Evaluating Signal Quality and System Performance in NB-IoT Communications

An Empirical Analysis Using the SIM7020 Module

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Abstract: The expansion of the Internet of Things (IoT) has created a need for reliable and fault-tolerant communication networks. However, ensuring consistent signal quality and power efficiency has proven to be challenging. This study evaluated the performance of Narrowband IoT (NB-IoT) communications using the SIM7020 module connected to a Raspberry Pi 4 Model B, focusing on signal quality across indoor, outdoor, urban and rural areas. Supervised machine learning for indoor localisation based on Received Signal Strength Indicator (RSSI) has been introduced, for example, to enhance NB-IoT performance. However, this and other approaches have encountered difficulties in mobile and obstructed environments, including signal attenuation, connectivity variability and increased power consumption.

The objective of this study was to analyse NB-IoT signal strength and power consumption, providing guidance for deploying real-time communication IoT applications. Empirical data was analysed to understand the RSSI and Cellular Signal Quality (CSQ) in different locations. Signal quality in urban and outdoor environments was prone to fluctuations due to mobility and interference, whereas rural areas had weaker but more consistent signals. Indoor environments suffered from significant signal attenuation. This study's results emphasise the importance of improved handover mechanisms and adaptive deployment strategies to ensure reliable connectivity across various IoT applications.

Keywords: NB-IoT, signal quality, SIM7020 module, CSQ, RSSI

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Introduction

Reliable and fault-tolerant communication networks are needed, as shown by the rapid expansion of the Internet of Things (IoT), and are necessary for IoT applications, including smart homes, industrial automation, environmental sensing and healthcare monitoring (Badi & Mahgoub, 2021; Sadek & Elbadawy, 2022). The reliability and dependability of IoT networks can be measured using the Cellular Signal Quality (CSQ) and Received Signal Strength Indicator (RSSI) metrics (Maduranga & Abeysekara, 2021; Tsanousa *et al.*, 2021). Even with improvements in IoT communication technologies, it is still challenging to maintain a lower threshold value of decibel-milliwatts (dBm) in various scenarios, which may significantly affect the performance and data reliability of IoT devices (Herrnleben *et al.*, 2020; Pinem *et al.*, 2019).

Narrowband IoT (NB-IoT) is a radio technology standard known as low-power wide-area network (LPWAN), which is designed to allow long-range communication at low bit rates to allow communication for sensors that operate only on batteries. Its purpose is to connect various devices and services using cellular telecommunications bands. NB-IoT is designed to offer enhanced connectivity by supporting multiple devices across a large area while consuming minimal power.

NB-IoT is a cellular communication with a transmission bandwidth of 200 kHz spectrum for standalone mode, as shown in Figure 1, a 180 kHz spectrum for guard band and in-band modes as an LPWAN. The features of NB-IoT are wide coverage, allowing for multiple connections, and low power consumption and cost (Matz *et al.*, 2020; Tian & Wang, 2020).

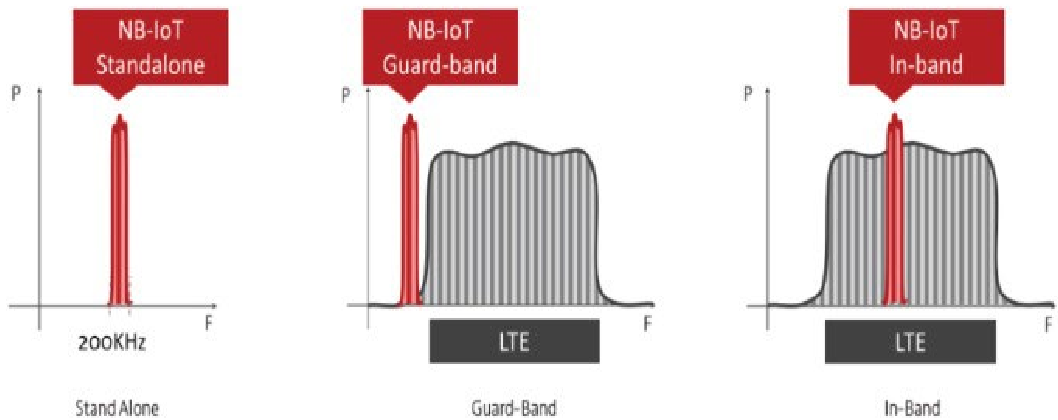

Figure 1. NB-IoT three deployment modes. (Source: Tian & Wang, 2020)

NB-IoT applications depend on the performance and reliability of the transmitted wireless signal (Alobaidy *et al.*, 2022). Connectivity, transmission of data rate, power consumption, and overall system efficiency are all directly impacted by signal quality (Basu *et al.*, 2019).

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Thus, to successfully integrate NB-IoT networks, it is crucial to understand the factors that affect signal quality and discover how to prevent poor signal conditions.

Table 1 summarises specific applications of NB-IoT.

Table 1. Applications of NB-IoT

Application	Description	Type of Paper	Contribution	Reference
Environmental Monitoring	Used NB-IoT modules to transmit environmental data such as air and water quality to a cloud platform for analysis.	Technical Paper	Introduced an environmental monitoring system utilising NB-IoT for transmitting sensor data to a cloud platform, highlighting its applicability in monitoring environmental parameters.	Chen *et al.*, 2018
Smart Parking	Employed sensors to detect and report parking space availability via an NB-IoT-enabled system, easing urban parking challenges.	Technical Paper	Discussed the development of a service platform called NB-IoTtalk, which simplified the deployment of large numbers of NB-IoT devices in smart parking applications, enhancing the management and efficiency of urban parking spaces.	Lin *et al.*, 2019
Healthcare Monitoring	Monitored patient vitals remotely, facilitating continuous care through data transmission to healthcare providers.	Implementation Paper	Provided a comprehensive system design for integrating NB-IoT in various applications, including healthcare, showcasing how it supported continuous patient monitoring and data sharing with healthcare providers.	Chen *et al.*, 2017
Smart Metering	Enabled remote and real-time utility usage monitoring, including water, gas, and electricity, optimising resource management.	Survey/Review Paper	Offered an overview of the technological evolutions and challenges of NB-IoT, specifically addressing how it supports smart metering applications in efficiently managing utility resources.	Xu *et al.*, 2018

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Application	Description	Type of Paper	Contribution	Reference
Agricultural Monitoring	Facilitated precision agriculture by monitoring soil moisture and crop growth, assisting with better resource allocation.	Simulation Study Paper	Reported on a simulation framework for studying NB-IoT in device-to-device modes, applicable in agricultural monitoring to optimise resources like water and fertiliser through accurate data collection and analysis.	Althobaiti & Dohler, 2021

Related Work

Previous studies have pointed out the inconsistency of signal strength across various locations and its impact on the performance of IoT applications. These are listed in Table 2.

A study reviewing the NB-IoT performance in Malaysia focused on various metrics like coverage, path loss packet delivery and latency. The authors discovered that NB-IoT can manage high data rates under low signal conditions. However, NB-IoT had significant variations in the communication delay based on signal strength, which impacted the device's battery life. This study highlighted that there are trade-offs between connectivity and power efficiency in NB-IoT deployments, so signal quality can directly affect the operation of an IoT application (Alobaidy *et al.*, 2022).

Studies on NB-IoT performance in various locations

Several experiments have been conducted to evaluate the performance and effectiveness of NB-IoT in different environments, including indoor, industrial, and deep-indoor settings. These empirical studies highlight the challenges and potential solutions for effectively deploying NB-IoT technologies as follows.

A remote monitoring system based on NB-IoT by Ji *et al.* (2018) aimed to monitor indoor environments; this system utilised multiple sensor nodes to collect parameters such as temperature and humidity. The data was transmitted over Zigbee and NB-IoT to a service centre. The experiments showed that the system could achieve real-time indoor environment monitoring, demonstrating stability, low cost, low power consumption and ease of operation

Ruepp *et al.* (2018) did a practical field test to compare NB-IoT and LoRaWAN technologies regarding the RSSI in deep-indoor environments. The study found that while Constrained Application Protocol (CoAP)/UDP-based transport consistently performed better in latency, coverage and system capacity, Message Queuing Telemetry Transport (MQTT)/TCP also worked well when the system was less loaded. This demonstrated NB-IoT's potential for better connectivity in challenging conditions

Malarski *et al.* (2019) focused on understanding signal attenuation in deep-indoor scenarios; this experiment was conducted in a system of long underground tunnels. It provided insights into the accuracy of current empirical models for NB-IoT signal attenuation in such environments, identifying key factors that affected signal propagation.

Dangana *et al.* (2022) studied the impact of NB-IoT wireless transmission and introduced a methodological approach to reduce path loss significantly. Their research identified that the inherent limitations of NB-IoT in adverse conditions can be mitigated to improve the overall network performance and reliability.

An empirical study done by Yau *et al.* (2022) evaluated NB-IoT coverage and connectivity in dense urban environments. Over 100 NB-IoT sensor nodes were deployed in high-rise apartment buildings to collect high-resolution water flow data. The study provided empirical measurements that revealed correlations between NB-IoT connectivity and sensor installation environments, demonstrating the technology's effectiveness even in challenging outdoor and indoor conditions.

Recent studies on the time domain analysis of NB-IoT focused on LTE800 cells that were operated by different mobile network operators. Their findings characterised NB-IoT signals and compared the received power values using a spectrum analyser to assess signal quality. Their objective was to analyse the guard band deployment of NB-IoT (Barellini *et al.*, 2023).

Another study by Roosipuu *et al.* (2023) evaluated the signal quality of NB-IoT networks in an underground urban drainage system, to assist with flood risk management. Their findings suggested that there is a need for minimum signal strength to ensure communication.

A study by Lahoud *et al.* (2023) evaluated the performance of LoRa and NB-IoT under challenging conditions; they used non-line-of-sight reception to determine the suitability of each technology for specific scenarios in IoT applications.

The integration of NB-IoT technology for smart metering scenarios was studied to focus on Early Data Transmission (EDT) which significantly reduced transmission delays and improved efficiency, allowing the authors to confirm it as a powerful feature for smart metering (Stusek *et al.*, 2023).

A study by Nardis *et al.* (2023) presented a strategy for positioning, based on fingerprinting using coverage and radio information from multiple cells. Their strategies showed improved accuracy compared to current methods.

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The experiments in Table 2 highlighted NB-IoT's potential in addressing the unique challenges of indoor and deep-indoor environments. They offered insights into improving coverage, connectivity and system performance in various settings.

Table 2. Studies on NB-IoT performance in various locations

Study type	Location	Key Findings	Contribution	Reference
Remote Monitoring System Based on NB-IoT	Indoor	Demonstrated stable, low cost, low power real-time monitoring of the indoor location.	Emphasised the system's capability for real-time monitoring despite challenges.	Ji *et al.*, 2018
IoT Connectivity in Deep-Indoor Environments	Deep-Indoor	Compared NB-IoT and LoRaWAN, highlighting NB-IoT's potential for better connectivity in deep-indoor conditions.	Found CoAP/UDP-based transport to perform consistently better in challenging conditions.	Ruepp *et al.*, 2018
Performance Evaluation in Indoor Industrial Locations	Indoor Industrial	The industrial locations significantly affected wireless transmission due to large-scale fading and reflective characteristics.	Introduced a collaborative scheme, improving path loss value by 30.44%.	Dangana *et al.* 2022
Investigation of Deep Indoor NB-IoT Propagation Attenuation	Deep-Indoor (Underground Tunnels)	Identified inaccuracies in current empirical models for signal attenuation in deep-indoor scenarios.	Suggested that indoor distance and penetration depth do not fully explain signal attenuation.	Malarski *et al.*, 2019
NB-IoT Network Field Trial: Indoor, Outdoor, and Underground Coverage Campaign	Dense Urban (Indoor, Outdoor, Underground)	Provided empirical evidence of NB-IoT's effectiveness in various environments, including challenging indoor and outdoor settings.	Demonstrated the technology's effectiveness and proposed a transmission decision algorithm to mitigate energy waste due to transmission failures.	Yau *et al.*, 2022

Soft handover and hard handover

This is especially important for optimising deployments of IoT devices, and this is also considered a soft or hard handoff (Mahenthiran & Muruganadam, 2024). According to the authors, the device can experience latency during the handover process. There would, therefore, be a delay in receiving IP packets until the link is established.

De Oliveira *et al.* (2019) proposed a soft handover in 5G networks to enhance the handover process. They used a software-defined network (SDN) which is an approach in networking that uses a software-based controller to communicate with hardware infrastructure and network traffic on the network, thus the SDN-based handover decision multi-criteria mechanism was implemented during this study. However, the implementation may be limited to simulations and may not consider the complexity of real-world network environments and user mobility patterns.

According to Pinem *et al.* (2019), optimal soft handover performance in long-term evolution (LTE) networks can be achieved by setting the threshold value to 113 dBm at 15 m/s, minimising the number of handovers. Too many handovers can increase signalling traffic, burden the network, degrade user experience due to handover failure, and consume more power on the IoT device.

Optimising these parameters involves predictive algorithms and real-time adjustments based on network load and locations. NB-IoT devices need low power consumption, and an increased energy consumption in the network can cause the device to switch off to conserve power (Pinem *et al.*, 2019).

Although conceptual models are useful for conceptual designing and planning, real-world deployments often reveal unexpected challenges and possibilities for improvement, requiring flexible approaches that guarantee reliable and resilient IoT communications. Therefore, it is critical to conduct empirical research that assesses signal quality to understand the capabilities and limitations of NB-IoT comprehensively.

The need for continuous connectivity and minimal latency in critical IoT applications, like remote healthcare monitoring and autonomous vehicles, further highlights the importance of signal strength analysis.

Unlike previous studies that often focus on a single type of location, our research provided a systematic evaluation of NB-IoT signal strength and power consumption across four locations: indoor, outdoor, urban and rural settings. This approach offers a more holistic understanding of NB-IoT performance under varying real-world conditions.

We implemented a real-time data collection methodology using the SIM7020 module connected to a Raspberry Pi 4 Model B. This setup allowed us to capture and analyse dynamic changes in signal quality as the device moved through different locations. The real-time aspect of our study highlights the challenges and performance of NB-IoT in actual deployment scenarios.

Our study provides empirical data on the impact of handover mechanisms on signal quality and connectivity. By analysing the transitions between cell towers in mobile environments, we identify the challenges related to signal drops and latency, offering insights that can inform the development of more robust handover strategies for NB-IoT networks.

The results of our study have direct practical implications for the deployment of IoT applications. By understanding the variations in signal quality and power consumption across different environments, developers are now equipped with a methodology to optimise their applications for better performance and reliability.

Therefore, this study is built on previous research's foundational work using a methodological approach to systematically evaluate the SIM7020 module's NB-IoT communications performance in an LTE in-band deployment mode in indoor, outdoor, rural and urban locations. During the indoor location test, the device was stationed in a room with four walls and one window to check for interference, reflection or diffraction from the antenna and how the signal was affected. The outdoor, rural and urban tests were conducted while driving with the NB-IoT device powered on to do the signal testing, receiving real-time data from the device and storing the data on the Raspberry Pi. The signals from the cell towers varied from start to finish as the device moved through different locations.

Data Collection Methodology

Before the data collection process began, all measurement equipment, including NB-IoT devices with Raspberry Pi, used to record RSSI and CSQ values, were standardised. This step ensured that the NB-IoT devices were operating correctly and providing accurate measurements.

Data validation protocols using Python were implemented to automatically check the code when plotting the captured data. This helped ensure that the data points matched the dataset on the graphs, and quickly identified potential errors in data collection or processing.

Regular consistency checks were conducted throughout the data collection period to ensure the equipment continued to function properly. The battery attached to the Raspberry Pi used a 5V USB UPS battery to maintain backup power for the device.

After data collection, a systematic review of the collected data was conducted to clean any inconsistent or incomplete datasets. This step included a manual review where necessary to ensure that all data used in the analysis met the standards set for the study.

These measures ensured that the data used in the study followed iterations of tests and that the tests constantly showed values in the same range.

This study evaluated signal strength data obtained from an NB-IoT module using the Raspberry Pi to capture, process and analyse the data to understand how an NB-IoT module

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with a Vodacom LTE NB-IoT sim card deployed in a band mode with 180 kHz spectrum would handle a device moving in real time and while stationery affects the quality of the signal using four different locations within two weeks. It provides a detailed analysis of the RSSI and CSQ in different locations, namely indoor, outdoor, urban and rural.

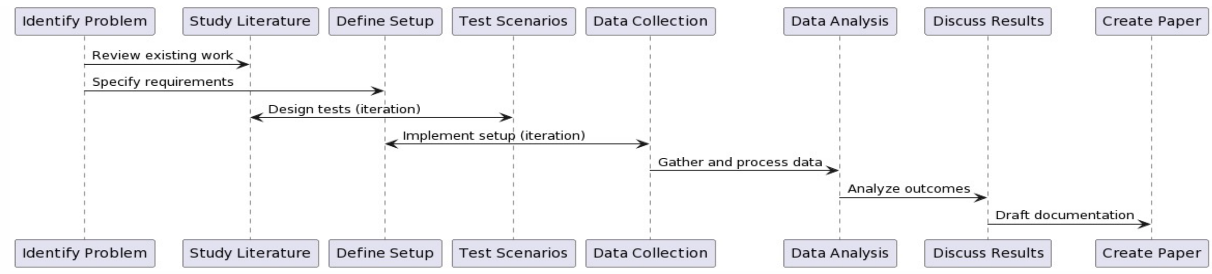

Figure 2. Scientific Method and Engineering Design (SMED) sequence diagram

The data was then analysed following Figure 2, which explained the methodological approach used for this study; the RSSI values were converted to dBm, the signal strength was categorised, and it was analysed based on the expectation that in some locations the NB-IoT device would receive signals from the different cell towers and would still be connected to the Vodacom network in-band deployment mode, while gathering real-time data and while moving at a faster speed; however, energy consumption and monitoring would be the extension of this study in future research.

Hardware and software setup

The data collection involved a SIM7020 NB-IoT module connected to a Raspberry Pi, as shown in Figure 3. The SIM7020 module was selected for its efficient power usage and robust connectivity options, which make it suitable for varied IoT applications. The Raspberry Pi was the control and data logging platform, interfacing with the SIM7020 module via serial communication to collect CSQ and RSSI values. The following GitHub repository shows the SIM7020 used: https://github.com/waldonhendricks/Network-Performance-Measurement-Framework-Using-SIM7020-IoT-Module.

Test locations

Data was gathered across multiple locations to assess the SIM7020 module's performance under different conditions. The test locations included:

- **Urban location:** Dense areas with high building concentrations.
- **Rural location:** Open spaces far from cell towers.
- **Indoor location**: Inside buildings with various structural materials.
- **Outdoor location**: Open spaces without significant obstructions.

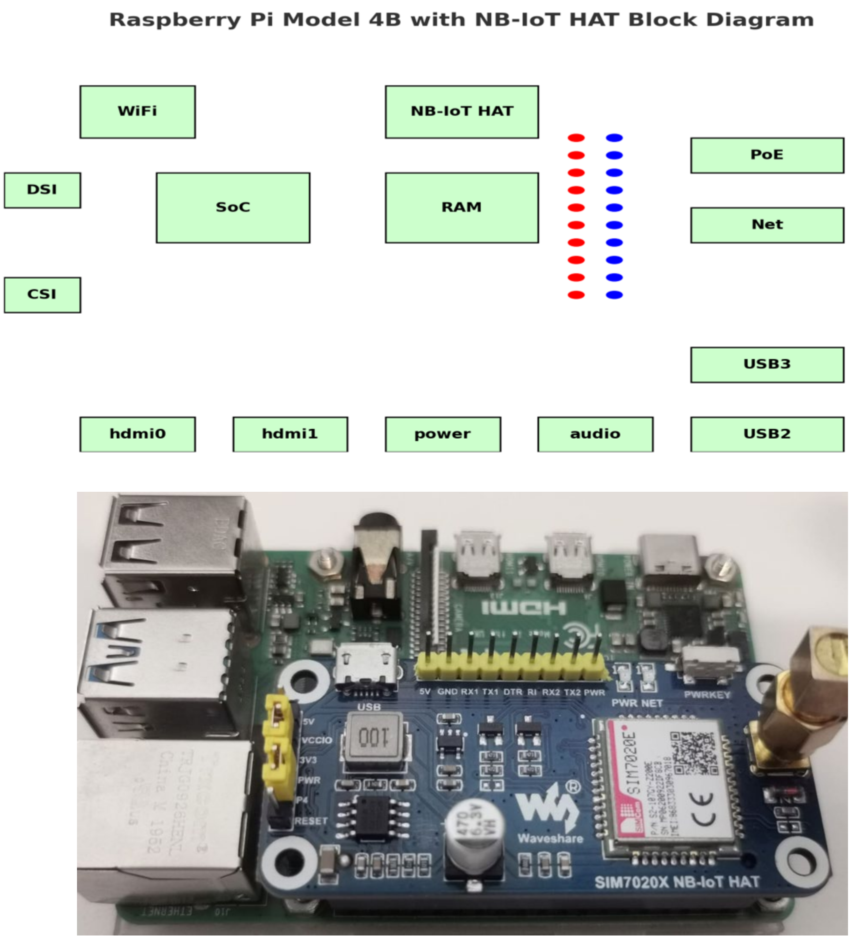

Figure 3. SIM7020X HAT with Raspberry Pi 4 model B

Routes and locations

Specific routes were chosen to evaluate different locations that could affect signal strength comprehensively. These routes spanned from densely populated urban areas, as shown in Figure 4, to remote rural paths, as shown in Figure 5, including indoor locations as shown in Figure 6 and outdoor locations in Figure 7, to simulate real-world usage scenarios as closely as possible.

As shown in Figure 4, the urban location test was done while moving from start to finish; the speed was 40–80km/h, as this was the speed limit restriction. The indicated cell towers are towers added by mobile users on the cell mapper mobile app, so these can be considered unverified LTE towers.

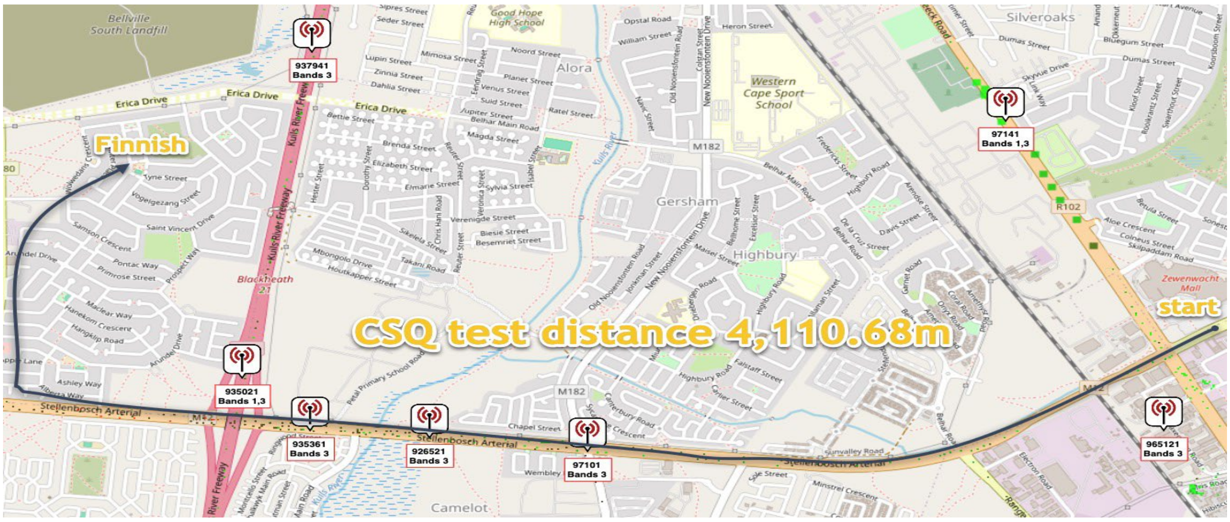

Figure 4. CSQ test distance 4,110.68m urban settings

As shown in [Figure 5](#), the rural location test was also done while moving from the start location to the finish location. During this test, the speed was adjusted to 100km/h while moving and doing the signal strength testing.

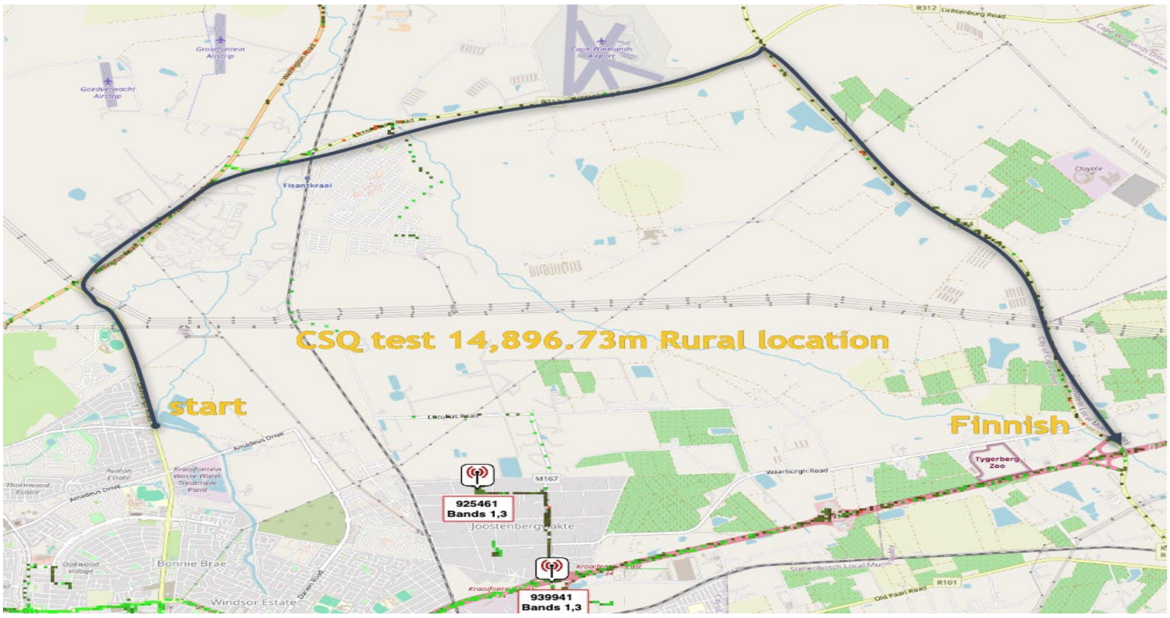

Figure 5. CSQ test 14,896.73m rural location

As shown in [Figure 6](#), the indoor location test was the only test out of the four at a fixed location and would, therefore, have no speed or movement; the interference, reflection, or diffraction would be key data while the signal quality test was done. Two cell towers, which were unverified, are shown when running the test.

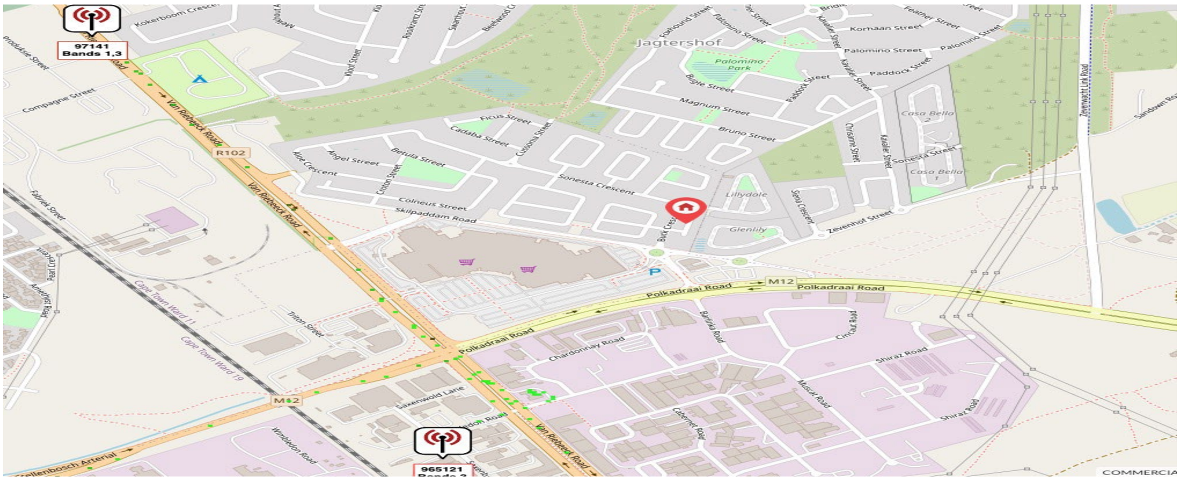

Figure 6. CSQ test indoor settings

As shown in Figure 7, the outdoor location test was done at varying speeds while moving as the device moved from an urban location towards the highway, from 60km/h to 120km/h on the highway from the start location to the finish location.

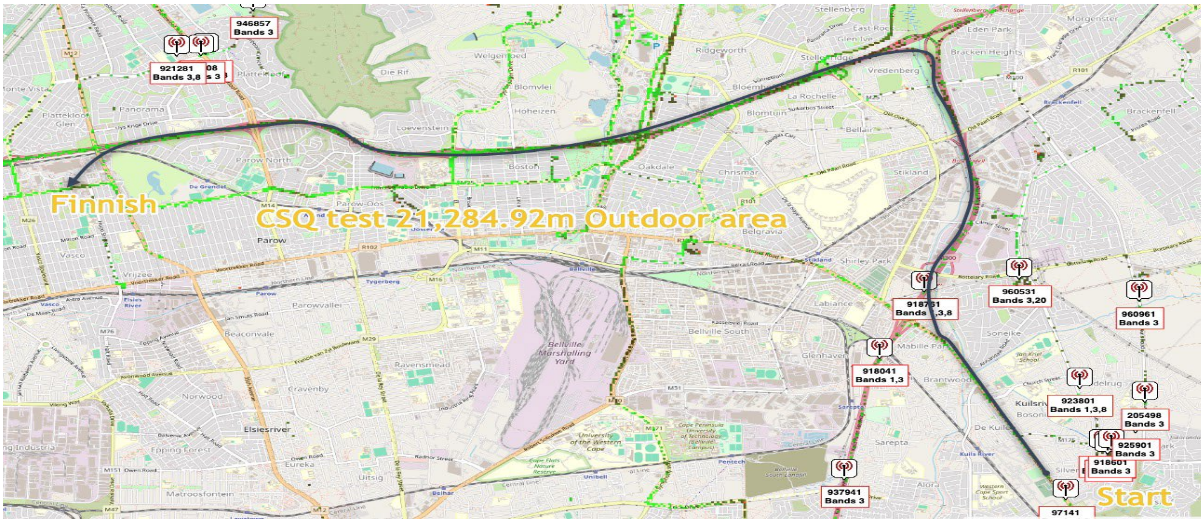

Figure 7. CSQ test 21,284.92m outdoor area

Data collection frequency and parameters

The data points were collected every five minutes, providing a good resolution to observe and analyse the dynamics of signal strength and quality over a relatively short period, in real time and stored after 15–30 minutes per location test, then saved to a CSV file, capturing the CSQ values and timestamp. This provided a view of signal quality fluctuations over time. Additional parameters noted during the data collection included the Bit Error Rate (BER), date stamp and time of day.

The tests were conducted during off-peak times and peak times:

- Outdoor testing was done during peak times (09.00–10.00 SAST).
- Indoor testing was done during off-peak times (21.00–22.00 SAST).

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- Urban testing was done during peak times (09.00–10.00 SAST).
- Rural testing was done during peak times (12.00–13.00 SAST).

The placement of the Raspberry Pi with the NB-IoT device was carefully controlled and standardised across different test locations. During the indoor test, the device was positioned near the window to minimise obstructions and interference. In mobile scenarios, the path and mode of device movement were set to keep within the road speed limit of the location to reduce variability in data due to different speeds.

The tests were done in real time to test the real-time conditions of the NB-IoT network; there was no indication of network congestion during the tests. The study monitored the network using instructions used to control the NB-IoT modem by using attention (AT) commands to check the network status before running tests to choose optimal times for data collection when the network was connected. This helped in reducing the impact of errors on the signal strength and quality measurements.

The study aimed to ensure that the categorisation of signal strength was as reliable and consistent as possible, despite the inherent challenges posed by environmental variability and other influencing factors

The script logged CSQ and BER, highlighting a modular approach with commands running in a script on the testing device for sending AT commands and logging data. This data was then saved to the CSV file.

Findings and Discussion

The data points were collected every five minutes, providing a detailed view of signal strength and quality fluctuations within a relatively short timeframe of 25 to 30 minutes. This consistent data collection approach was maintained throughout the entire study.

The sampling frequency for measuring the RSSI and CSQ, as indicated by the timestamps on the provided graphs, was set at every five minutes. This consistent interval was upheld across different locations and throughout the study period. This consistent sampling frequency was essential in accurately assessing signal quality variability and stability across different locations and enabling reliable comparisons between various testing scenarios, including indoor, rural, outdoor and urban locations.

By ensuring a consistent sampling rate, the study ensured that the collected data would be sufficient for identifying trends and detecting any anomalies or changes in signal quality over time. This methodological consistency proved advantageous for statistical analysis, enabling a clear understanding of how different factors and locations influenced the signal quality of cellular networks.

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In urban (Figure 10) and outdoor (Figure 8) environments where the device was in motion, the signal quality graphs displayed sharper variations and sudden drops in CSQ values, followed by recoveries. This pattern indicated that the device was moving in and out of different cell coverage areas, experiencing changes in signal obstruction caused by buildings.

Data collected in the indoor location (Figure 9) showed more stable signal strength and quality. This graph showed fewer fluctuations and maintained a relatively steady level, suggesting that stationary conditions offered a more stable connection. The rural location (Figure 11) also showed a stable signal due to the presence of fewer cell coverage areas.

The connection between signal strength and mobility identified that when a device moves, the stability of the cellular connection will be challenged in different network conditions and challenges. The device would transition between cell towers caused by the handover process, which could temporarily affect signal quality until the device establishes a stable connection with the next tower. The speed of movement and the physical characteristics of the location amplified signal instability by causing changing interference patterns and obstacles that block the line-of-sight pathways to cell towers (Mahenthiran & Muruganadam, 2024).

The collected CSQ and RSSI values were mapped to dBm, as shown in Table 3, using a standard conversion formula to measure the signal strength accurately. This conversion was crucial as dBm values provide a more universally understood measure of signal quality, allowing for comparisons with other studies or signal strength standards (Rahman *et al.*, 2016). Note the following general interpretation:

> **RSSI value**: An arbitrary unit ranging from 0 to 31, where higher values indicate stronger signal strength. Some devices may report this in a wider range of dBm directly.
>
> **dBm:** A physical unit that measures the power level of the received signal.

Real-time test outdoor location

Based on the outdoor area results shown in Figure 8, the study observed a cellular signal quality between 15 and 20 CSQ. Suddenly, there was a drop in the signal due to real-time testing between buildings and density areas. As the device moved through these areas between cell towers, the signal dropped to zero for about three to four minutes due to the device not reaching any cell towers. This delay in communication suggests the device was out of reach of cell towers, could not connect to the cell tower, and had a disconnect from the network. The device then recovers at a CSQ of 25, which would impact any applications or services dependent on this connection. This graph shows the distance from each cell tower affects the CSQ value.

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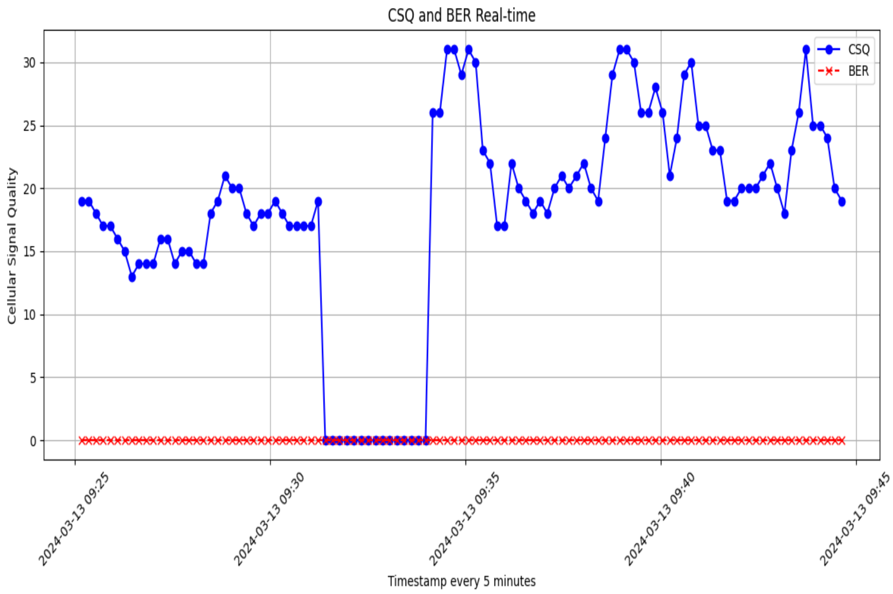

Figure 8. CSQ and BER over 20-minute real-time test – outdoor area

Real-time test indoor location

Based on the indoor real-time test results, as shown in Figure 9, the study observed a sudden drop at two points in time. This suggests the signal was very weak to measure. This would be due to signal interference, such as the walls of the building and signal reflection from the antenna trying to establish a connection to the cell tower. The random drops also suggests that while the device was in a fixed position, the device was connected to two or more cell towers, which suggests a drop in signal quality. These drops are important to note as they can lead to potential disruptions in service, especially for IoT applications that require a continuous and stable connection.

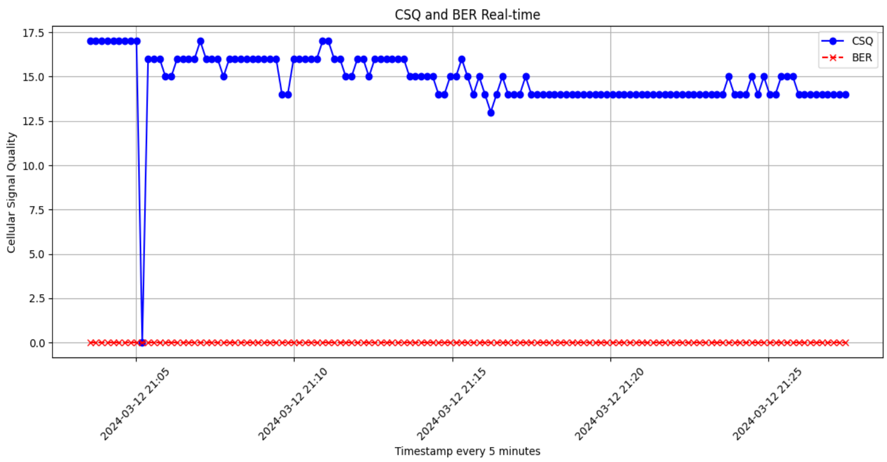

Figure 9. CSQ and BER over 30-minute real-time test – indoor area

Real-time test urban location

Based on the real-time urban test results, the signal quality suddenly dropped while running the test. The graph in Figure 10 shows how the signal quality increases while moving through the urban area. This would also indicate the device connected to several cell towers, and with each connection, there was a signal drop due to the transition between the coverage zones of the cell towers. This was due to a soft handover between cell towers, a process in cellular networks where a mobile device is simultaneously connected to more than one cell tower before switching completely to the new tower. This handover affected the performance of the NB-IoT device.

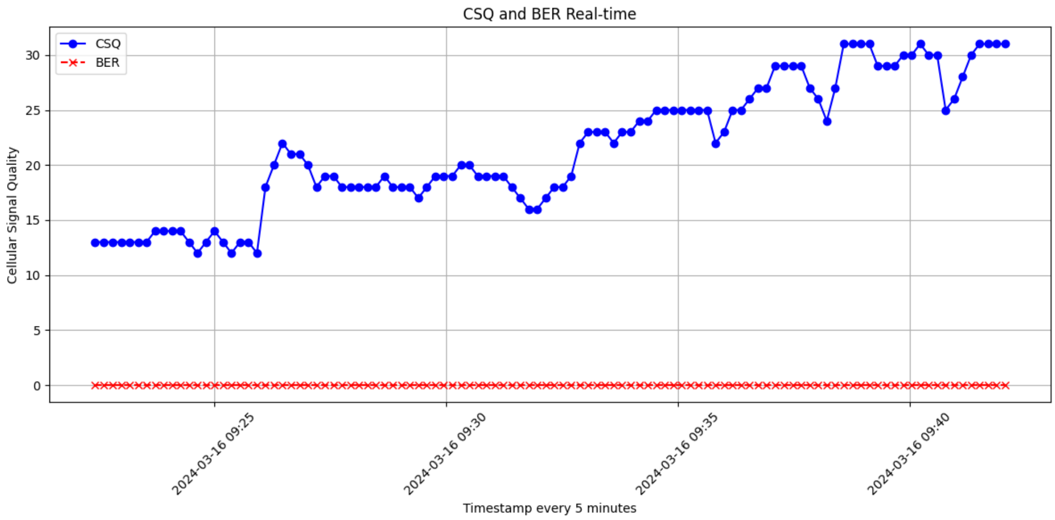

Figure 10. CSQ and BER over 15-minute real-time test – urban settings

Real-time test of rural location

Based on the rural location test results shown in Figure 11, the signal quality started between 15 and 20 CSQ values. Then, for around five minutes during the test, the device moved past a density area while moving towards the rural area for testing. At 12.25, there was a sudden drop in signal quality as the device entered the rural area and moved away from the cell tower; this significant drop in CSQ values at around the middle of the testing period possibly indicated a temporary loss of signal or transition between cell towers. However, it remained connected to the network as no BER values were detected.

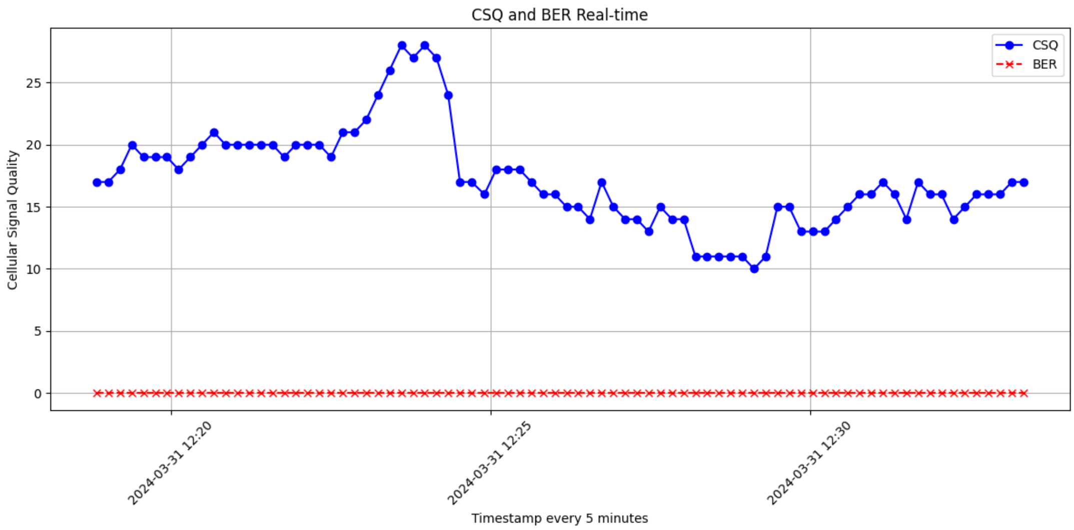

Figure 11. CSQ and BER over 15-minute real-time test – rural location

Performance of the proposed model with various parameters

To evaluate the performance of the proposed model, the study measured several key parameters and analysed the data collected during different test scenarios.

Received Signal Strength Indicator

RSSI measures the power level received by the device from the signal source, expressed in dBm. It is crucial to determine how well the device can receive signals from the cell towers. The study converts RSSI values to dBm to provide a more standardised measure of signal strength.

Observations:

Urban test: Higher RSSI values were observed due to the proximity to multiple cell towers, leading to better signal strength.

Rural test: Lower RSSI values were noted, indicating weaker signal strength, likely due to fewer cell towers.

Indoor test: Significant signal attenuation was observed indoors, resulting in lower RSSI values compared to outdoor measurements.

Outdoor test: During movement, RSSI values fluctuated more compared to the indoor test. The fluctuations were more noticeable in urban settings due to frequent handovers between cell towers.

Cellular Signal Quality

CSQ is an indicator of the quality of the received signal, essential for reliable data transmission. Higher CSQ values suggest better signal quality and lower bit error rates, leading to more efficient power usage,

Observations:

Urban test: The study observed high CSQ values, which indicated good signal quality. However, occasional drops were observed during handovers.

Rural test: Lower CSQ values were consistent, reflecting poorer signal quality due to the sparse distribution of cell towers.

Indoor test: Lower CSQ values were typical, similar to RSSI trends, due to signal degradation caused by the building.

Outdoor test: CSQ values showed more variability during movement, particularly while moving through urban areas with frequent cell tower handovers, which temporarily degraded signal quality.

Bit Error Rate

BER measures the rate of errors in a transmission system, indicative of the integrity of the data being transmitted. Maintaining a low BER across all test locations suggests effective error correction mechanisms, contributing to energy efficiency by reducing the need for retransmissions.

Observations:

Overall trend: BER remained consistently low across all test environments, suggesting healthy error correction mechanisms in the NB-IoT network.

The RSSI dBm was the measurement value obtained during the study; this determined how well the SIM7020E module could receive the signal from the cell tower. RSSI and dBm are different measurements that measure signal strength. dBm represents power levels and RSSI is just a relative index (see Table 3).

Based on the converted dBm values taken from the CSQ values, the signal strengths were categorised into four conditions: ‘Marginal’, ‘OK’, ‘Good’, and ‘Excellent’. These categories are defined as follows:

- **Marginal**: Signal strength is lower, indicating potential connectivity issues. Suitable for basic communication needs but may not support high-bandwidth applications.
- **OK**: Adequate signal strength for general usage, including voice calls and low to medium data rate applications.

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- **Good**: High-quality signal strength, supporting most data services and applications without significant issues.
- **Excellent**: Optimal signal strength, ideal for all types of data communication, including high-speed internet and streaming services.

Table 3. Signal strength categories (Rahman *et al.*, 2016)

Value CSQ	RSSI dBm	Condition
2	-109	Marginal
3	-107	Marginal
4	-105	Marginal
5	-103	Marginal
6	-101	Marginal
7	-99	Marginal
8	-97	Marginal
9	-95	Marginal
10	-93	OK
11	-91	OK
12	-89	OK
13	-87	OK
14	-85	OK
15	-83	Good
16	-81	Good
17	-79	Good
18	-77	Good
19	-75	Good
20	-73	Excellent
21	-71	Excellent
22	-69	Excellent
23	-67	Excellent
24	-65	Excellent
25	-63	Excellent
26	-61	Excellent
27	-59	Excellent
28	-57	Excellent
29	-55	Excellent
30	-53	Excellent

From the results of the tests on the different locations, it is clear that the cellular signal quality dropped over time in all four locations: indoor, outdoor, urban and rural. This indicated that the device constantly tried to improve the signal to the cell tower while initiating a connectivity test using the AT-CSQ command each time. The BER remained at zero during all four real-time tests, which suggested that the device had no problem with bit-sending during the transmission to the cell tower.

Comparative analysis

For this comparison, the study selected several existing techniques used in NB-IoT performance studies, focusing on models that optimise signal quality and manage handovers effectively. These were discussed in the Related Work section.

With regards to signal strength and quality metrics, the study demonstrated consistent improvement in CSQ and RSSI across the various locations. Existing performances in Table 2 showed improvements but were not consistent through all locations.

Some instances were reported by existing techniques where high BER rates were reported in challenging locations. However, this study maintained a low BER across all tested locations.

The related work described earlier focused on only specific environments, while this study focused on four different locations.

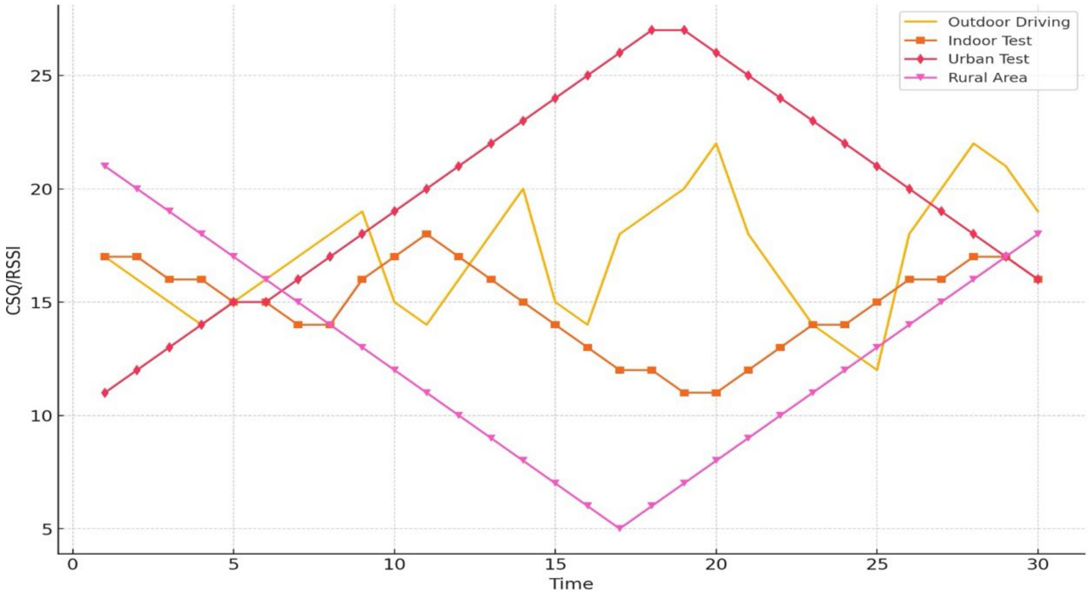

Figure 12. Comparative analysis of signal quality (CSQ/RSSI)

As shown in Figure 12, the indoor test offered a clear benchmark for signal stability. It showed how, in controlled locations, NB-IoT can maintain consistent performance. This stability was crucial for real-time applications requiring reliable connectivity, such as smart home systems and indoor monitoring. This suggests that with proper infrastructure, NB-IoT can achieve the reliable performance needed in these settings.

The urban test illustrated the potential for signal quality improvement over time. The study saw a steady improvement in signal strength. It showed promise for NB-IoT's application in smart city projects, where consistent and improved connectivity is essential.

The outdoor driving and rural area tests reveal the challenges of maintaining signal quality in dynamic and less urbanised environments. The fluctuations and occasional drops in signal strength highlighted the difficulties faced in these locations. These locations require more solutions to overcome inconsistency and ensure consistent NB-IoT performance.

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Conclusions and Further Research

This study aimed to evaluate the NB-IoT device with a Raspberry Pi and gather the data. This gathered data highlights that NB-IoT performance in the four locations still provides a good signal to run IoT applications; the RSSI dBm values show that NB-IoT is sufficient to run IoT applications in the four locations. The gathered empirical data confirms that NB-IoT performs well in the four locations where the tests and evaluations were done.

The method can be applied in any other area or location to test the NB-IoT network and see how the signal varies from point to point. This would provide data to a developer building an application for IoT real-time applications to test the signal and power consumption of the application using NB-IoT deploying in-band mode.

The study compiled data for rural, indoor, outdoor and urban settings, and the results highlight how signal quality varies across these locations.

Signal strength in rural areas was inconsistent, with noticeable fluctuations. These variations were due to fewer cell towers, greater distances to cover, and possibly fewer obstructions.

The signal's consistency indoors seemed relatively stable, but the overall signal strength was lower compared to outdoor settings. This was due to structural interferences such as walls and electronic appliances, which weaken or block signal propagation.

Outdoor signals generally offered better strength and consistency, with fewer obstructions and a clearer line of sight to the cell towers.

Urban settings displayed variability, possibly due to the high density of buildings, infrastructure, and competing signals. Despite these potential sources of interference, the urban locations benefited from more cell towers, which could have helped maintain adequate signal levels.

CSQ and RSSI metrics are crucial for assessing network connectivity performance and for software developers to understand the quality of service they can expect when their IoT applications operate in different locations. These metrics are vital to understanding and improving the performance and reliability of NB-IoT applications. More studies are needed on data collection focused specifically on the random access (RA) procedure metrics, which are crucial for understanding the behaviour and performance of NB-IoT devices during the initial access and network entry processes, and for understanding the soft and hard handover processes within NB-IoT networks.

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The study was limited to specific geographical areas and locations, which could affect the applicability of the results to other regions with different environmental conditions or network infrastructures.

While the study covered urban, rural, indoor and outdoor environments, there may be other relevant scenarios like underground, underwater and high altitude, which were not considered for this study.

The study was conducted using a single network operator and the findings may not be generalisable to other networks with different configurations. Multi-operator studies provide a more holistic view of NB-IoT performance across different network setups (Dangana *et al.*, 2022).

To the best of our knowledge, this study's findings highlight the importance of considering locations and placement of NB-IoT devices and mobility when evaluating NB-IoT network performance. The collected empirical data provide valuable insights into how different parameters impact signal strength and quality, offering a foundation for optimising NB-IoT deployments in various scenarios.

Future research should focus on refining handover mechanisms for NB-IoT and further exploring the impact of environmental factors on signal performance to enhance the reliability and efficiency of NB-IoT applications for real-time applications; conduct studies across more diverse geographical areas and environmental conditions to enhance the generalisability of the findings; and extend the duration of data collection to capture long-term trends and variations in signal quality and performance.

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