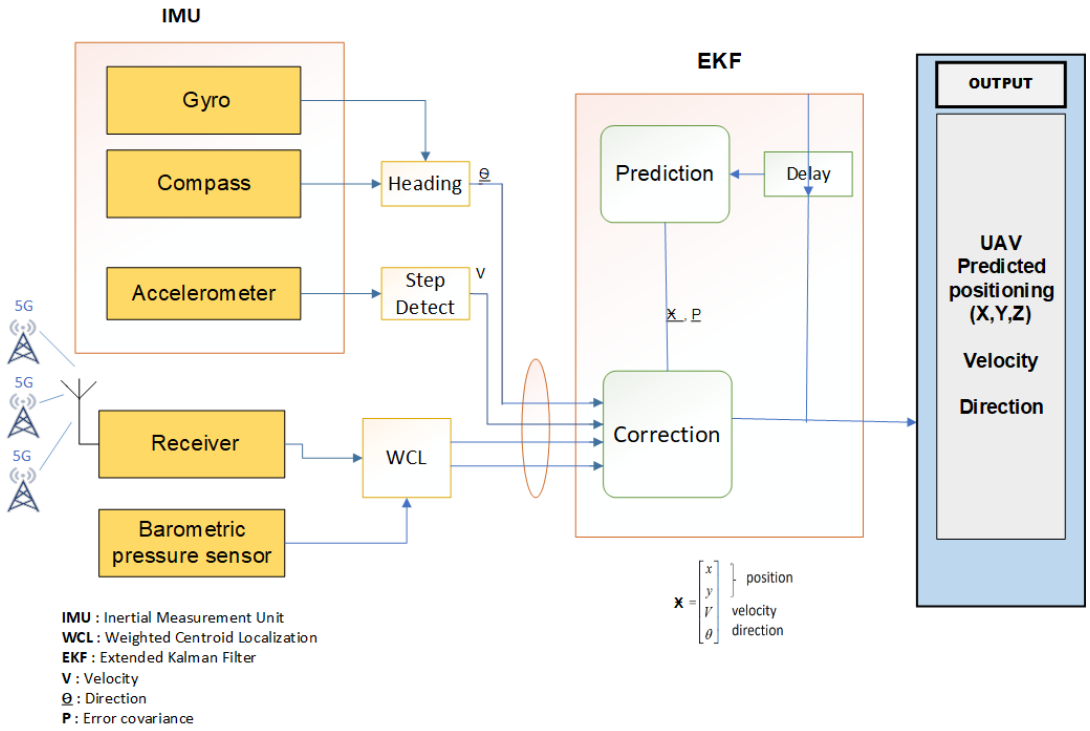

Figure 4.1: UAV system platform architecture development

The 5G receiver provides communication between the UAV and the ground station. It allows the UAV to transmit signals and receive them in real-time. The integration of a 5G receiver in a UAV offers numerous advantages that can boost its performance, such as:

- 5G networks can provide much quicker data transfer speeds than previous generations of cellular networks. This can enable UAVs to transmit large amounts of

data quickly and efficiently, which can be particularly useful for real-time video streaming, remote sensing, and data collection applications.

- Higher bandwidth and reduced latency in 5G networks contribute to an improved video streaming experience from UAVs, facilitating real-time viewing of high-quality footage.
- The minimal latency present in 5G networks heightens the responsiveness of UAVs in real-time control situations, such as remote piloting or autonomous navigation.
- 5G networks can provide location data that the UAV's positioning system can use to determine its location and orientation. This can be particularly useful in situations where GNSS signals may not be available or unreliable, such as in urban canyons, indoors, or in areas with high electromagnetic interference [135].

In this work, the subsequent algorithm has undergone optimisation through the employment of MATLAB software, thereby facilitating the augmentation of UAV 5G NR position estimation accuracy.

4.3.1 Position Estimation Algorithm

procedure UAV_5G_NR_POSITION_ESTIMATION($UAV_positions, interval$)
    P_RS_Config
    P_DSCH_Config
    for $i = 1 : \text{size}(UAV_positions) : interval$ **do**
        $UAV_pos \leftarrow UAV_positions(i)$
        ranges $= \text{TOA}(UAV_pos)$ ▷ ToA
        $t_start \leftarrow$ current_time
        $p_hcp = \text{HCP}(UAV_pos, \text{ranges})$ ▷ Hybrid Cost-based Positioning
        $p_pso = \text{PSO}(UAV_pos, \text{ranges}, 200, 1000)$ ▷ Particle Swarm Optimization
        $p_ga = \text{GA}(UAV_pos, \text{ranges}, 50, 200)$ ▷ Genetic Algorithm
        $t(i) \leftarrow$ current_time $- t_start$
    end for
end procedure

The procedure takes in two inputs: a set of UAV positions and an interval parameter. The interval parameter determines how often the procedure is run for each UAV position. The procedure initialises two configuration variables: P_RS_Config and

P_DSCH_Config. These variables likely contain configuration settings for the physical uplink reference signal (P-RS) and downlink shared channel (PDSCH). The procedure then iterates through each UAV position in the input set, with a step size determined by the interval parameter. For each UAV position, the method performs the following steps:

- Calculates the ranges using TOA measurements. It is a positioning technique that estimates distance based on the time it takes for a signal to travel from the base station to the UAV.
- Measures the time it takes to perform the positioning algorithms by recording the current time and subtracting it from the start time.
- Uses three different algorithms to estimate the UAV position: Hybrid Cost-based Positioning (HCP), Particle Swarm Optimisation (PSO), and Genetic Algorithm (GA). These algorithms likely use range measurements and other known information about the network to estimate the UAV's position.
- Records the time it took to perform the positioning algorithms.

The procedure outputs a time series of the positioning algorithm execution times. This information can be used to evaluate the positioning algorithms' performance and optimise their parameters. In the study, Fig.4.2 illustrates a positioning scenario, which involves a reference next generation node B (gNB), which serves as the primary gNB, and two neighbouring gNBs.

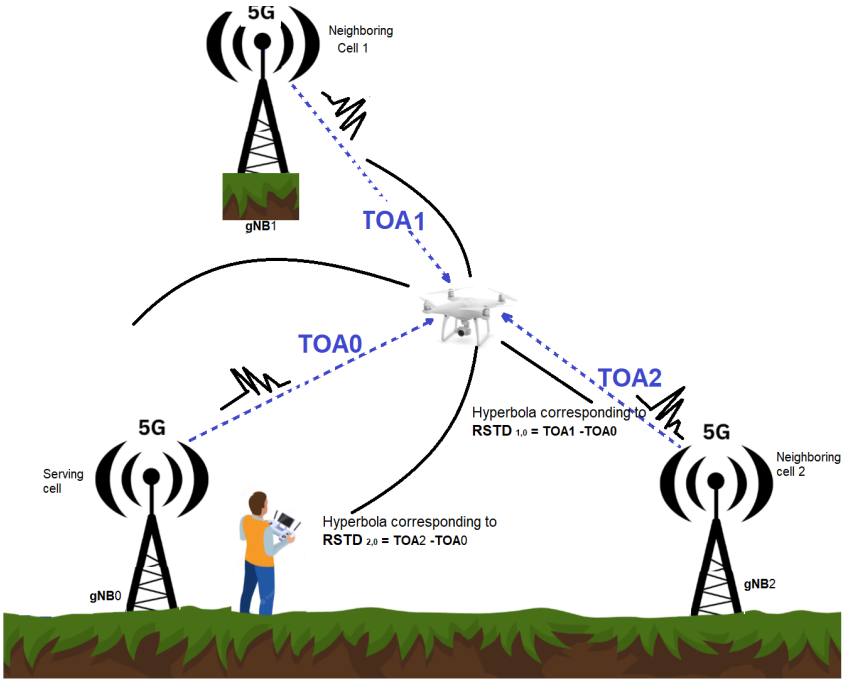

Figure 4.2: Positioning scenario with one reference and two neighbouring gNBs

The UAV receives the PRS signals from all three gNBs at distinct timing instances TOA0, TOA1, and TOA2 based on the geographical distance between the UAV and

gNBs. The TOA values are used to obtain two RSTD values, corresponding to two hyperbolic equations, which are assumed to locate the UAV. The intersection of these hyperbolas is computed to estimate the UAV's position in 2-D.

4.3.2 Sensor Fusion Techniques

Sensor fusion techniques combine data from multiple sensors to obtain more accurate and reliable information about the environment or the object being observed. These techniques aim to overcome the limitations and uncertainties associated with individual sensors.

4.3.3 Barometric Air Pressure

The Barometric Air Pressure (BAP) sensor measures atmospheric air pressure. It is an essential component found in almost every UAV because it plays a crucial role in stabilising flight by helping to determine altitude and maintain balance. The way this works is simple: the sensor measures air pressure, which decreases with altitude, allowing the UAV to estimate its height [178]. However, wind and changes in the UAV's movement can affect air pressure readings, so it is essential to use the onboard barometer to get more accurate data about the altitude [179]. When measuring altitude, the z-axis coordinate system is used, and the altitude of the UAV is calculated using an ultrasonic sensor. The altitude factor is considered the z-axis of the UAV, meaning that it can be flown up and down based on its altitude. To measure the UAV's altitude, a barometric pressure sensor is used to measure the air pressure. Using the barometric formula (4.1), the altitude of the UAV can be calculated. This formula accounts for factors such as the Earth's gravitational force, the molar mass of air, and the temperature in Kelvi[180].

$$P = P_0 \times \exp\left(-g \times M \times \frac{h - h_0}{R \times T}\right) \tag{4.1}$$

- P is the air pressure of the AUV at altitude $'h'$
- P_0 is the reference pressure taken when the UAV is placed on the ground
- g The gravitational force of earth, g =9.80665
- h is the altitude of the UAV,
- M is the molar mass of air, M = 0.0289644kg/mol.
- T is the temperature in Kelvins, T = 288.15k.
- R is the universal gas constant, R = 8.31432 N*m /(mol*K).

4.3.4 Inertial Measurement Unit

IMU consists of a set of sensors that measure acceleration, angular velocity, and sometimes the magnetic field around the UAV. These measurements are processed to determine the UAV's orientation, velocity, and position. An IMU typically includes a combination of accelerometers, gyroscopes, and, in some cases, magnetometers. The accelerometers measure the UAV's linear acceleration in three dimensions, while the gyroscopes measure the UAV's rotational velocity around three axes [3]. The magnetometers measure the magnetic field, which can be used to determine the UAV's orientation with respect to the Earth's magnetic field. By combining the measurements from these sensors, an IMU can estimate the UAV's position and orientation in space relative to its starting position. This is useful for applications such as autonomous flight control and navigation, where the UAV needs to know its position and orientation to perform specific tasks or missions. It's important to note that while an IMU can provide accurate positioning information over short periods, its accuracy can drift over more extended periods due to sensor noise, bias, and other factors. The basic equations of an IMU are:

Accelerometer Equations:

$$\begin{aligned} a_x &= a_{bx} + a_{nx} \\ a_y &= a_by + a_ny \\ a_z &= a_bz + a_nz \end{aligned} \tag{4.2}$$

where a_x, a_y, a_z are the measured acceleration components in x, y, and z directions, respectively. a_bx, a_by, a_bz are the bias components in x, y, and z directions, respectively, and a_nx, a_ny, and a_nz are the noise components in x, y, and z directions.

Gyroscope Equations:

$$\begin{aligned} \omega_{\mathrm{x}} &= \omega_{\mathrm{bx}} + \omega_{\mathrm{nx}} \\ \omega_{\mathrm{y}} &= \omega_{\mathrm{bx}} + \omega_{\mathrm{ny}} \\ \omega_{\mathrm{z}} &= \omega_{\mathrm{bx}} + \omega_{\mathrm{nz}} \end{aligned} \tag{4.3}$$

Where _x, _y, _z are the measured angular velocity components in x, y, and z directions, respectively. _bx, _by, _bz are the bias components in x, y, and z directions, respectively, and _nx, _ny, _nz are the noise components in x, y, and z directions, respectively.

Quaternion Equations:

$$\mathrm{q_dot} = 0.5 * [0, \omega_\mathrm{x}, \omega_\mathrm{y}, \omega_\mathrm{z}] * \mathrm{q} \tag{4.4}$$

Where q is the quaternion that describes the rotation of the IMU frame with respect to the global frame, and q_dot is the derivative of the quaternion. [0, _x, _y, _z] is the

angular velocity vector expressed in quaternion notation.

$$\begin{aligned} p_dot &= R * v \\ v_dot &= a \end{aligned} \tag{4.5}$$

Where p_dot is the derivative of the position vector, v_dot is the derivative of the velocity vector, R is the rotation matrix derived from the quaternion, and a is the acceleration vector measured by the accelerometer. These equations can be used to estimate the position, velocity, and orientation of an IMU over time. However, due to the accumulation of errors and biases over time, it is common to use a combination of other sensors, such as GNSS, to correct for these errors and improve the overall accuracy of the estimation [47].

4.3.5 Extended Kalman Filter

The EKF estimates the state of the UAV based on the sensor measurements and the system's dynamics. It provides a way to fuse the sensor data and estimate the UAV's position, velocity, and orientation. The EKF can also handle the uncertainty and noise in the sensor measurements, which can improve the reliability of the positioning system. Integrating 5G, sensor fusion, BPSs, and EKF can enhance the positioning accuracy of UAVs, which is critical for applications such as aerial surveying, mapping, and inspection. A benefit of 5G technology is that it provides high-speed, low-latency communications that enable real-time data transmission and reception [77]. Integrating barometric pressure data with IMU data can improve the accuracy of altitude measurements and enhance overall positioning accuracy. Using EKF can handle the uncertainty and noise in the sensor measurements and provide a way to fuse the sensor data to estimate the position, velocity, and orientation of the UAV [78].

Sensor Fusion Algorithm Workflow

- The algorithm begins by collecting data from multiple sensors, including accelerometers, gyroscopes, magnetometers, and BPSs.
- The collected data is then pre-processed to eliminate noise, outliers, and other anomalies that could affect the accuracy of subsequent computations.
- Once cleaned, the sensor data is fused to estimate the UAV's positioning state. Common fusion techniques include Kalman filtering, particle filtering, and extended Kalman filtering.
- Based on the fused data, the algorithm estimates the UAV's state variables such as position, velocity, and orientation.
- The estimated state is then provided as output, enabling applications to accurately determine the UAV's positioning.

- This process is continuously repeated, with ongoing data collection, pre-processing, fusion, and state estimation steps to ensure real-time positioning updates [181].

Kalman filter (KF) is a popular technique for sensor fusion that can be used to combine data from multiple sensors to provide more accurate and reliable estimates of position, velocity, and other states of a system [182]. Systems can be linearised by the system dynamics and measurement functions. Here is an overview of how the EKF can be used for sensor fusion [183].

- The process begins by determining the state vector, which represents the system's current status. In navigation systems, this typically includes parameters such as position, velocity, and acceleration.
- The system dynamics are then defined to describe how the state vector evolves over time. This often involves motion equations that account for the vehicle's current state and control inputs.
- Next, the observation model is established to express how sensor measurements relate to the components of the state vector. For example, GNSS measurements of position and velocity are mathematically linked to the corresponding state variables.
- Based on the defined dynamics and the current state vector, the EKF predicts the future state at the next time step.
- As new sensor measurements become available, the filter updates the predicted state using the observation model. It computes the difference between predicted and actual measurements, referred to as the residual.
- The Kalman Gain is then computed, which determines how much weight to assign to the predicted state versus the actual sensor measurements. This is based on the relative uncertainties of both.
- Using the Kalman Gain and the residual, the predicted state is corrected to produce a more accurate and updated estimate of the system's state.
- Through this fusion of data from multiple sensors, the EKF enables more accurate

The mathematical equations for the EKF algorithm can be expressed as follows,[43].

Initialization:

$$\begin{aligned} x_\text{hat}\,(0) &= x_0 \\ P(0) &= P_0 \end{aligned} \tag{4.6}$$

Prediction:

$$\begin{aligned} \mathrm{x}_{\text{hat}_{\text{pred}}} &= \mathrm{f}\left(\mathrm{x}_{\text{hat(k)}}, \mathrm{u(k)}\right) \\ \mathrm{P}_{\text{pred}} &= \mathrm{J_f} * \mathrm{P(k)} * \mathrm{J_f^T} + \mathrm{Q} \end{aligned} \tag{4.7}$$

Where f(x, u) is the nonlinear system model, J_f is the Jacobian matrix off with respect to x, u is the control input, Q is the process noise covariance matrix, and k is the current time step.

Update:

$$
\begin{aligned}
&y = z(k) - h\left(x_{\text{hat}_{\text{pred}}}, u(k)\right) \\
&S = J_h * P_pred * J_h\text{^}T + R \\
&K = P_pred * J_h\text{^}T * S\text{^} - 1 \\
&x_{\text{hat}\,(k)} = x_{\text{hat}_{\text{pred}}} + K * y \\
&P(k) = (I - K * J_h) * P_{\text{pred}}
\end{aligned}
\tag{4.8}
$$

Where z(k) is the measurement, h(x, u) is the measurement model, J_h is the Jacobian matrix of h with respect to x, R is the measurement noise covariance matrix, I is the identity matrix, and S is the innovation covariance matrix [184]. These equations form the core of the EKF algorithm and can be used to estimate the state of nonlinear systems in real-time [183]. In this study, we aimed to develop a system for UAV positioning in urban environments using 5G NR technology. To achieve this, we used a combination of hardware and software tools, including an IMU sensor, a pressure sensor, a 5G receiver, and Simulink and MATLAB simulation tools.

Data Collection, we conducted experiments to collect data on the UAV's position and altitude using the above-mentioned sensors. The IMU sensor provides information on the UAV's acceleration, orientation, and angular velocity in three dimensions (x, y, and z). The pressure sensor provided data on the UAV's altitude. The 5G receiver was used to collect positioning data from the 5G network. We collected data for different UAV trajectories and flight scenarios to ensure that the system was robust and could work in different conditions. To analyse the data collected, we used the EKF algorithm to fuse the information from the sensors and estimate the UAV's position and altitude in real time. The EKF algorithm is a widely used method for sensor fusion in UAV positioning systems and has been shown to be effective in various studies.

Simulation Modelling, using MATLAB 5G Toolbox, we configured and generated PRS signals according to the 5G NR specifications. We carefully selected PRS parameters such as time-frequency pattern and sequence length for optimal performance. The PRS sequence for each gNB was generated using the 'nrPRS' function, and the transmitted signal was obtained after applying appropriate windowing and precoding operations to the PRS sequence. The received signal at the UAV was simulated by passing the transmitted PRS signal through the channel model. Next, we detected the PRS signals at the UAV and estimated the TDOA values. Suitable synchronisation and channel estimation techniques were applied to the received signal, and matched filtering and thresholding were employed to detect the PRS signals from the gNBs. Cross-correlation techniques were then used to estimate the TDOA for each detected PRS signal, and the TDOA values were determined with sub-sample accuracy using interpolation methods such as polynomial fitting or sinc interpolation. We then estimated the position of the UAV using the TDOA values. Hyperbolic equations that

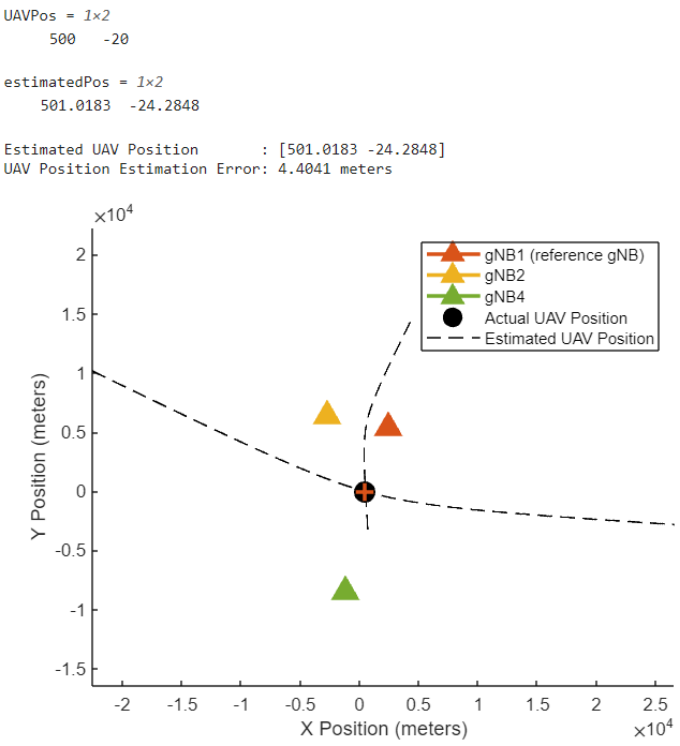

Figure 4.3: Estimated UAV Positioning in Scenario 1

relate the UAV position to the positions of the gNBs were computed, and nonlinear least squares or other optimisation techniques were employed to solve the hyperbolic equations and obtain the UAV position estimate. We evaluated the performance of the 5G PRS positioning system by comparing the estimated position with the true position, using metrics such as RMSE and circular error probable (CEP).

4.4 Results And Discussion

The results presented in this chapter illustrate four different scenarios, which are studied to enhance the UAV positioning estimation. The results of this study have important implications for UAV positioning in urban environments using 5G NR technology. Our experiment has demonstrated the 5G PRS positioning system's effectiveness in accurately estimating a UAV's position. The simulation model used in the study shows that the proposed system can provide accurate UAV positioning in urban environments, outperforming traditional methods. In the first scenario, the estimated UAV position was denoted by the coordinates (500, 20), while the simulated estimation provided the coordinates (501, 24.2). This resulted in a positional error of 4.4 meters. This outcome can be visually observed in Figure 4.3. In the second scenario, the actual position was represented by the coordinates (550, 30), and the estimated position derived from the simulation was (547.9, 23.5). The discrepancy amounted to an error of 6.77 meters, as depicted in Figure 4.4. In the third scenario, the actual position was char-

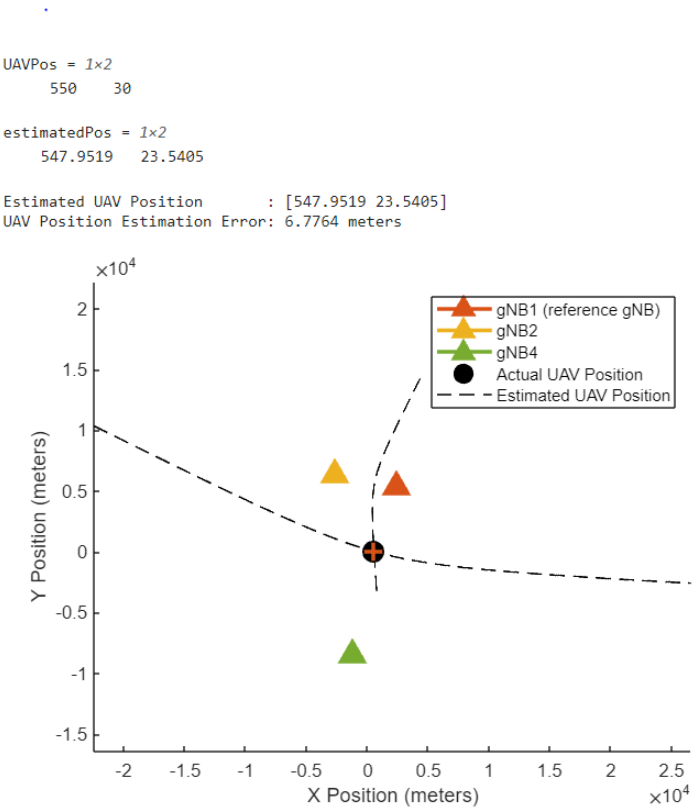

Figure 4.4: Estimated UAV Positioning in Scenario 2

acterised by the coordinates (600, 80), whereas the simulation produced an estimated position of (593.6, 81.8). This led to a positional error of 6.6 meters, which can be examined in Figure 4.5. Lastly, in the fourth scenario, the true position was given by the coordinates (800, 280), and the simulation-generated estimated position was (793.3, 278.8). The resulting error was 3 meters, as illustrated in Figure 4.6. The presented outcomes, which display the results from four different UAV scenarios, demonstrate that the proposed methodology is both robust and versatile for different UAV positions. Estimation errors range from 2.8 to 7 meters, indicating the effectiveness of the technique. Compared to GNSS-based methods, the 5G PRS positioning system offers significantly better performance in urban environments. While standard GNSS accuracy can degrade to 15–50 m in dense urban canyons due to signal blockage, multipath, and NLOS conditions, the 5G system consistently achieves 2.8–7 m accuracy. In such scenarios, this represents a 3–7× improvement over GNSS. Additionally, 5G requires only three or more base stations (versus four or more satellites for GNSS) and can maintain positioning capability in environments where GNSS may fail, such as indoors or heavily obstructed areas. Nevertheless, 5G-based positioning remains sensitive to noise, multipath, channel conditions, and TDoA estimation errors. It is also worth noting that these results are based on simulations and do not fully account for real-world sensor uncertainties. Hardware factors such as clock synchronisation errors, RF front-end delays, antenna placement, and IMU drift can further impact performance. Incorporating these uncertainties in future evaluations will be essential to provide more realistic performance estimates. To further improve the system, poten-

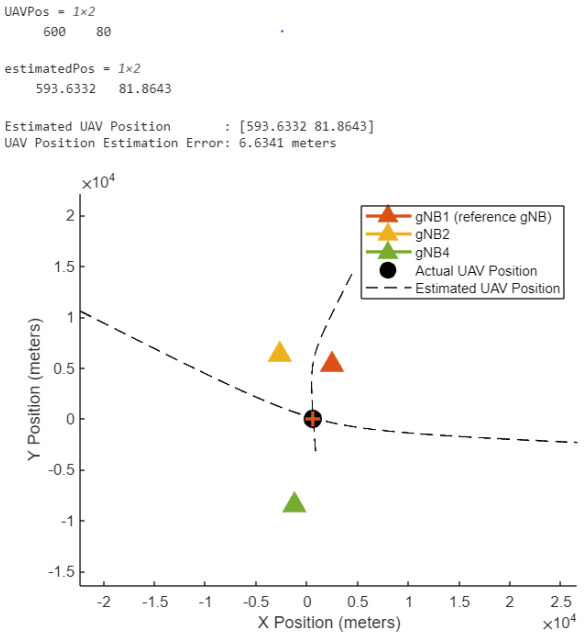

Figure 4.5: Estimated UAV Positioning in Scenario 3

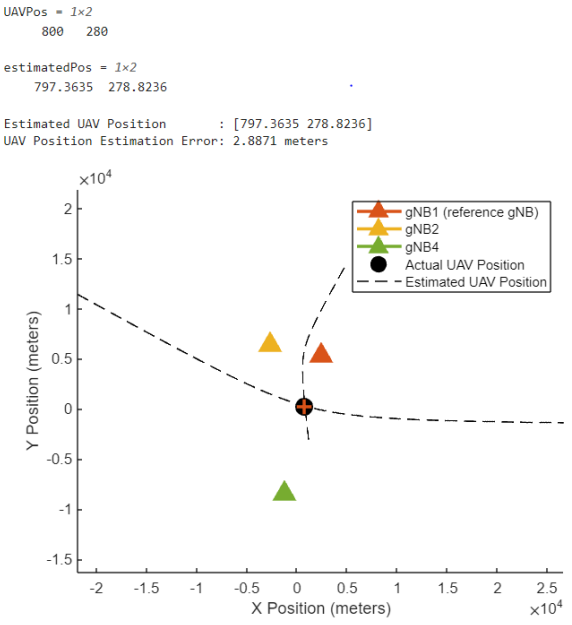

Figure 4.6: Estimated UAV Positioning in Scenario 4

tial research directions include refining the PRS signal design, enhancing TDoA estimation algorithms, adopting more advanced channel models, and investigating the effect of system parameters and network configurations. The integration of additional onboard sensors, such as IMUs and barometric pressure measurements through EKF, also offers a promising pathway for improving robustness. Overall, these findings suggest that the 5G PRS positioning system offers a robust foundation for accurate UAV positioning in challenging urban environments, with distinct advantages over GNSS-based methods and considerable potential for future development.

4.5 Conclusions

In conclusion, the study makes significant contributions to UAV positioning and communication in urban environments using 5G NR. The study showcases the potential of this technology for accurate and reliable UAV positioning, with implications for a range of applications. The study also underlines the importance of the OTDOA technique for UAV positioning, which has not been extensively explored in the existing literature. The research also highlights the importance of considering UAV positioning as an integral part of future communication and navigation systems. By incorporating 5G capabilities, such as enhanced connectivity and low-latency communications, the study opens up new avenues for advanced UAV operations and applications. Finally, this study underscores the potential of 5G NR and the OTDOA technique in revolutionising UAV positioning and communication, opening the way for enhanced capabilities and improved performance in various domains, including aerial surveillance, package delivery, and disaster response. The findings contribute valuable insights that can drive further research and development in the field, ultimately benefiting both academia and industry.

Chapter 5

AI-Driven 5G UAV Positioning

This chapter introduces the concept of AI-based NLOS mitigation and its importance for accurate UAV positioning in 5G environments. Further, it presents the proposed system combining statistical filtering, Kalman filtering, and neural network-based correction for robust positioning in dense urban areas. Lastly, it presents the experimental results and their implications for reliable UAV navigation under challenging signal conditions. This chapter is linked to the second and fourth objectives.

5.1 Introduction

The rapid evolution of UAVs has initiated a new era of applications in many sectors, including logistics, surveillance, agriculture, and disaster management. UAM represents a transformative solution to address transportation and logistics challenges in densely populated areas. Using UAVs and electric vertical take-off and Landing (eVTOL) aircraft, the UAM aims to reduce travel times, alleviate traffic congestion, and reduce greenhouse gas emissions, making it a promising alternative to traditional land-based transportation systems [185]. However, a critical challenge for UAVs in urban environments is accurate positioning and navigation through complex urban structures. Traditional GNSS often struggle in cities due to signal reflections (multipath propagation) and obstructions NLOS, or NLOS, conditions [186]. These limitations are intensified in dense urban environments where GNSS signals reflect off buildings and other structures before reaching the UAV receiver, causing positioning errors that can exceed several meters [187],[188]. Moreover, any requirement for clear LOS to multiple satellites is often challenging in urban canyons, tunnels, and areas with dense foliage, further reducing the accuracy and reliability of GNSS-based navigation systems [189]. To address these challenges, 5G PRS have emerged as a promising approach to improve UAV positioning accuracy. The deployment of 5G networks

offers unique advantages, such as higher frequency carriers, wider bandwidths, and improved infrastructure, enabling precise positioning, navigation, and timing services in urban areas [190],[188],[191]. Unlike GNSS, which is highly susceptible to multipath errors and environmental obstructions, 5G PRS can even utilise reflected signals to enhance accuracy, achieving meter-level precision in urban scenarios [192],[193],[194]. This makes 5G PRS a strong candidate technology for improving UAV navigation, particularly in areas where GNSS performance is compromised [195]. Despite these advancements, current UAV positioning systems in urban environments face significant limitations. Hybrid approaches that integrate GNSS, 5G, and additional sensors such as LiDAR and IMUs have demonstrated improved robustness. However, they often fail to adapt dynamically to challenging conditions such as severe multipath interference and dynamic NLOS scenarios, especially in real-time applications [196]. Furthermore, traditional model-based GNSS methods remain computationally demanding and less effective in dynamically noisy environments, limiting their usability in critical applications such as disaster management and last-mile delivery [197],[198]. These challenges underscore the urgent need for innovative frameworks that combine high-precision 5G PRS with adaptive deep-learning methods to achieve reliable real-time UAV positioning in complex urban environments.

- Our objective in this chapter is to address these challenges by introducing a novel approach that integrates 5G PRS data with deep learning techniques to improve the accuracy of UAV positioning. Specifically, the key contributions of this study are as follows.
- The design and implementation of a fully connected FNN to correct 3D position estimates derived from 5G TOA measurements.
- The development of a comprehensive simulation framework that incorporates both LOS and NLOS conditions, ensuring robustness and practical applicability in real-world urban environments.
- A real-time correction mechanism that demonstrates significant improvements in positioning accuracy, outperforming traditional GNSS-based and hybrid methods.
- Extensive evaluation of the proposed framework using mean absolute error (MAE) and root mean squared error (RMSE) metrics, demonstrating the potential of this approach for scalable and resilient UAV navigation.

This research uses the unique characteristics of 5G signals and combines them with advanced neural network architectures to provide a scalable solution to the limitations of existing UAV positioning systems. These innovations pave the way for the broader adoption of UAM technologies, which enable precise and reliable navigation in densely populated urban environments.

5.2 AI-Based NLOS Mitigation

The accurate and reliable positioning of UAVs is critical for applications of UAM, including logistics, surveillance, and disaster response. UAV-based services within urban airspace demand precise navigation to ensure operational safety and efficiency[189]. Traditionally, positioning systems have relied heavily on GNSS; however, these systems frequently experience significant accuracy degradation in densely populated urban environments. Signal obstruction by high-rise buildings, multipath reflections, and NLOS propagation severely impair GNSS accuracy and reliability [190]. Specifically, GNSS positioning accuracy is compromised due to signal blockages, multipath propagation errors, and poor satellite geometry, making it challenging to achieve reliable UAV positioning in high-density urban areas [189],[190],[199]. Moreover, GNSS requires a clear LOS to multiple satellites, a condition that is often difficult to achieve in urban canyons, tunnels, or areas with dense foliage. These environments significantly degrade the integrity of the GNSS signal, leading to positioning errors that frequently exceed tens of metres [190]. The high sensitivity of GNSS to multipath interference and NLOS conditions highlights the need for alternative positioning technologies that can overcome these limitations, particularly for real-time UAV navigation tasks [190], [188]. Traditional GNSS solutions, including advanced hybrid approaches that integrate sensors such as LiDAR and IMU, still struggle to adapt in real time to severe multipath interference and dynamic NLOS conditions [187]. Hence, innovative solutions beyond conventional GNSS methods are urgently needed. Recent advances in 5G mobile networks offer promising alternatives to traditional GNSS for accurate positioning in complex urban scenarios. Specifically, 5G PRS provide higher frequency carriers, wider bandwidths, and enhanced infrastructure capabilities, significantly improving positioning precision and reliability in urban environments [193],[194]. Unlike GNSS, which suffers significantly from multipath errors, 5G PRS effectively uses both LOS and reflected NLOS signals to achieve meter-level accuracy even in challenging environments. The distinct characteristics of 5G, including high-frequency carriers and wider bandwidths, facilitate precise timing measurements, enabling high-resolution positioning and superior multipath mitigation [195],[196],[197]. Furthermore, dense urban deployment of 5G BSs offers additional geometric diversity, thereby reducing dilution of precision and enhancing positioning reliability [196]. Nevertheless, current 5G-aided positioning systems encounter practical implementation challenges. Accurately discriminating LOS and NLOS signals in real-time remains difficult, significantly affecting the precision of positioning estimates [9]. Furthermore, while 5G positioning methods such as OTDOA demonstrate promising theoretical capabilities, real-world implementations encounter issues related to computational complexity and environmental variability[196],[197]. Thus, incorporating adaptive and computationally efficient algorithms is vital for the practical deployment of these technologies in UAV navigation systems.

To overcome these limitations, DL techniques have emerged as a powerful tool for enhancing UAV positioning accuracy. Neural network-based methods, particularly fully connected FNN, have demonstrated the capability to learn and mitigate complex

positioning errors through pattern recognition and adaptive modeling [198],[190],[200]. Unlike traditional GNSS and hybrid methods that rely heavily on deterministic or statistical modelling, NN-based solutions adapt dynamically, offering potential real-time positioning corrections even under severe multipath or NLOS conditions [12], [13]. Recent studies highlight that ML methods effectively correct 5G TOA measurements by reducing biases and improving accuracy in both LOS and NLOS environments [190],[188]. Given these considerations, this thesis proposes an integrated ML framework combining 5G PRS with NNs to enhance UAV positioning accuracy in dense urban scenarios. The key contributions of this study include:

- Developing a fully connected FNN to correct 3D UAV positioning errors using 5G TOA measurements.
- Establishing a comprehensive simulation environment covering both LOS and NLOS scenarios, ensuring robustness and practical applicability.
- Proposing a real-time error correction mechanism significantly improves UAV positioning accuracy over traditional GNSS and hybrid approaches.
- Evaluating the proposed framework using MAE and RMSE, demonstrating substantial improvements in positioning accuracy and resilience in urban conditions.

This research combines the strengths of 5G signals and neural networks to build a reliable and adaptable positioning system, aimed at improving UAV navigation in challenging urban areas.

5.3 System Design and Implementation

This section outlines the complete workflow of our 5G-aided UAV positioning framework, structured into cohesive stages for clarity. A summary diagram is provided in Figure 5.1 to illustrate the end-to-end system. We begin with the simulation setup, which replicates realistic urban environments using MATLAB, incorporating UAV trajectories and 5G base station (gNodeB) deployment. Next, PRS are generated, and Time-of-Arrival (TOA) data are collected and converted into Time-Difference-of-Arrival (TDOA) for initial position estimation. A Kalman filter is then applied to refine these estimates. The dataset creation stage logs both the estimated and actual UAV positions along with contextual parameters such as signal strength and NLOS/LOS conditions. This structured dataset supports training of a fully connected FNN to learn and correct for systematic positioning errors. Finally, we describe the training process, including preprocessing, optimisation, and evaluation. Metrics such as MAE, RMSE, and R-squared (R^2) are used to assess model performance under various signal conditions.

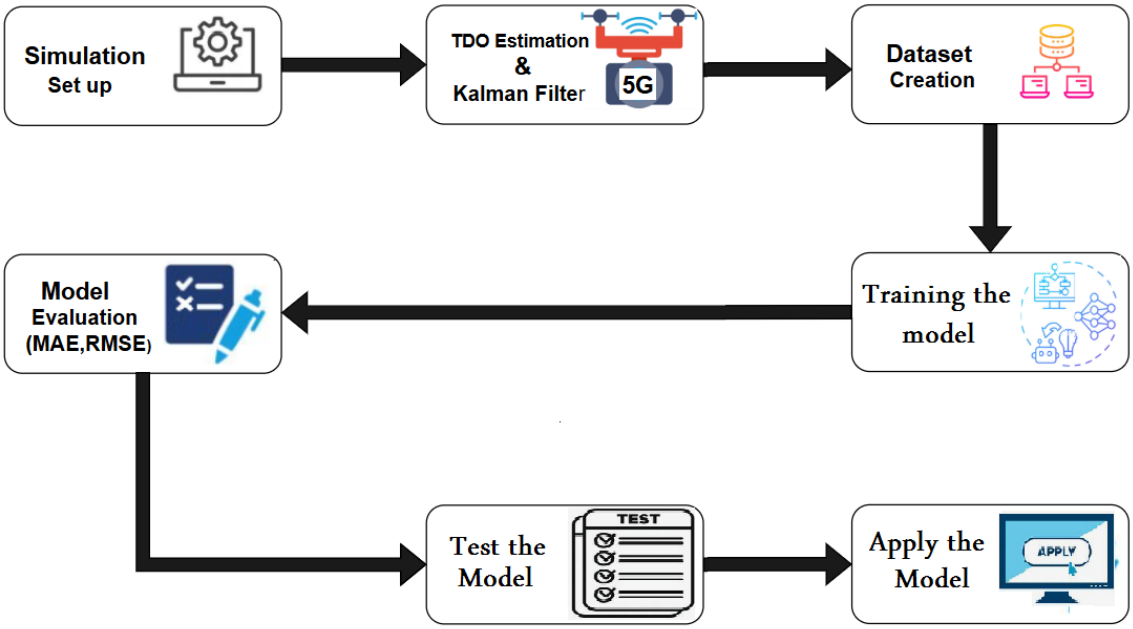

Figure 5.1: 5G-Aided UAV Positioning Implementation-Flow

5.3.1 Urban Environment and Simulation Setup

This study utilises a MATLAB-based simulation environment (Figure 5.2) to generate a synthetic dataset for UAV positioning in urban environments. The simulation framework builds on the 3GPP TR 38.901 Urban Macro (UMa) and 5G positioning reference signal (PRS) specifications, which are widely adopted for modelling 5G channel behaviour. Our contribution is in extending and integrating these models into a fully developed machine learning system, including scenario generation, signal simulation, time-of-arrival (TOA) estimation, and position tracking.

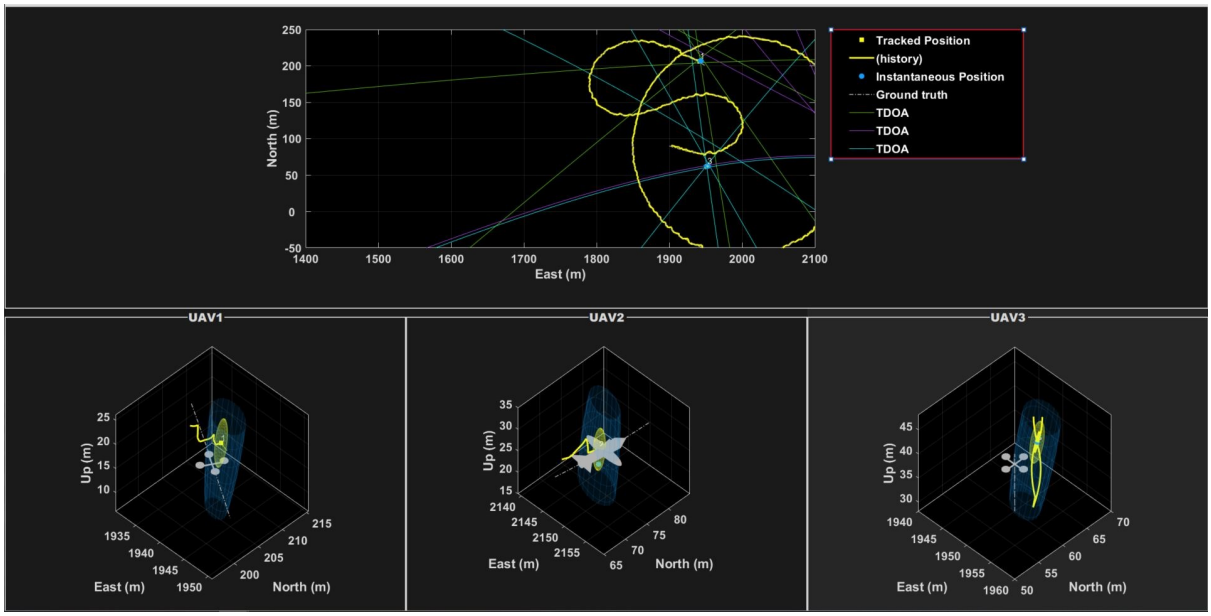

Figure 5.2: 5G-enabled Urban UAV Positioning Scenarios

The data generation process included several critical steps:

- Simulation parameters such as building density, PRS configuration, and urban propagation models were chosen to reflect realistic 5G deployments, as summarised in Table 5.1.

- While the simulation includes LOS/NLOS-dependent path loss, multipath fading, and receiver noise, it excludes some advanced physical-layer effects such as log-normal shadowing, inter-cell interference, and Doppler spread. These factors have been shown to introduce localisation errors even at low UAV speeds (5-15 m/s) in prior studies [201],[202],[203], their impact is moderate under controlled conditions, which supports our phased approach: starting with an idealised environment to validate algorithm performance. Future work will incorporate these effects through extended simulations and hardware-in-the-loop testing.

- To ensure the relevance of the results to real-world scenarios, we adopted parameters in line with regulatory standards and industry practices. For instance, the UAV altitude range (50–120 m) and speed (5–15 m/s) align with urban air mobility guidelines, while the use of 3 GHz carrier frequency and rooftop-mounted gNodeBs (10–75 m height) mirrors common 5G infrastructure deployments. The use of orthogonal PRS with unique resource allocations for each cell replicates standard network configurations aimed at minimising interference and enabling high-accuracy positioning.

- Three UAVs fly semi-randomised trajectories through a 3D urban environment. Each trajectory consists of straight-line segments, turning points, and vertical movements, simulating realistic missions such as aerial delivery or surveillance.

Table 5.1: Simulation Parameters for Data Generation

Parameter	**Value / Range**
Urban channel model	3GPP TR 38.901 UMa
Carrier frequency	3 GHz
Number of UAVs	3
UAV altitude range	50–120 m
UAV speed range	5–15 m/s
Number of gNodeBs	6
gNB placement	Rooftop (height: 10–75 m)
Building density	20 / 50 buildings/km^2
PRS configuration	Orthogonal, unique per gNB/UAV
LOS/NLOS labeling	Explicit per link
TOA estimation method	Cross-correlation with PRS
Positioning method	TDOA + Kalman filter
Dataset output	(X_e, Y_e, Z_e) and (X_t, Y_t, Z_t) per timestep

UAV altitudes vary between 50–120 m, and horizontal speeds range from 5–15 m/s. These trajectories are designed to expose the UAVs to both LOS and NLOS conditions.

- To test generalisation under diverse urban conditions, we define two distinct environments:
  - **LOS-Dominant**: Low building density ($\sim$20 buildings/km^2) representing open urban or suburban areas.
  - **NLOS-Dominant**: Dense urban layout ($\sim$50 buildings/km^2) mimicking signal blockages and multipath effects in city centres.
- Each UAV receives 5G PRS signals from six rooftop-mounted ground gNodeBs (gNBs). All gNBs operate at the same carrier frequency (3 GHz), with unique cell identities and non-overlapping PRS resource allocations. This ensures orthogonality across signals, enabling time-synchronised TOA measurement without inter-cell interference.
- PRS signals propagate through the 3D urban environment based on LOS/NLOS-dependent path loss models. UAVs record the received PRS waveforms at each time step and estimate the TOA via cross-correlation. LOS/NLOS status for each UAV-gNB link is explicitly labelled. These TOA values are converted to time difference of arrival (TDOA) measurements, which are used for geometric position estimation via a spherical intersection algorithm.
- A Kalman filter smooths the TDOA-based position estimates, reducing random noise and improving temporal consistency. The filtered trajectories provide high-fidelity position estimates for each UAV.
- At each time step, for every UAV, the dataset records:

- Estimated 3D position: (X_e, Y_e, Z_e)
- True ground-truth position: (X_t, Y_t, Z_t)
- Metadata: LOS/NLOS label, UAV ID, scenario ID, time index, visible gNBs

The final dataset contains approximately 9,000 labelled samples. These are used to train and evaluate supervised ML models for UAV positioning.

5.3.2 Dataset Description

We created a comprehensive dataset of 9,000 samples using MATLAB's UAV simulation, capturing a wide range of 285 urban navigation scenarios. The input matrix has shape (N, 3), where N = number of samples (500), and each row corresponds to the estimated (Xe, Ye, Ze) coordinates. The target matrix also has shape (N, 3), representing the true positions (Xt, Yt, Zt). Auxiliary parameters like RSS and path loss were evaluated but not used in the final model to reduce complexity. To ensure transparency, we simulated semi-random UAV trajectories at altitudes ranging from 50 to 120 m and horizontal speeds of 5 to 15 m / s, including straight runs, turns, and altitude changes. The different trajectories provided a mix of LOS and NLOS situations near virtual buildings, generating varied signal propagation conditions. For each time step, the dataset records the PRS-based position estimate, the true location of the UAV, and the estimation error in X, Y, and Z coordinates, allowing for post-analysis of error trends. While this dataset provides a controlled and reproducible environment for model training, we acknowledge that it does not include real-world imperfections such as hardware-related delays, environmental interference, or dynamic changes in 5G propagation. To address this, future extensions will incorporate real measurement data from aerial 5G testbeds (e.g., NSF AERPAW) to calibrate our simulation parameters. Additionally, we plan to apply domain randomisation techniques such as varying base station densities, signal fading models, and environmental layouts to improve the model's generalizability beyond fixed simulated scenes. We also log contextual data such as received signal strength, path loss, and a binary label for LOS/NLOS conditions at that time. Each sample of the data set includes a timestamp indicating when the measurement was taken for the temporal analysis of the movements of the UAV, the estimated position of the UAV in (X, Y, Z) from TDOA measurements refined by a KF, the ground truth position (X, Y, Z) for the accuracy assessment, and the estimation error the difference between the estimated and ground truth positions. It also contains signal parameters such as signal strength, path loss, and LOS/NLOS conditions to show how environmental factors affect positioning accuracy, along with unique identifiers for each UAV and gNodeB to support multi-object tracking. Furthermore, the data set provides time series error data for all three UAVs in three dimensions, plus binary NLOS labels that mark signal obstruction conditions at each time step, making it possible to assess how these obstructions impact estimation errors and the overall robustness of the tracking algorithm. Our simulation framework is grounded in the 3GPP TR 38.901 model, offering a representative approximation of urban signal

behaviour. However, additional enhancements, as described above, are necessary to fully bridge the gap between simulation and deployment. To account for this, Gaussian noise is injected into TOA readings to simulate practical conditions. Future work will extend the simulator to model frequency fading, Doppler effects, and pedestrian-induced fluctuations for deeper realism.

5.3.3 Robust Handling of Real-Time Noisy Data

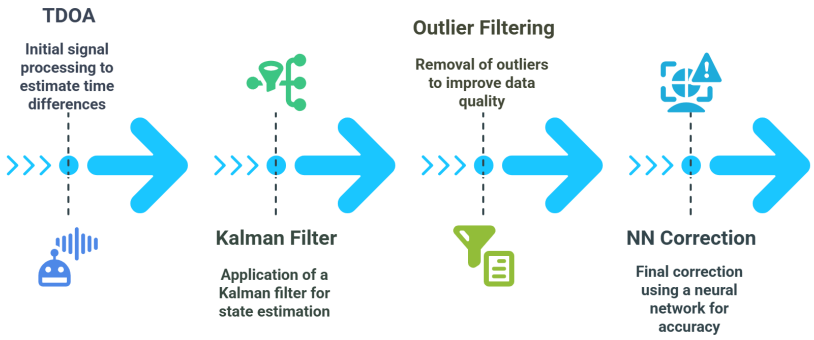

Figure 5.3: Signal Processing Pipeline for Position Estimation

Figure 5.3 illustrates a sequential flowchart representing a signal processing pipeline used for refining and improving the accuracy of location estimation, likely in applications such as UAV positioning, wireless localisation, and navigation systems.

1. TDOA ; measures the time differences at which a signal arrives at multiple receivers or sensors. This initial data is used to estimate the position of a signal source (e.g., a UAV or mobile device) based on propagation delays. TDOA provides the raw location information that serves as the starting point for position estimation, but it is often noisy and requires further refinement through additional processing steps.

2. Kalman Filter; an optimal recursive data processing algorithm used to estimate the state of a system from noisy measurements. It smooths the TDOA data by predicting and updating position estimates based on both measurement and motion models. While it effectively reduces random noise, it may still leave some irregular outliers.

3. Outlier Filtering; a preprocessing step aimed at detecting and removing abnormal or highly deviated data points that may distort position estimation. Common techniques include statistical methods, median filtering, or robust thresholding. This enhances the system's robustness by eliminating errors caused by multipath propagation, interference, or sensor faults.

4. Neural Network (NN) Correction; a trained neural network model is applied to refine the filtered data. The network uses historical or labelled data to learn

non-linear patterns and systematic biases that traditional filters may overlook. This step provides a final, high-precision position correction, making the system adaptive and resilient to complex conditions such as NLOS environments.

To provide a visual summary of our proposed methodology, we present a high-level flow diagram in Figure 5.4. This diagram outlines the sequential steps involved in enhancing UAV position estimation using ML and 5G PRS data, starting from the simulation of the urban environment to the deployment of the trained neural network model for real-time UAV position correction.

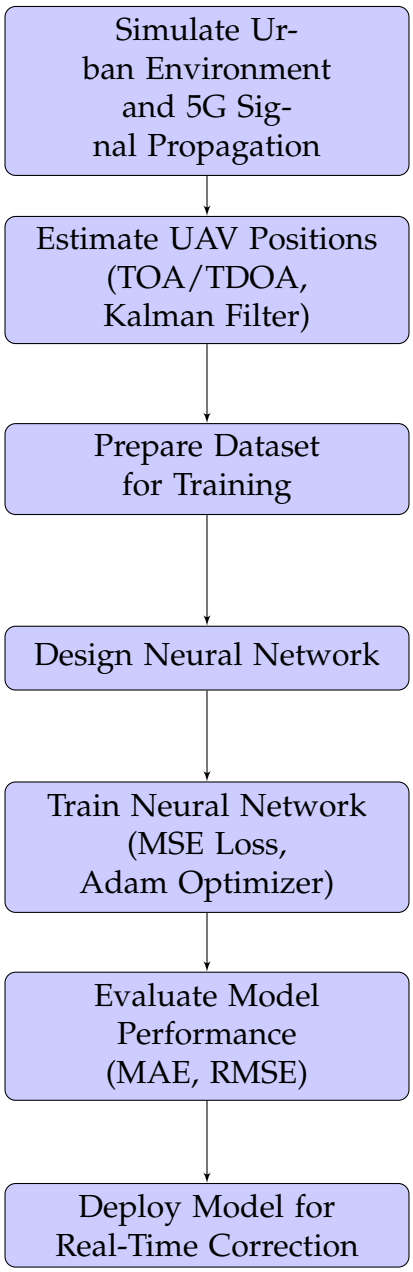

Figure 5.4: High-Level Flow Diagram of the Proposed Methodology

To address the inherent noise in real-world 5G data, the proposed system integrates statistical outlier rejection (using $\pm 3\sigma$ limits), Kalman filtering, and neural network-based error correction. These layers dynamically adjust signal trust levels and discard

unreliable data flagged as NLOS. First, we apply the statistical outlier rejection Algorithm 1, continuously monitoring incoming measurements and filtering outliers that deviate beyond a trusted range, ensuring that sudden interference-based glitches do not corrupt the position solution. Next, a KF combined with sensor fusion smooths out noise by optimally weighing the UAV motion model against incoming observations. If the 5G data is momentarily too noisy, the filter more trusts the predicted state. Additional onboard sensors, such as IMUs, provide short-term stability when signals degrade, preventing the position estimate from drifting. We also implement real-time NLOS mitigation in dense urban environments: the system uses a neural network to detect and correct NLOS-induced errors and can lower or discard measurements flagged as NLOS when enough other signals are available. A neural network further enables adaptive error correction, learning from recurring biases, e.g., systematic underestimates near certain buildings, and outputting a data-driven correction. Robust estimation techniques, such as RANSAC, allow us to exclude inconsistent base stations in the multilateration step. The entire process is computationally lightweight, avoiding the need for heavy batch computations or excessive smoothing that would introduce lag. By combining predictive filtering, outlier detection, sensor fusion, learnt corrections, and robust estimation techniques, the trajectory of the UAV remains stable and accurate despite momentary disturbances, which is crucial for real-time navigation and tracking. The dataset is structured to support multiple analytical tasks, including performance evaluation of the UAV tracking system in dense high-rise areas, open spaces, and various LOS/NLOS scenarios; algorithm development by training and testing new tracking algorithms through the analysis of estimation errors and their correlation with signal parameters; and statistical analysis to study how environmental factors such as NLOS conditions or gNodeB density affect tracking performance. By simulating realistic urban flight scenarios and incorporating detailed 5G signal propagation models, the dataset provides a solid foundation for evaluating and enhancing UAV tracking algorithms in UAM applications.

5.3.4 Algorithm for UAV Position Estimation

Algorithm 1 Simplified UAV Position Estimation Enhancement

Require: Simulation parameters, 5G PRS settings, UAV trajectories, gNodeB positions

Ensure: Trained neural network model for position correction

1: **Simulate Urban Environment and 5G Signal Propagation**

1.1 Simulate UAV flights and gNodeB placements

1.2 Model 5G PRS transmission and propagation effects

2: **Estimate UAV Positions**

2.1 Receive PRS signals and estimate TOA

2.2 Calculate TDOA and estimate positions

2.3 Refine estimates using a KF

2.4 Detect outliers in real time using TDOA prediction comparison.

2.5 Exclude or down-weight NLOS/unreliable measurements temporarily.

3: **Prepare Dataset for Training**

3.1 Collect estimated and ground truth positions

3.2 Normalize data and split into training/test sets

3.3 Include NLOS labels and cleaned measurements to train under realistic conditions.

4: **Train Neural Network**

4.1 Define network architecture

4.2 Train using MSE loss and Adam optimiser

4.3 Incorporate systematic error patterns.

5: **Evaluate and Deploy Model**

5.1 Evaluate model performance (RMSE)

5.2 Deploy for real-time UAV position correction

5.3 Monitor performance in flight; retrain/update thresholds when needed.

This presents a simplified algorithm outlining the key steps of our method to improve the estimation of the position of the UAV using ML and 5G PRS data.

5.3.5 Neural Network Architecture

For simplicity and deployability, the neural network will be trained on only the 3D estimated coordinates (X, Y, Z). Auxiliary features such as RSS and LOS/NLOS flags will be evaluated during feature selection but will be excluded from the final model to maintain low complexity and avoid overfitting, given the relatively small sample size.

We designed a fully connected FNN to map the estimated UAV coordinates (derived from 5G PRS measurements) to the actual UAV coordinates, as illustrated in Figure 5.5.

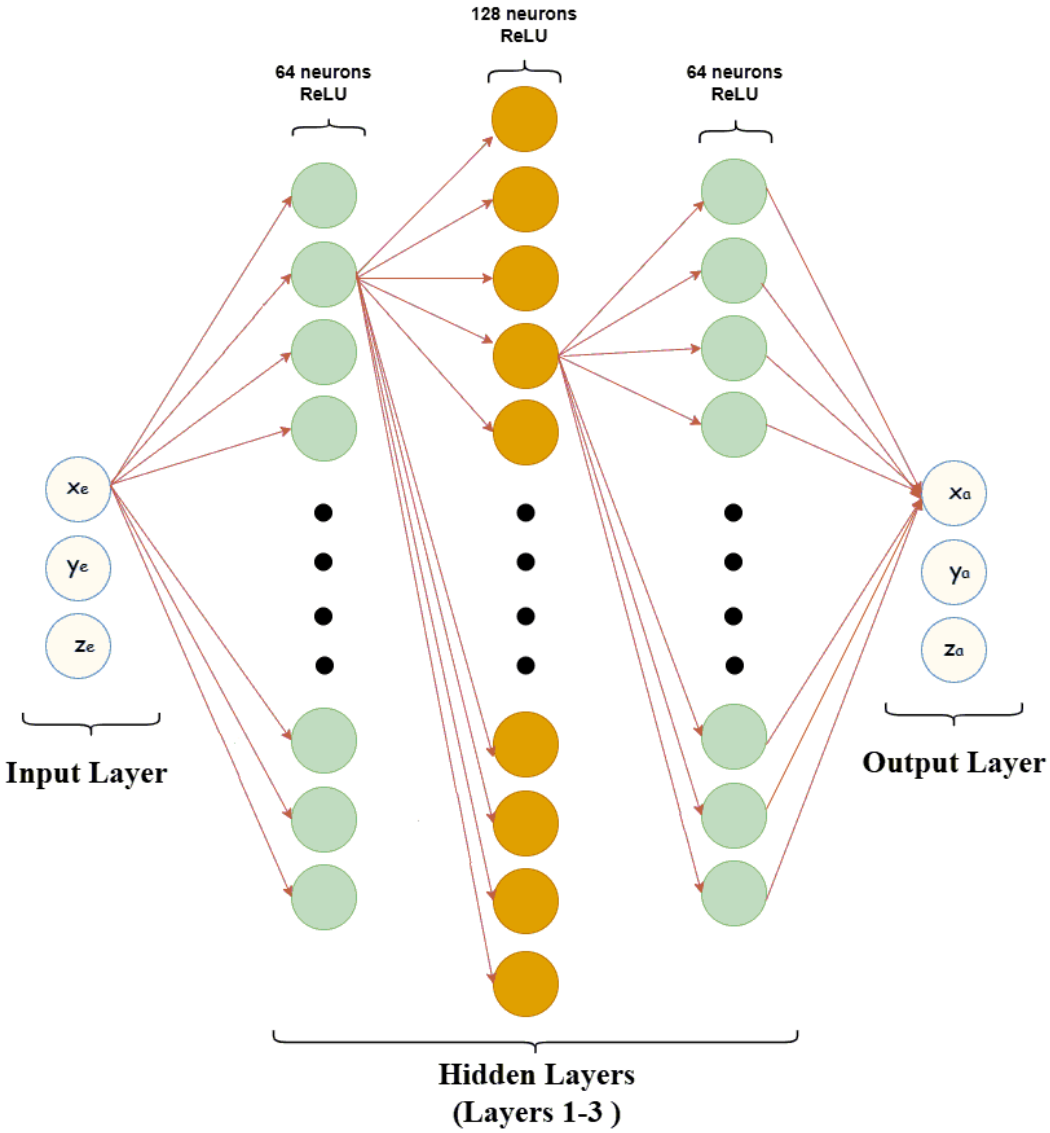

Figure 5.5: Diagram of the neural network architecture.

Architecture Overview: The model follows a structured design:

- **Input Layer:** Accepts three input features representing the estimated UAV coordinates.
- **Hidden Layers:** The network includes three intermediate layers:

  - **First Hidden Layer:** Expands the input to 64 neurons, applying the ReLU activation function.
  - **Second Hidden Layer:** Increases the complexity with 128 neurons, capturing deeper relationships.
  - **Third Hidden Layer:** Reduces the feature space to 64 neurons to refine the representation before prediction.

- **Output Layer:** Produces three output values representing the actual UAV coordinates. No activation function is applied to allow unrestricted predictions.

Figure 5.5, Simplified Block Diagram of the Correction Process. The input consists of TDOA-based estimated positions; corrections are applied using learned neural mappings, without relying on auxiliary features such as RSS.

Activation Function: The ReLU (Rectified Linear Unit) activation function introduces non-linearity in the hidden layers. It ensures the network can learn complex patterns by allowing positive values to pass through unchanged, while setting negative values to zero, which is defined in Equation eq:relu.

$$\text{ReLU}(x) = \max(0, x). \tag{5.1}$$

Justification for Architectural Choices

1. The structure (64–128–64 neurons) balances learning capacity and computational efficiency. Expanding first helps capture detailed patterns, while reducing later prevents overfitting.

2. This design also ensures feasibility for deployment on UAVs with limited compute and memory.

3. ReLU helps the network learn complex relationships without suffering from vanishing gradients.

4. Our three-layer neural network architecture proved to be the optimal configuration for our specific requirements. When we explored a five-layer architecture, the marginal improvements in accuracy were practically negligible, falling within our measurement uncertainty range, making the results essentially almost identical to the three-layer model. The three-layer architecture stood out because it perfectly balanced our key priorities: it delivered the accuracy that we needed without overcomplicating the model, maintained strong performance under various test conditions, and kept computational costs reasonable. The network was empirically optimised using validation loss. Starting from a single hidden layer, we incrementally increased the number of layers and neurons (from 16 to 128 per layer). Beyond three layers, validation loss plateaued and overfitting was observed, as monitored by a rise in validation error despite continued training accuracy improvements. Thus, the three-layer architecture with 64 neurons

each was chosen for optimal generalisation. The deeper architectures we tested did not justify the additional computational overhead, especially when the three-layer design effectively met our accuracy targets. The choice of three layers was not just about raw performance numbers it represented the most pragmatic solution for our real-world constraints and objectives. It provided everything we needed: robust accuracy, efficient processing, and sustainable computational demands. Sometimes simpler is better; in this case, the three-layer architecture proved precisely what we needed.

5. Fully connected layers were chosen because the input features (5G PRS-derived coordinates) do not have spatial or sequential dependencies, making convolutional or recurrent networks unnecessary.

5.3.6 Training Procedure

Before training, the full dataset of 9000 samples was split into 70% training, 15% validation, and 15% test. Splits were performed randomly while ensuring a balanced mix of LOS and NLOS samples across all sets to preserve statistical representativeness. Each sample includes: estimated 3D coordinates from 5G TOA $\rightarrow$ TDOA conversion (input), ground-truth coordinates (target), path loss, signal strength (RSS), and LOS/NLOS flag (auxiliary features). The researchers used the training set to train the model, the validation set to fine-tune and stop early, and the test set for final evaluation. For data cleaning, outliers were removed using the three-sigma rule $|\text{error}| > 3\sigma$, where denotes the standard deviation of the error distribution. This statistical filtering removes extreme anomalies in positioning errors that may result from multipath signal spikes or simulation artifacts [204]. We normalised input features, such as estimated coordinates, using min-max scaling to maintain numerical stability, applying the same parameters across all data splits for consistency. We also created additional features, such as received signal strength (RSS), path loss, and LOS/NLOS labels, to help the model understand environmental conditions. These steps ensured a clean, consistent, and realistic dataset, allowing the model to generalise well to new data. The primary input to the neural network consists of 3D coordinates (X, Y, Z) estimated from TDOA measurements refined with a Kalman Filter. Optional auxiliary inputs (e.g., RSS, LOS/NLOS flags) were evaluated, but in the final model, only the estimated coordinates were used for regression to simplify deployment. Feature normalisation was applied using min-max scaling based on the training set. The model was trained using the MSE loss function, which is defined in Equation 5.2.

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5.2}$$

Equation 5.2 defines the MSE loss function, where L represents the loss, y_i is the ground truth value, $\hat{y}_i$ is the predicted value and n is the total number of samples. The

MSE penalises significant errors more heavily, making it a suitable choice for regression tasks in neural network training. MSE was chosen because it strongly penalises significant errors, which is critical in the accuracy of UAV positioning. Although MSE can be sensitive to outliers, data cleaning, normalisation, and additional metrics monitoring (such as MAE) mitigated its potential drawbacks.
We used Adam Optimiser with a learning rate of 0.001. This adaptive optimisation method efficiently handles noisy data and sparse gradients. We used default hyperparameters ($\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$) as recommended in [205],[206].
The model was trained for 20 epochs with a batch size of 32. The training loop followed these key steps:

- **Forward Pass:** Compute the predictions for the input batch.
- **Loss Computation:** Calculate the MSE loss.
- **Backwards Pass:** Compute gradients via backpropagation.
- **Parameter Update:** Update model weights using the Adam Optimiser.

The validation loss was monitored at the end of each epoch. Although early stopping was not explicitly implemented in the provided code, this mechanism can be easily integrated by halting training when the validation loss does not improve after a predefined number of epochs.

5.3.7 Model Evaluation, Testing, and Deployment

The model was evaluated using a held-out test set comprising 15% of the total dataset, which was not used during training or validation. The data were split into 70% for training, 15% for validation, and 15% for testing. This approach ensures an unbiased assessment of the model's generalisation capability. To maintain fairness in comparative evaluation, all internally developed models and baseline methods were tested under identical simulation conditions. These included consistent UAV trajectories, signal propagation characteristics based on the 3GPP TR 38.901 standard, and matching LOS/NLOS distributions. This uniform setup ensures that observed differences in performance are attributable solely to model behaviour rather than variations in the data or environment. For real-time operation, the trained model is integrated into an inference pipeline suitable for onboard deployment. Input features are normalised prior to prediction and are inverse-transformed post-inference to restore physical coordinate outputs compatible with UAV navigation systems.

5.3.8 Implementation Details

Hardware Setup: The experiments were conducted on the following system configuration:

- CPU: Intel Core i7-10750H @ 2.60 GHz (6 cores, 12 threads)
- GPU: NVIDIA GPU with 4 GB VRAM (e.g., GTX-series, laptop-class)
- RAM: 32 GB DDR4
- Storage: 954 GB SSD
- Operating System: Windows 10 (64-bit)

Software Implementation: The methodology was implemented using:

- PyTorch for deep learning
- pandas and scikit-learn for data preprocessing and normalisation
- matplotlib for result visualisation

Performance Metrics:

- Training Dataset: 6,300 samples (70% of 9,000)
- Batch Size: 32
- Training Time: $\sim$45 minutes for 20 epochs
- Inference Time: $\sim$4.2 ms per sample (average on GPU)

All experiments were accelerated using the available NVIDIA GPU, enabling efficient training and fast inference. This configuration demonstrates the feasibility of integrating deep learning with 5G PRS data for scalable UAV positioning under both LOS and NLOS conditions.

5.4 Results and Discussion

5.4.1 Overview of Results

The proposed ML-based UAV positioning system significantly improves accuracy and robustness in urban environments. Key evaluation metrics, Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared, demonstrate that the model effectively refines position estimates based on 5G Positioning Reference Signal (PRS) data. The clear distinction between LOS and NLOS performance highlights the system's ability to manage signal degradation. These results confirm the system's potential for deployment in urban delivery, disaster response, and surveillance, where reliable navigation is essential.

5.4.2 Training and Validation Loss Convergence

As illustrated in Figure 5.6, the training and validation losses show smooth convergence over 20 epochs, stabilising by the third epoch. This indicates that the model quickly learned most patterns in the data early in training. The final loss values are as follows:

Training Loss: 0.000009

Validation Loss: 0.000156

These results confirm that the model achieves generalisation without overfitting. The small gap between training and validation loss indicates robust model performance on unseen data, a critical factor for real-world deployment. The rapid convergence observed in training and validation indicates that the model is computationally efficient, reducing the time and resources needed for model training and fine-tuning in real-world applications.

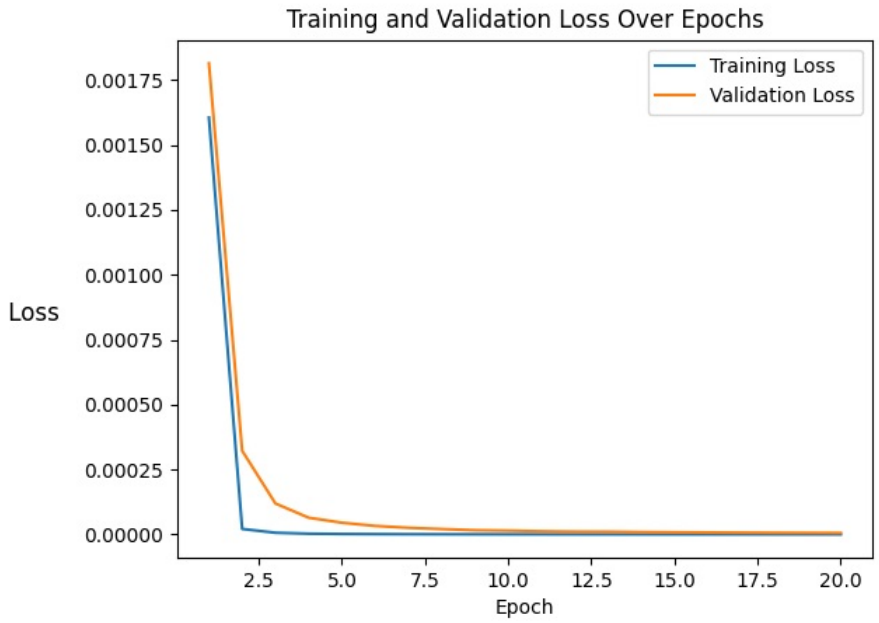

Figure 5.6: Convergence of Training and Validation Loss over Epochs.

5.4.3 Quantitative Analysis of Position Estimation

This subsection presents the core performance metrics used to assess the accuracy of the proposed positioning model. The evaluation quantifies the differences between predicted and actual UAV positions under both LOS and NLOS conditions. The primary metrics used are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which capture the average and variance-sensitive components of the localisation error, respectively. These are defined in Equations (5.3) and (5.4).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5.3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5.4}$$

Here, y_i denotes the ground truth position, $\hat{y}_i$ is the model's predicted position, and n is the total number of test samples. In addition to MAE and RMSE, the coefficient of determination (R^2) was used to assess the proportion of variance in the actual positions that is explained by the model's predictions. Table 5.2 summarises the overall performance of the model on the full test set. The average MAE across all samples is approximately 2.63 m, with an RMSE of 3.12 m and $R^2 = 0.666$. These results confirm the model's ability to significantly reduce positioning error, even in dense urban environments.

Table 5.2: Overall Performance Metrics for Position Estimation

Metric	**Value**
MSE	0.000012
MAE	2.63 m
RMSE	3.12 m
R-Squared (R^2)	0.666549

These results demonstrate that the model effectively refines raw position estimates. While the average error is acceptable for general navigation tasks such as delivery and surveillance, further optimisation may be necessary for high-precision use cases. A breakdown of performance under LOS and NLOS conditions is presented in Section 4.4.

5.4.4 LOS vs. NLOS Performance

To evaluate the model's robustness under varying signal propagation conditions, performance was assessed separately for LOS and NLOS scenarios. As expected, localisation accuracy declines in NLOS settings due to signal obstruction, multipath propagation, and attenuation. Nevertheless, the model demonstrates consistent and reliable performance across both environments. Table 5.3 summarises the key performance metrics under each condition. The Mean Absolute Error (MAE) under LOS is 1.30 m, increasing to 1.70 m in NLOS. Similarly, the RMSE increases from 1.60 m to 2.05 m.

Despite this degradation, the model maintains sub-2 m accuracy under NLOS and significantly outperforms traditional baseline methods.

Table 5.3: Positioning Accuracy Under LOS and NLOS Conditions

Condition	**MAE (m)**	**RMSE (m)**	**MSE (m^2)**
LOS	1.30	1.60	2.56
NLOS	1.70	2.05	4.20

These results confirm the model's ability to maintain high positioning accuracy in both ideal and obstructed urban environments, supporting its suitability for real-world UAV applications such as navigation, surveillance, and delivery in complex cityscapes.

5.4.5 Scatter Plot and Residual Analysis

Scatter plots in Figure 5.7 compare the model's predicted UAV positions with the ground-truth coordinates across the X, Y, and Z axes. The horizontal axis represents actual values, while the vertical axis shows predicted values, with a dashed grey identity line ($y = x$) indicating perfect agreement. Marker colour encodes the absolute error for each sample (green = small, red = large), with the scale defined by the accompanying colour bar. The strong clustering of points along the diagonal line demonstrates high prediction accuracy, consistent with findings in similar UAV positioning studies [207].

Residual analysis in Figures 5.8 and 5.9 provides further insight into error distribution. The residuals, defined as the difference between predicted and actual positions, are centred around zero and show no significant bias across the operating range. This unbiased behaviour indicates that the model's predictions are both accurate and consistent, supporting its robustness for UAV positioning tasks. While scatter plots illustrate axis-wise accuracy, UAV navigation requires the evaluation of the total three-dimensional error. By combining deviations across all three axes, the Euclidean distance is computed as shown in Equation (5.5).

$$\text{3D Error} = \sqrt{(x_{\text{pred}} - x_{\text{actual}})^2 + (y_{\text{pred}} - y_{\text{actual}})^2 + (z_{\text{pred}} - z_{\text{actual}})^2}. \tag{5.5}$$

As detailed in Table 5.3, the resulting 3D localisation errors are 1.3 m under LOS and 1.7 m under Non-Line-of-Sight (NLOS) conditions. These values provide a realistic measure of navigation accuracy, significantly outperforming GNSS in dense urban environments where errors typically degrade to 15–50 m due to multipath and NLOS effects [208]. All axes, insets, and annotations are expressed in meters, avoiding the underestimation introduced by previous 0 –1 normalised scales.

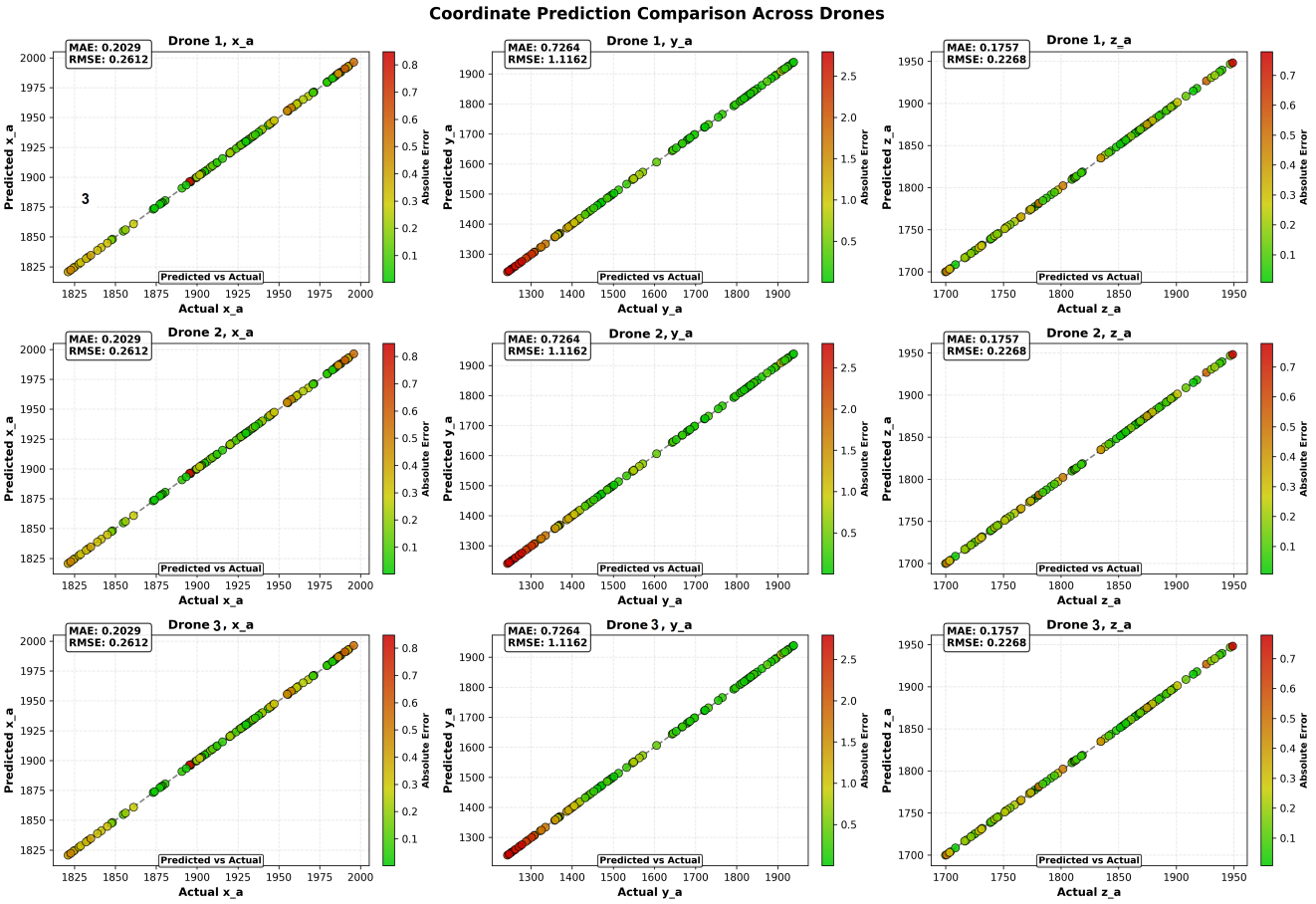

Figure 5.7: Scatter Plot of Actual vs. Predicted Values for UAV 1, 2, and 3 (X, Y, and Z).

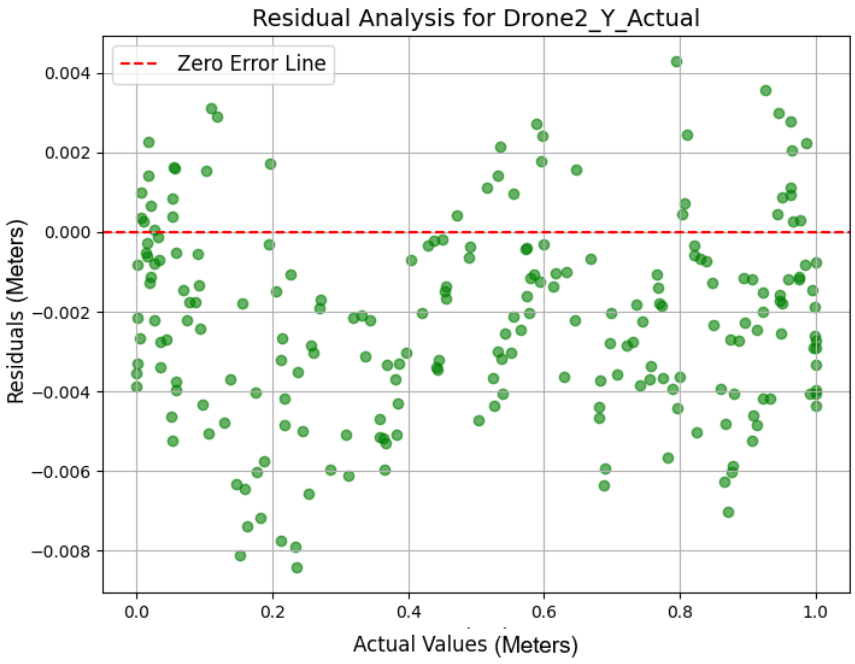

Figure 5.8: Residual Analysis for UAV 1.

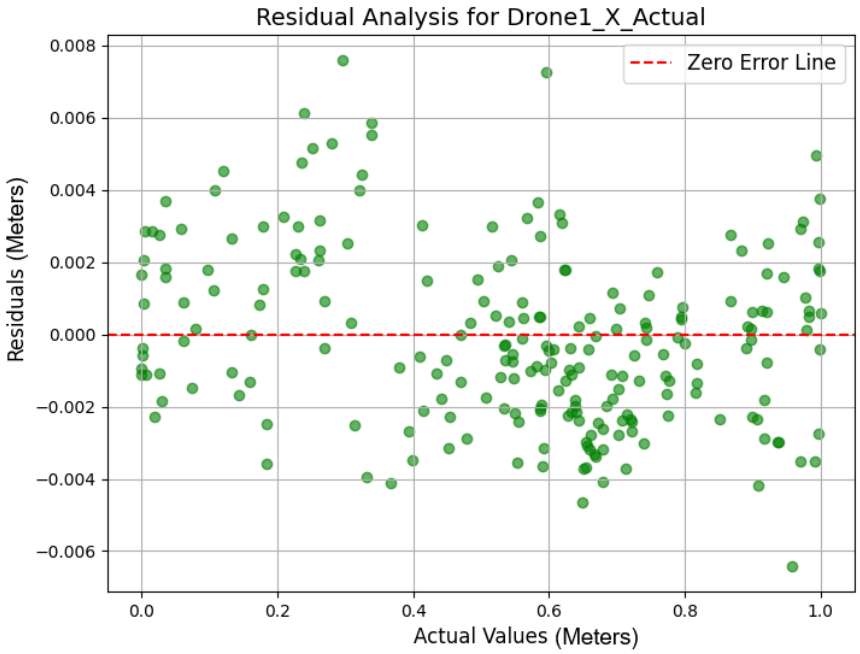

Figure 5.9: Residual Analysis for UAV 2.

5.4.6 Spatial Error Distribution

An analysis of prediction errors along the X, Y, and Z dimensions reveals that the model performs more accurately in the horizontal plane (X and Y) than in the vertical (Z) dimension. Specifically, errors in the Z-axis are more pronounced, particularly under NLOS conditions. This reflects an anisotropic error distribution, where lateral estimates are more stable than vertical ones. This degradation in vertical accuracy is likely due to increased multipath propagation and reduced signal quality when direct paths are obstructed. Additionally, the geometry of terrestrial 5G base station antennas is optimised for horizontal coverage, limiting vertical angular resolution for UAVs operating above rooftop level. Residual analysis (Section 5.4.5) confirms a wider spread in Z-axis residuals under NLOS conditions, consistent with increased signal dispersion and elevation uncertainty in obstructed urban environments. While the model effectively handles horizontal localisation, vertical positioning requires further refinement. This is particularly important for applications involving complex 3D flight paths, such as rooftop landings, multilevel navigation, and autonomous inspections in urban canyons. Future work may address this limitation by incorporating altitude-aware neural architectures or fusing radio-based predictions with complementary modalities such as barometric sensors, LiDAR altimetry, or inertial navigation systems. These enhancements could mitigate Z-axis ambiguity and improve vertical accuracy under challenging propagation conditions.

5.4.7 Comparison of Raw vs. Corrected Position Estimates

To quantify the benefit of the proposed learning-based approach, we compare the final corrected position estimates with the raw outputs derived from 5G TDOA-based multilateration refined using a Kalman filter. Here, "raw" refers to traditional estimates computed without any neural correction. Table 5.4 presents the MAE and RMSE under both LOS and NLOS conditions. The raw MAE under LOS and NLOS is 3.8 m and 5.1 m, respectively, compared to 1.3 m and 1.7 m after correction, a reduction of over 60%.

Table 5.4: Comparison of Raw vs. Corrected Positioning Error

Condition	**MAE (Raw)**	**MAE (Corrected)**	**RMSE (Raw)**	**RMSE (Corrected)**
LOS	3.8 m	1.3 m	4.7 m	1.6 m
NLOS	5.1 m	1.7 m	6.3 m	2.05 m

These results demonstrate that the proposed model substantially improves positioning performance under both propagation conditions. Even under NLOS, where multipath and signal degradation are most pronounced, the corrected error remains below 2 m, confirming the model's robustness and effectiveness in real-world urban environments.

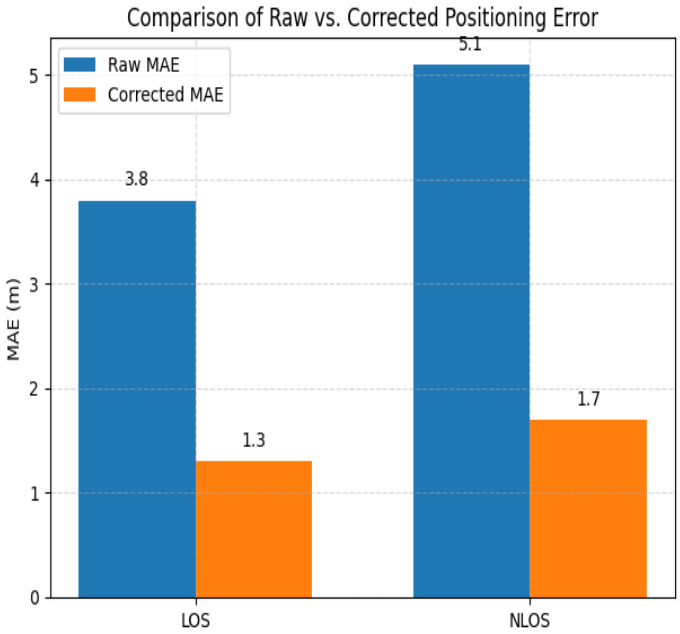

Figure 5.10: Visual comparison of raw vs. corrected position estimation error under LOS and NLOS.

5.5 Conclusion

This thesis proposed a 5G PRS-aided UAV positioning system that combines TDOA measurements with Kalman filtering and a lightweight FNN to improve accuracy in urban environments. The system was evaluated in a simulation framework under both LOS and NLOS conditions. Results show that the proposed method achieves an MAE of approximately 1.3 m in LOS and 1.7 m in NLOS, with an RMSE of around 2.3 m. These results represent a significant improvement over standard multilateration and neural fingerprinting approaches. As Table 5.5 shows, the proposed method balances accuracy and efficiency, especially in challenging NLOS environments. This makes it suitable for urban UAV applications such as package delivery, inspection, and low-altitude navigation. The model is designed for embedded deployment using a compact FNN, with scope for further optimisation through quantisation and pruning [209]. Furthermore, Integration with 5G Mobile Edge Computing (MEC) and low-power design could enhance real-world deployment [210],[211]. Nevertheless, the evaluation was limited to simulation. Assumptions such as ideal PRS synchronisation, fixed gNodeB placement, and simplified propagation models restrict direct transfer to field environments. Real-world factors, including antenna placement, clock drift, Doppler effects, shadowing, interference, and regulatory constraints, especially for BVLS flights, remain untested. Future work will aim to bridge the gap between simulation and real-world deployment through the following directions:

- Implementing real-time inference pipelines optimised for embedded UAV systems with limited computational resources.
- Integrating multi-sensor data sources such as GNSS, IMUs, and LiDAR to enable more robust and resilient hybrid localisation.
- Scaling the framework for fleet-level deployment, including support for distributed localisation and UAV swarm coordination.
- Improving simulation fidelity by incorporating Doppler spread, shadowing, synchronisation errors, and other signal distortion effects.

The proposed system is compatible with real-world 5G/UAV testbeds such as AERPAW and 5GRAIL, which provide access to live network signals, mobile UAV operations, and timing synchronisation effects [212],[213],[214]. These platforms offer a foundation for end-to-end testing and hardware-in-the-loop validation under realistic conditions. In conclusion, this study demonstrates that accurate, real-time UAV localisation in complex urban environments is achievable by integrating 5G positioning reference signals with lightweight neural network-based correction. The results highlight the potential for deployment in autonomous UAV fleets operating within next-generation urban airspace frameworks, supporting the advancement of urban air mobility and enabling new applications that demand precise positioning in challenging conditions.

Table 5.5: Comparison of Positioning Techniques for Urban UAV Applications.

Approach	Accuracy	Computational Efficiency	Remarks	Ref
Proposed 5G PRS + Neural Network Correction (5G TDOA + Kalman + FNN)	$\sim 1.3\,m$ MAE (LOS), $\sim 1.7\,m$ MAE (NLOS), $\sim 2.3\,m$ RMSE. Significantly reduces baseline error.	High – Designed for urban NLOS; ML model compensates for multipath and removes outliers in real time.	Moderate – Real-time feasible. Lightweight FNN inference with Kalman filtering. Suitable for onboard UAV use.	Our approach
Baseline 5G TDOA + Kalman Filter (Conventional Multilateration)	$3.8\,m$ (LOS), $5.1\,m$ (NLOS) MAE. Degrades in dense urban areas.	Medium – Effective in LOS; poor in NLOS due to lack of multipath mitigation.	Medium – Effective in LOS; poor in NLOS due to lack of multipath mitigation.	[34]
Neural Network Fingerprinting (Deep Learning + GNSS)	Few-meter-level accuracy in mapped urban areas. Drops with environmental changes.	High in mapped areas. Requires large training datasets; less adaptive to online changes.	Medium – Heavy offline training; fast inference. Needs storage for fingerprint database.	[35]
Hybrid GNSS/5G EKF Fusion (EKF + 5G + GNSS)	$\sim 1-3\,m$ static, $\sim 1-4\,m$ in motion. Better than GNSS- or 5G-only.	High – Dual-system robustness. Effective fallback if one signal is degraded.	Medium – EKF is real-time friendly, but processing 5G + GNSS increases complexity.	[36]
Graph-Based 5G + IMU Fusion (Graph Optimization)	$\sim 0.15-0.3\,m$ indoor LOS. Centimeter-level in ideal setups.	High – Robust in structured environments. Still being evaluated outdoors with multipath.	Moderate – Real-time capable but computationally heavier than EKF.	[37]

Chapter 6

Conclusion and Future Work

The integration of 5G NR technology with AI represents a significant step forward in enabling reliable BVLOS operations for UAVs. This thesis addresses critical challenges in UAV positioning and communication within complex and dynamic urban environments. By developing novel algorithms, combining sensor fusion, and enabling AI-driven models, this work introduces a cutting-edge approach to improving connectivity and localisation for UAVs. The combination of theoretical insights, simulation models, and empirical validation provides substantial contributions to the evolving landscape of UAV deployment in next-generation wireless networks.

6.1 Conclusion

This thesis began with an evaluation of 5G network performance for UAVs across different altitudes, focusing on key QoS metrics such as latency, RSRP, and handover success rates (Chapter 3). The field trials and simulations showed altitude-dependent fluctuations, highlighting the need for UAV-specific connectivity protocols. While 5G demonstrated reliable handovers, LTE exhibited limitations for aerial operations. Chapter 4 presented a hybrid positioning system that fused 5G OTDOA signals with IMU and barometric sensor data using an Extended Kalman Filter (EKF). This approach reduced positioning errors to 2.8–7 m in dense urban canyons, offering a more reliable alternative to GNSS in challenging environments. Chapter 5 introduced an AI-based correction model for NLOS mitigation. The proposed lightweight feedforward neural network (FNN) further reduced errors to approximately 2.6 m MAE and demonstrated strong real-time applicability in GNSS-denied scenarios. Overall, the research objectives set out at the beginning of this thesis have been successfully achieved. UAV connectivity in 5G networks was evaluated and shown to be superior to LTE. A hybrid positioning framework was designed and validated, delivering improved ac-

curacy. An AI-driven correction mechanism was developed to mitigate NLOS errors. Finally, the broader implications for UAV operations were assessed, confirming the system's potential for practical applications in delivery, surveillance, and emergency response. These findings demonstrate that the proposed framework provides a reliable and scalable solution for UAV communication and positioning in 5G-enabled urban environments, offering a solid foundation for future autonomous aerial systems and urban air mobility.

6.2 Future Work

While this thesis presents substantial contributions, several avenues for further research remain:

1. QoS analysis in Chapter 3 was constrained to a rural environment, which may not fully represent the complexity of urban network dynamics. Future studies should conduct field trials in densely built-up areas, where multipath propagation, interference, and high user density pose significant challenges to UAV connectivity. Collaborations with telecommunications providers to develop UAV-optimised connectivity hardware will yield more reliable results for real-world UAV deployment.

2. The positioning framework developed in Chapter 4 faced IMU drift and barometric sensitivity to weather conditions. Advanced filtering techniques, such as Unscented Kalman Filters (UKF) or particle filters, could improve robustness. Further, integrating LiDAR or vision-based systems as additional sensors could increase redundancy, enhancing reliability in GNSS-denied environments.

3. The neural network correction model introduced in Chapter 5 was validated using simulated data. The next critical step is to test these models under real-world conditions, accounting for hardware noise, environmental variability, and compliance with aviation regulations. Moreover, for real-time deployment, the model must be computationally efficient. Future work could explore lightweight neural network architectures or offloading processing to edge/cloud platforms to facilitate practical on-board implementation.

4. Cooperative positioning where multiple UAVs share localisation data could significantly improve accuracy in swarm operations. Integrating federated learning will enable decentralised intelligence while maintaining data privacy. Furthermore, integration with 6G technologies, network slicing, and edge AI will be essential for building adaptive and self-optimising UAV systems.

5. Ethical and regulatory frameworks must evolve to accommodate the growing presence of UAVs in urban environments. Developing standards, privacy policies, and transparent governance structures will ensure the safe and socially

responsible deployment of UAV systems, fostering public trust and long-term adoption.

In conclusion, this research provides actionable insights into UAV-5G integration, blending empirical research with innovative algorithms. The proposed methods enhance the reliability, accuracy, and safety of autonomous UAV systems in complex environments. As the field progresses, interdisciplinary collaboration and stakeholder engagement will be pivotal in translating these technical advances into real-world impact. Ultimately, this work lays the groundwork for intelligent aerial networks that support smart cities, disaster response, and next-generation logistics.

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