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Adaptive network switching algorithm for sensor data transfer: a simulation framework integrating GSM, Wi-Fi, and LoRa networks

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The growing deployment of IoT devices necessitates reliable sensor data transfer under diverse network conditions. This study introduces an adaptive network switching framework to enhance data dependability across GSM, Wi-Fi, and LoRa networks. By leveraging delay tolerant networking (DTN) principles and real-time performance metrics, the algorithm dynamically selects the optimal channel for transmitting sensor data—text, audio, image, and video—across urban, suburban, and rural settings. Simulations demonstrate an average 33% improvement in throughput, 24% reduction in latency, and 45% decrease in packet loss when using the adaptive framework compared to standalone networks. The adaptability score averaged 0.7 in rural scenarios, with peak performance scores reaching 1,000 for video data at night. A beehive monitoring case study validates these results in real-world conditions. This work contributes a robust, adaptable solution for sensor data optimization in IoT applications.

KEYWORDS

GSM, Wi-Fi, LoRa networks, delay tolerant networking (DTN), sensor data, text, audio, image

1 Introduction

The rapid proliferation of Internet of Things (IoT) devices has led to an exponential surge in sensor installations across a range of industries, including agriculture, healthcare, and environmental monitoring Mylonas et al. (2021). These sensors collect vital data that is necessary for real-time monitoring and decision-making Al-Fuqaha et al. (2015). However, dynamic network elements including physical obstacles, signal interference, and fluctuating network coverage provide significant challenges for sensor data transmission, leading to delays, greater latency, data loss, and inaccurate data transfer Soro and Heinzelman (2009). This inconsistency may have a substantial impact on critical applications where timely data is required for efficient operations, like precision agriculture, environmental monitoring or remote patient monitoring in healthcare Nguyen et al. (2021). Therefore, it is crucial to address the challenges of reliable sensor data transfer in various network scenarios to fully exploit the potential of IoT technologies Fuller et al. (2020).

Despite significant advancements in communication technology, the existing literature demonstrates an inadequate level of understanding of the optimal integration of many network technologies, including the Global System for Mobile Communications (GSM), Wireless Fidelity (Wi-Fi), and Long Range (LoRa), to offer reliable sensor data transfer Jouhari et al. (2023). Most studies focus on single technologies or predefined combinations without accounting for changing network circumstances or user needs Kloza et al. (2025). Moreover, there are not many comprehensive frameworks that effectively manage switching between diverse networks using the ideas of Delay Tolerant Networking (DTN) Rodrigues (2020). The development of an adaptive network architecture that can dynamically select the optimal communication channel based on network conditions and real-time performance data is necessary to fill this research gap Akyildiz et al. (2020).

By integrating GSM, Wi-Fi, and LoRa communication technologies, the main objective of this research was to create an efficient adaptive network switching algorithm that permitted reliable and smooth sensor data transfer. To do this, it was necessary to first analyze the performance of individual technology using real-time communication metrics to create a baseline for comparison Akpakwu et al. (2017), then design and implement an adaptive switching algorithm that used a combination of predefined performance metrics such as throughput and latency to dynamically choose the best communication technology Lim et al. (2020), assess the algorithm's performance under different network conditions using real-time metrics from empirical research Marsch et al. (2018), and validate the algorithm's effectiveness through comprehensive simulations and comparisons with individual network performance Li et al. (2020).

This article presents unique contributions to the field of adaptive network architectures and sensor data transfer. First, it incorporates DTN store-and-forward concepts into the suggested switching algorithm, guaranteeing data dependability during downtimes and strong performance under sporadic connectivity Kodheli et al. (2020). Second, before going over the adaptable switching architecture, it offers a thorough examination of each network, highlighting both its advantages and disadvantages. The study concludes by quantifying the algorithm's performance and offering a standardized method for evaluating adaptive network solutions in sensor data applications through the definition and use of performance indicators such as performance score and adaptability. When taken as a whole, these contributions open the door for further developments in IoT communication techniques, improving the reliability and effectiveness of sensor data transfer in practical applications such as beehive monitoring Namugenyi et al. (2024).

The remainder of the article is structured as follows: Section 2 discusses related work; Section 3 presents the methodology and the proposed hybrid framework and associated equations; Section 4 discusses the results; and Section 5 concludes and outlines future directions.

2 Related work

With the growing deployment of IoT devices across industries, various approaches have been proposed to address the reliability and efficiency of sensor data transfer over heterogeneous networks. Research in this field primarily focuses on improving data transmission quality under different network conditions by optimizing connectivity across multiple technologies, such as GSM, Wi-Fi, and LoRa.

2.1 Literature review on adaptive networking

Sensor data can now be transferred in various ways due to the increasing diversity in data volumes and heterogeneity, primarily through communication technologies like GSM, Wi-Fi, and LoRa. As stated by Mishra and Natalizio (2020), GSM has been widely used for transportation and logistics applications due to its extensive coverage and dependability, particularly in urban areas. Research continuously demonstrates that GSM is a reliable method of transmitting data, especially in situations with high levels of mobility. Imam-Fulani et al. (2023) and Adedoyin and Falowo (2020) have noted that GSM has various drawbacks, namely, lower data rates and high power consumption, which are crucial for sensor systems that need constant data flow.

In comparison, Wi-Fi provides significantly faster data rates and is commonly used in settings with reliable power sources and strong infrastructure. According to Wang et al. (2020), Wi-Fi works well for applications that need a lot of bandwidth, such as streaming videos and transferring big datasets. The features of Wi-Fi make it perfect for these kinds of jobs, as demonstrated further by Lim et al. (2020). However, Zhou et al. (2021) pointed out that Wi-Fi's reliance on fixed infrastructure poses serious problems, especially in rural or outdoor areas where it is harder to maintain a steady connection. Furthermore, according to Uwaechia and Mahyuddin (2020), Wi-Fi networks may encounter congestion and interference, which could result in decreased dependability, especially during periods of high usage.

In the meantime, LoRa has become a promising technology for long-range, low-power communication, particularly for Internet of Things applications. According to De Alwis et al. (2021), LoRa's special spread spectrum modulation makes it possible to communicate over great distances with little power consumption, which makes it perfect for uses like environmental monitoring and smart agriculture. The promise of LoRa has been emphasized by Pagano et al. (2022) in situations where devices need to function over wide distances and have long battery lives. But as Daousis et al. (2024) point out, applications that require quicker data transmission may find that LoRa's comparatively low data rate is a barrier. Furthermore, LoRa's wider use in hybrid communication systems is constrained by the lack of a standardized framework for integrating it with other communication technologies, according to Jouhari et al. (2023).

Recent developments in adaptive networking are being investigated as a solution to these individual constraints. Concepts like network slicing and cognitive radio, which enable devices to switch between various communication channels based on interaction with the surrounding environments, have been covered by Akyildiz et al. (2020) and Pham et al. (2020). These methods demonstrate the increasing emphasis on creating flexible solutions that may leverage the advantages of many communication technologies, improving the dependability of data transport across heterogeneous and diversified networks.

2.2 Limitations of standalone networks

Even if the technologies under discussion have advanced significantly, a rigorous examination of previous research and methodologies identifies a number of flaws Budhwar et al. (2023). Without considering the possible advantages of integration, many studies tend to concentrate on separate performance assessments of every communication technology Tataria et al. (2021). For example, research that compares GSM and Wi-Fi independently ignores situations in which hybrid solutions might offer higher reliability De Lima et al. (2021). Also, integration with other networks, which could lessen LoRa's inherent data rate constraints, is frequently overlooked in studies on the technology.

Furthermore, the methods used in previous studies usually overlook the dynamic character of network situations by depending on static performance indicators Wang et al. (2022). Assuring data transfer dependability requires switching between networks adaptively based on real-time performance, which is hampered by this restriction Gill et al. (2022). Additionally, a lot of research fails to sufficiently address the difficulties caused by sporadic connectivity, which is typical in practical implementations. Compounding these problems is the absence of comprehensive frameworks that integrate DTN ideas Rodrigues (2020) into adaptive network topologies.

2.3 Research gap

The literature reveals a significant research gap in the integration of several network technologies for reliable sensor data transfer Dwivedi et al. (2022). Although particular networks have been the focus of earlier research, comprehensive strategies that dynamically adjust to changing network circumstances and user needs are lacking. By creating an adaptive network switching method that integrates GSM, Wi-Fi, and LoRa technologies to improve data transfer reliability, this study seeks to close this gap [De Lima et al. (2021); Wang et al. (2022); Gill et al. (2022)]. By including real-time performance measurements, the suggested architecture ensures optimal data transfer by allowing devices to move between networks according to the current conditions. This research improves data transfer reliability and offers a scalable solution for a variety of IoT applications starting with our beehive monitoring scenario by incorporating DTN store and forward concepts Rodrigues (2020).

3 Methodology

This chapter outlines the methodology used to develop, simulate, and evaluate the adaptive network switching algorithm for efficient sensor data transfer across GSM, Wi-Fi, and LoRa networks. The methodology includes the conceptual framework for adaptive switching, the simulation environment, data parameters, and evaluation metrics.

3.1 Conceptual framework

By leveraging the unique advantages of each technology—Wi-Fi's high data rates for bandwidth-intensive data (e.g., video and images), GSM's extensive coverage and reliability for mobile scenarios, and LoRa's low-power, long-range capabilities for remote areas—the proposed framework combines GSM, Wi-Fi, and LoRa networks to optimize beehive monitoring applications. The adaptive network architecture, shown in Figure 1, integrates an adaptive switching algorithm that assesses area type, time of day, and network parameters, such as throughput, latency, packet loss, signal strength and power measurement at the implementation stage.

The adaptive algorithm dynamically selects the best communication channel, improving data transmission reliability, reducing latency, and maximizing throughput. This optimization raises the Performance Score and Adaptability Score, enhancing the effectiveness of beehive data collection and monitoring.

3.2 Simulation setup

The simulations were executed using Python and network simulation libraries, incorporating real-time parameters for each network. Table 1 outlines the parameters used for modeling each network technology in a controlled environment.

The following components were used.

- LoRa Grove E5 Module: The LoRaWAN protocol is used by this module Hochenbaum et al. (2013), which offers low power consumption and long-range communication capabilities. Applications needing long battery life and long-distance transmission of tiny data packets are best suited for the Grove E5.
- Wi-Fi 802.11: In places with well-established infrastructure, the Wi-Fi network Engst and Fleishman (2003) offers dependable connectivity and high data speeds thanks to its operation under the TCP/IP protocol. To evaluate Wi-Fi's performance, the simulations took into account a number of scenarios, including network congestion and interference.
- GSM 800L Module: The GSM 800L Nain and Vipparthi (2020) offers dependable data transfer and wide coverage in urban settings, operating on the TCP/IP protocol. The effects of signal intensity and mobility on data transmission performance were examined using simulations.

Three different region types—rural, suburban, and urban—were examined in the network topology design to ensure thorough performance evaluation in a range of environmental situations. During the simulations, four different kinds of sensor data were also sent: text, audio, pictures, and video. The performance characteristics of each data type were evaluated to determine how they impact the overall performance of the network.

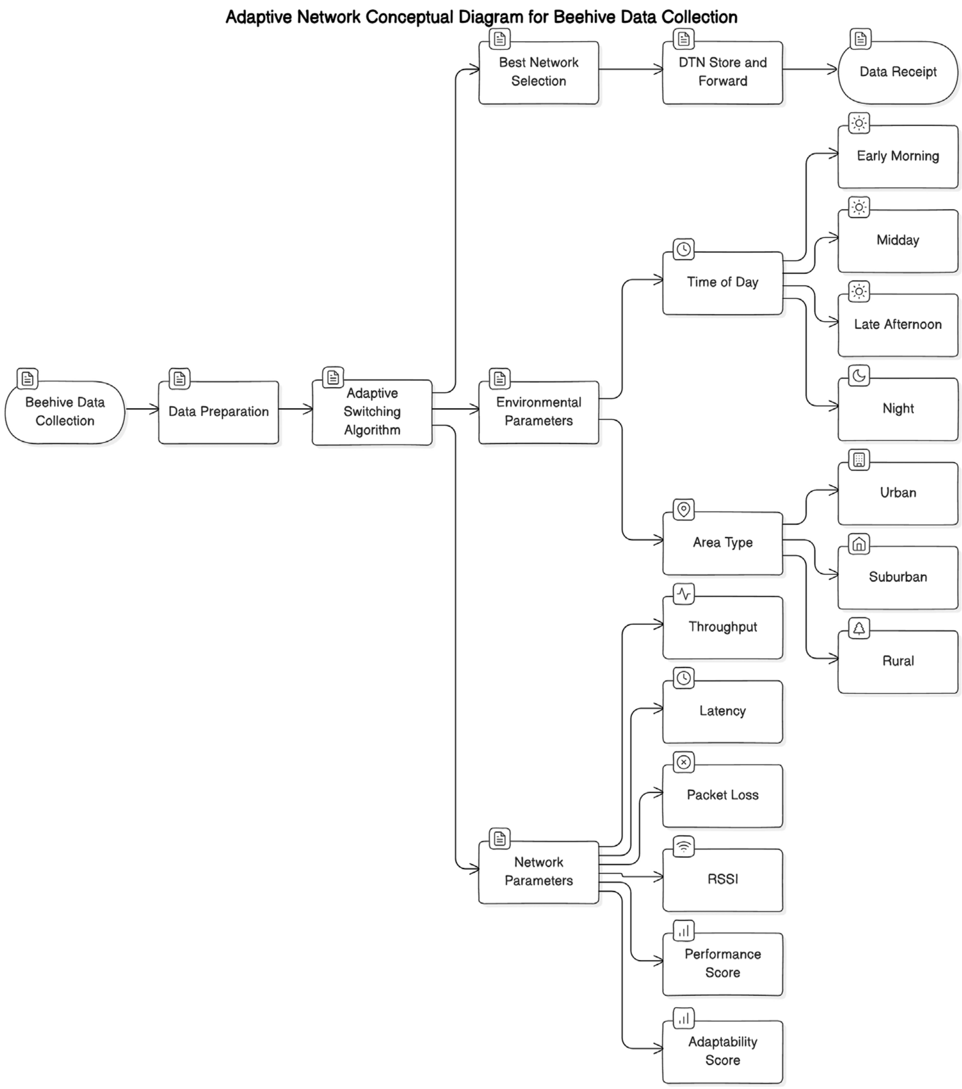

FIGURE 1
Conceptual Framework for Adaptive Network in Beehive Monitoring Applications—This diagram illustrates the integration of GSM, Wi-Fi, and LoRa within an adaptive switching framework. The framework dynamically evaluates throughput, latency, and packet loss to ensure efficient data transfer across varying environments.

To reflect the changes in network performance brought on by environmental conditions, user density, and interference, simulations were run at various times of day, notably early morning, midday, late afternoon, and night. When paired with the adaptive switching algorithm, this integrative approach made it possible to thoroughly analyze the advantages and disadvantages of each network technology.

3.3 Switching algorithm

The adaptive network switching algorithm, illustrated in Figure 2, facilitates seamless transitions among GSM, Wi-Fi, and LoRa to enhance data transfer reliability. Key components include.

- Decision Criteria for Switching: The system selects the optimal network based on real-time metrics, such as throughput, latency, and signal strength. For example, the algorithm may favor Wi-Fi under ideal conditions if latency is a priority.
- DTN (Delay Tolerant Networking) Implementation: By incorporating DTN store-and-forward principles, the algorithm ensures consistent data transfer even during sporadic connectivity, buffering data until a reliable connection is restored.

3.4 Performance metrics

The performance of the adaptive network switching algorithm is evaluated using the following metrics.

3.4.1 Performance score (PS)

This metric assesses the overall efficiency of data transmission and is calculated based on the following pseudo code:

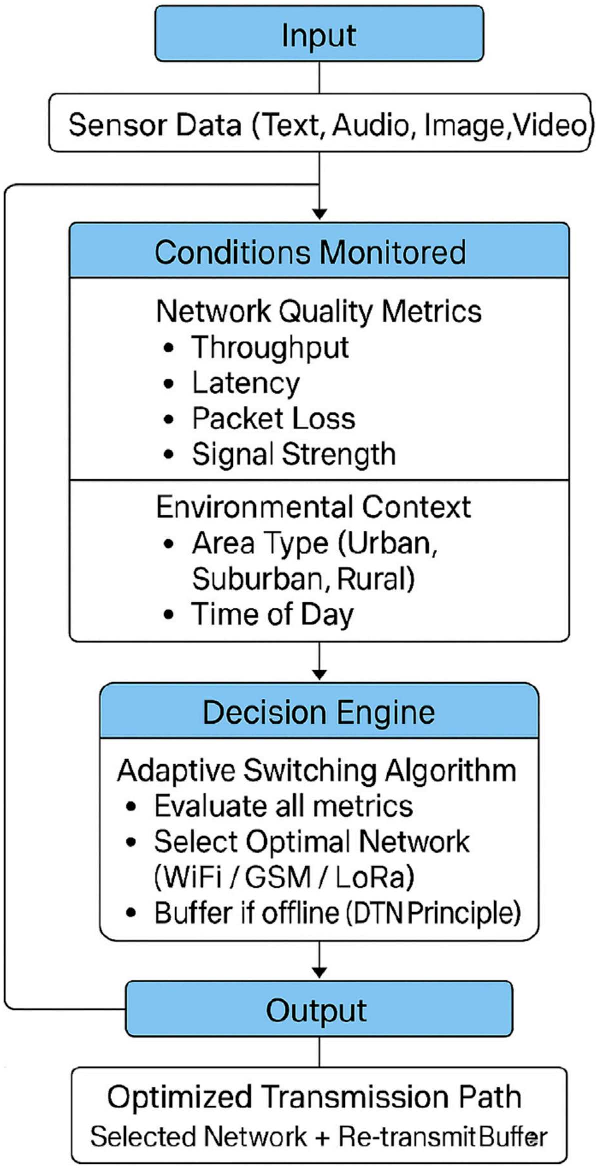

FIGURE 2
Flow Diagram for the Adaptive Network Switching Algorithm–The figure shows the decision-making process of the switching algorithm. Networks are chosen dynamically based on performance metrics (throughput, latency, packet loss) and DTN store-and-forward mechanisms ensure reliability under intermittent connectivity.

```
def calculate_performance_score(metrics: Dict[str, float]) -> float:
    # Normalize throughput, latency, and packet loss
    throughput = metrics["throughput"] / 1000000 # Convert to Mbps
    latency = metrics["latency"] # Measured directly
    packet_loss = metrics["packet_loss"] # Packet loss as a percentage
    # Calculate performance score with balanced weight
    performance_score = throughput - latency - packet_loss
    return performance_score
```

In this code.

- Throughput measures the amount of data successfully transmitted over a defined period and is normalized to Mbps.

- Latency is the time taken for data to travel from source to destination, measured directly in milliseconds.

- Packet Loss represents the percentage of packets lost during transmission.

By normalizing these values, the Performance Score provides a comprehensive measure of data transmission efficiency.

3.4.2 Adaptability score (AS)

This metric, as shown in Equation 1, measures the system's ability to maintain performance when facing dynamic conditions from a combination of Shannon's Channel Capacity Theorem, Queueing Theory and Latency Modeling, Control Theory and Optimization, Multi-Objective Optimization, Empirical Modeling and Machine Learning Lu (1999), Moore et al. (1977), Boyd et al. (1994), Deb and Kalyanmoy (2001), and Ahmed et al. (2010). The weights w_1, w_2, w_3 and w_4 in the equations are a result of optimization criteria different metrics (i.e., channel switching frequency, data rate, error rate, throughput, and latency) combined and balanced for maximum adaptability, reflecting a control-theoretic approach to system optimization. Adjusting the weights allows for prioritization based on the specific network scenario. The general adaptability score as in Equation 1 is calculated as a normalized summation of the product of weights w_i and each term f_i corresponds to individual metrics for each case described in Table 2 and Equations 2–4.

$$AS = \sum_{i=1}^{4} w_i f_i \tag{1}$$

where w_i represents the weight of each factor, and f_i corresponds to specific metrics as defined in the equations that follow.

3.4.3 Wi-Fi network adaptability measurement

The Wi-Fi network adaptability Andrews et al. (2014) is based on the following criteria.

- Channel Switching Efficiency: The ability of the network to efficiently switch channels to avoid interference and optimize performance.
- Data Rate Performance: The network's ability to maintain a good data rate under varying conditions, considering both average data rate and maximum achievable data rate.
- Error Resilience: The network's ability to handle transmission errors effectively.

The Measurement Metrics include.

- Channel Switch Frequency: How often the network switches channels to avoid interference.
- Average Data Rate: The average rate at which data is transmitted.
- Max Data Rate: The maximum achievable data rate for the network.
- Error Rate: The percentage of data packets that are corrupted during transmission.

TABLE 1 Real-time simulation modeling parameters for Wi-Fi, GSM, and LoRa networks.

Parameter	Wi-Fi (802.11)	GSM (800L)	LoRa (grove E5)
Antenna Gain (dB)	5	5	2
Average Data Rate (bps)	500,000	2,400	3,000
Base Power Consumption (W)	0.5	0.5	0.02
Channel Switch Frequency (Hz)	1	1	0.01
Distances Tested (m)	2–500 m	2 to 10,000 m	2 to 10,000 m
Frequency Band (MHz)	2,400	900	868
Latency Coefficients	U: 0.12, S: 0.18, R: 0.25	U: 0.15, S: 0.2, R: 0.25	U: 0.3, S: 0.35, R: 0.4
Max Data Rate (bps)	1,000,000	9,600	50,000
Max Packet Size (bytes)	2 MB	1 MB	255 bytes
Max Throughput (bps)	600 Mbps	171.2 kbps	50 kbps
Modulation Technique	OFDM	GMSK	LoRa Modulation (CSS)
Noise Floor (dBm)	−95	−95	−120
Packet Loss Coefficients	U: 0.03, S: 0.015, R: 0.007	U: 0.03, S: 0.015, R: 0.005	U: 0.02, S: 0.015, R: 0.01
Packet Sizes (Audio)	64 KB	128 KB	150 bytes
Packet Sizes (Image)	512 KB	500 KB	255 bytes
Packet Sizes (Text)	1 KB (1,024 bytes)	0.5 KB (512 bytes)	100 bytes
Packet Sizes (Video)	2 MB	1 MB	255 bytes
Target Latency (ms)	100	150	1,000
Transmit Power (dBm)	20	20	14

U-Urban, S-Sub-Urban, R-Rural.

TABLE 2 Network switching patterns.

Switching	Initial network	Switched to network	Counts
1	GSM 800L	WiFi 802.11n	288
3	LoRaGrove E5 with LoRaWAN	WiFi 802.11n	288
4	WiFi 802.11n	LoRaGrove E5 with LoRaWAN	288
0	GSM 800L	LoRaGrove E5 with LoRaWAN	240
2	LoRaGrove E5 with LoRaWAN	GSM 800L	240

- Throughput-WiFi: The actual data transfer rate experienced on the WiFi network.
- Latency-WiFi: The time it takes for data packets to travel from source to destination on the WiFi network.

The adaptability for Wi-Fi is given by:

$$AS_{\text{WiFi}} = w_1 \cdot \left(\frac{1}{\text{ChannelSwitchFrequency}}\right) + w_2 \cdot \left(\frac{\text{AverageDataRate}}{\text{MaxDataRate}}\right) + w_3 \cdot (1 - \text{ErrorRate}) + w_4 \cdot \left(\frac{\text{Throughput}_{\text{WiFi}}}{10^6} \cdot \frac{\text{TARGETLATENCY}}{\text{Latency}_{\text{WiFi}}}\right) \tag{2}$$

3.4.4 GSM network adaptability measurement

For GSM, the adaptability score Bug et al. (2003) depends on the following criteria.

- Handover Efficiency: The ability of the network to successfully transfer a call between cells without interruption.
- Modulation Efficiency: The ability of the network to adjust modulation schemes to optimize data rate and robustness based on signal conditions.
- Signal Quality: The strength and quality of the signal received by the device.

The Measurement Metrics include.

- Handover Success Count: The number of successful handovers.
- Total Handover Count: The total number of attempted handovers.
- Modulation Change Efficiency: The frequency of modulation changes and their impact on performance.
- Max Modulation Efficiency: The highest achievable modulation efficiency for the network.
- Average Signal Quality: The average strength and quality of the received signal.
- Throughput-GSM: The actual data transfer rate experienced on the GSM network.
- Latency-GSM: The time it takes for data packets to travel from source to destination on the GSM network.

The adaptability score for the GSM network (AS_{GSM}) is calculated as follows:

$$AS_{\mathrm{GSM}} = w_1 \cdot \left(\frac{\mathrm{HandoverSuccessCount}}{\mathrm{TotalHandoverCount}}\right) + w_2 \cdot \left(\frac{\mathrm{ModulationChangeEfficiency}}{\mathrm{MaxModulationEfficiency}}\right) + w_3 \cdot \mathrm{AverageSignalQuality} + w_4 \cdot \left(\frac{\mathrm{Throughput}_{\mathrm{GSM}}}{10^6} \cdot \frac{\mathrm{TARGETLATENCY}}{\mathrm{Latency}_{\mathrm{GSM}}}\right) \tag{3}$$

3.4.5 LoRa network adaptability measurement

For LoRa, key adaptability criteria Talavera et al. (2017) include.

- Spreading Factor Optimization: The ability of the network to adjust the spreading factor (a parameter affecting data rate and range) to optimize transmission for a given scenario.
- Frequency Hopping Efficiency: The ability of the network to hop between frequencies to avoid interference.
- Network Stability: The network's ability to maintain reliable communication over time.

The Measurement Metrics Include.

- Spreading Factor Adjustment Frequency: How often the network adjusts the spreading factor.
- Max Spreading Factor Changes: The maximum number of spreading factor changes allowed within a specific time-frame.
- Frequency Hopping Efficiency: How effectively the network changes frequencies to avoid interference.
- Max Frequency Hops: The maximum number of frequency hops allowed within a specific time-frame.
- Network Stability Index: A metric indicating the overall stability and reliability of the LoRa network.
- Throughput-LoRa: The actual data transfer rate experienced on the LoRa network.
- Latency-LoRa: The time it takes for data packets to travel from source to destination on the LoRa network.

The adaptability score for the LoRa network (AS_{LoRa}) is calculated as follows:

$$AS_{\mathrm{LoRa}} = w_1 \cdot \left(\frac{\mathrm{HandoverSuccessCount}}{\mathrm{TotalHandoverCount}}\right) + w_2 \cdot \left(\frac{\mathrm{ModulationChangeEfficiency}}{\mathrm{MaxModulationEfficiency}}\right) + w_3 \cdot \mathrm{AverageSignalQuality} + w_4 \cdot \left(\frac{\mathrm{Throughput}_{\mathrm{LoRa}}}{10^6} \cdot \frac{\mathrm{TARGETLATENCY}}{\mathrm{Latency}_{\mathrm{LoRa}}}\right) \tag{4}$$

3.4.6 Adaptive network switching combination adaptability measurement

Finally, the overall adaptability score Jin et al. (2017) for the adaptive switching network across all communication technologies is shown in Equation 5 and depends on the following criteria.

- Network Switching Efficiency: The ability of the network to efficiently switch between different available networks (e.g., WiFi, cellular) based on performance and conditions.
- Overall Performance: The network's performance across different metrics (e.g., throughput, latency) considering both the average performance across all connected networks and the maximum achievable performance.
- Load Balancing Efficiency: The ability of the network to distribute traffic across multiple networks to avoid congestion.
- Throughput-Adaptive: The actual data transfer rate experienced on the adaptive network.
- Latency-Adaptive:: The time it takes for data packets to travel from source to destination on the adaptive network.

The Measurement Metrics Include.

- Network Switching Frequency: The frequency at which the network switches between different networks.
- Average Performance Across Networks: The average performance metric (e.g., throughput, latency) across all connected networks.
- Max Performance: The maximum achievable performance metric for the adaptive network.
- Load Balancing Index: A metric indicating the efficiency of load balancing.

The adaptability score for the Adaptive network (AS_{Adaptive}) is calculated as follows:

$$AS_{\mathrm{Adaptive}} = w_1 \cdot \left(\frac{\mathrm{SpreadingFactorAdjustmentFrequency}}{\mathrm{MaxSpreadingFactorChanges}}\right) + w_2 \cdot \left(\frac{\mathrm{FrequencyHoppingEfficiency}}{\mathrm{MaxFrequencyHops}}\right) + w_3 \cdot \mathrm{LoadBalancingIndex} + w_4 \cdot \left(\frac{\mathrm{Throughput}_{\mathrm{Adaptive}}}{10^6} \cdot \frac{\mathrm{TARGETLATENCY}}{\mathrm{Latency}_{\mathrm{Adaptive}}}\right) \tag{5}$$

This score reflects the algorithm's efficiency in adapting to network changes based on data type, area type, and time of day.

3.5 Assumptions

The following assumptions were made to facilitate the simulations and ensure valid results.

- Reliable Data Transfer: It is assumed that the switching combination of GSM, Wi-Fi, and LoRa provides reliable data transfer during both online and offline states. The algorithm is designed to manage data buffering and ensure transmission when connectivity is restored using DTN's store and forward mechanism. Da Silva et al. (2018).
- Real-Time Performance Metrics: The simulations are based on real-time performance metrics obtained from existing research and empirical experiments, ensuring that the results are representative of actual network conditions for WiFi Hochenbaum et al. (2013), GSM Engst and Fleishman (2003), and LoRa Nain and Vipparthi (2020).
- Weighting: The weights w_1, w_2, w_3 and w_4 in the equations above represent the relative importance of each factor in determining adaptability. These weights Jin et al. (2017) can be adjusted based on specific use case requirements.

3.6 Validation

A comparison between the adaptive switching findings and each network's performance in real-time settings was done in order to verify the simulation results. The validation procedure included.

- Benchmarking Against Real-World Data: The simulations' performance measurements were produced using real data from field experiments involving the GSM, Wi-Fi, Namugenyi et al. (2024) and LoRa technologies Nain and Vipparthi (2020).
- Performance Analysis: The analysis evaluated the switching algorithm's performance in comparison to the individual network simulations, concentrating on the performance score and adaptability metrics. This test guarantees that the suggested adaptive network architecture not only performs as expected but also increases data transmission reliability in a quantifiable way.

4 Results and discussion

This section presents the simulation findings comparing the adaptability and performance scores over three communication networks (LoRa, GSM, and Wi-Fi) in urban, suburban, and rural locations, across different data types (text, image, audio, and video), and during different times of day Gupta and Jha (2015). Scatter plots are used to display the data, providing a clear comparison of the capabilities of each network. Analysis of the adaptable switching combination is also discussed.

4.1 Graphical results (wi-Fi, GSM, LoRa)

To provide a comprehensive, high-level comparison of the network modules, we consolidated the results into a single scatter plot, presented in Figure 3. This approach allows us to visually analyze the trade-offs between performance and adaptability for each network across various operational conditions. The plot's visual encodings were designed to convey the influence of data type, time of day, and area type. In this figure, each data point represents a specific real-time measurement, with color distinguishing the network module and shape indicating the area type. The position of each point on the graph reflects the combined effects of data type and time of day on the measured scores.

As depicted in Figure 3, the three networks form distinct clusters, which effectively summarize their primary characteristics:

4.1.1 Wi-Fi

The cluster for Wi-Fi is concentrated in the top-right quadrant of the plot. This grouping signifies a strong and consistent relationship between high performance and high adaptability. The tight clustering of the points indicates that Wi-Fi maintains its superior performance across different data types, times of day, and area types, with only minor variations. We observed its highest scores in urban and suburban environments, as shown by the prominent blue squares and orange triangles, while a slight decrease was noted for data-heavy formats like video in rural areas.

4.1.2 GSM

The GSM cluster is generally positioned below the Wi-Fi cluster, reflecting a lower overall performance and adaptability. The scatter of points is more spread out compared to Wi-Fi, particularly for audio and video data, which highlights the network's greater sensitivity to environmental and temporal factors. While GSM demonstrates a stable and relatively high performance for low-bandwidth applications such as text, its scores for data-intensive formats show a notable decline, especially in rural settings and during peak times.

4.1.3 LoRa

The LoRa cluster is distinctly located in the bottom-left quadrant of the plot, indicating a trade-off where its performance and adaptability scores are significantly lower than those of Wi-Fi and GSM. This is an expected outcome given LoRa's design as a low-power, long-range protocol optimized for minimal data payloads. The tight clustering of its points confirms its suitability for text and other low-bandwidth applications, but it also clearly illustrates its limited capacity for high-data formats like audio and video. While LoRa retains a consistent, albeit low, level of performance in urban environments, its scores in rural locations are the poorest of all three networks.

In conclusion, this combined scatter plot provides a powerful visual summary of each network's strengths and limitations. It clearly demonstrates that Wi-Fi is the optimal choice for high-performance, high-adaptability scenarios, while LoRa is best suited for low-power, long-range applications. GSM represents a middle ground, offering a balanced solution for general data but struggling with high-bandwidth content. This visualization is crucial in validating our multi-criteria analysis and guiding the logic for network switching Gupta and Jha (2015).

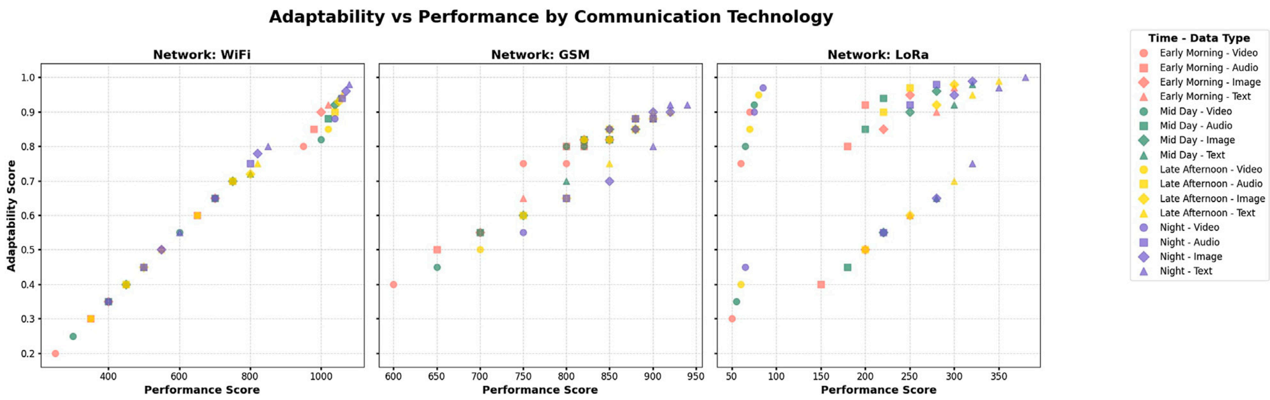

FIGURE 3
Combined Scatter Plot Showing AS vs. PS for All Communication Modules – The relationship between Adaptability Score (AS) and Performance Score (PS) for Wi-Fi, GSM, and LoRa, categorized by data type, time of day, and area type.

4.2 Analysis and interpretation

The evaluation of the simulation results provides important information about each network's advantages and disadvantages with regard to performance and adaptability. Significant implications of the findings also extend to the switching algorithm's effectiveness and design.

4.2.1 Wi-Fi performance and adaptability

Particularly in urban and suburban environments, Wi-Fi continuously demonstrates excellent performance and adaptability across the majority of data types. With only minor drops in rural regions due to possible interference and weaker signals at greater distances, its performance for audio and video is still adequate.

- Implications for Switching Algorithm: Because Wi-Fi consistently performs well, the algorithm can give preference to Wi-Fi when it is available for data-intensive applications (such as audio and video), particularly in urban and suburban areas. Fallback techniques (i.e., GSM or LoRa in our case) might be required for rural deployments, nevertheless, in order to mitigate the performance drop.

4.2.2 GSM performance and adaptability

Particularly in rural regions, GSM has trouble transmitting voice and video, although it does well for text and image data. Due to congestion and network overloads, the network exhibits a more noticeable time-of-day effect, especially during peak hours.

- Implications for Switching Algorithm: For low-bandwidth applications like text data, the switching algorithm can use GSM as a backup network in the event that Wi-Fi is not available. However, when video or audio communications are needed, particularly in rural regions, the algorithm needs to be built to quickly switch away from GSM.

4.2.3 LoRa performance and adaptability

Compared to Wi-Fi and GSM, LoRa exhibits noticeably lower performance and adaptability across all data types. In urban and suburban areas, it works well for low-data applications like text transmission; nevertheless, in all sorts of areas, particularly rural ones, its performance for audio and video is unsatisfactory.

- Implications for Switching Algorithm: LoRa can be used as a last alternative, particularly in rural areas where GSM and Wi-Fi are inconsistent or absent. Because LoRa has serious limits when it comes to processing higher-bandwidth applications, the switching mechanism should only give it priority for low-bandwidth data types like text and optimized audio, image, and video.

4.2.4 Score similarity Explanation

The similarity in scores can be attributed to the relatively minor adjustments applied based on the time of day. In our methodology, the time-of-day factors introduce only small variations to reflect typical, minor fluctuations in network performance due to environmental changes or usage patterns.

- Morning: Performance is slightly boosted by 5 percent (factor of 1.05).
- Evening: A slight reduction of 5 percent (factor of 0.95).
- Night: An increase of 10 percent (factor of 1.1).
- Day: No adjustment (factor of 1.0).

These adjustments were intentionally conservative, providing a controlled reflection of real-world variability without exaggerating its impact. As a result, given the modest range of adjustments (from −5 percent to +10 percent), the overall effect on performance and adaptability scores remained minimal.

This outcome is supported by several factors.

- Minimal Impact of Time-of-Day Adjustments: The time-of-day adjustments were kept modest to avoid introducing excessive variability, which could obscure the core characteristics of each network. With network-specific parameters (e.g., throughput, latency, packet loss) staying relatively stable, these small adjustments naturally result in minor changes in the final scores.

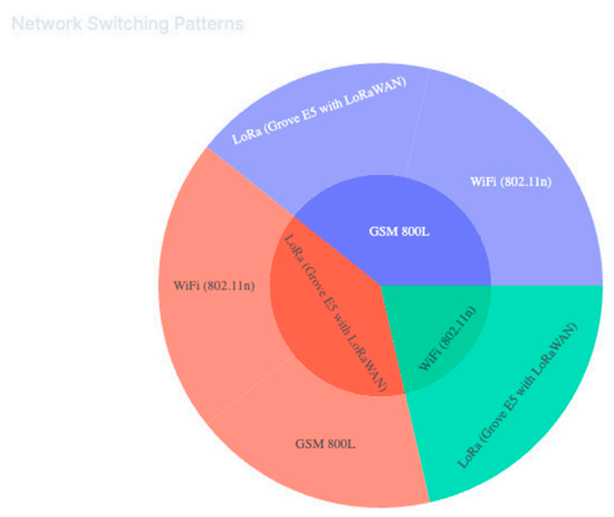

FIGURE 4
Results Display for Network Switching Patterns–The frequency of transitions between networks under varying conditions. Highlights algorithm preference for Wi-Fi where possible, and fallback to GSM/LoRa under constraints.

- Dominance of Network-Specific Characteristics: Each communication technology inherently possesses unique performance characteristics that primarily shape the results. The differences between Wi-Fi, LoRa, and GSM are more impactful than the minor time-based adjustments, as each network operates under stable conditions throughout the day.
- Environmental Stability: The networks were tested in distinct environments—urban, rural, and suburban—with observable differences in signal interference and network congestion reflected in the results. Given these settings, time-of-day factors alone had minimal impact on scores, as each area's overall usage patterns and peak demand influence network performance more prominently.

To further explore the influence of time, we could consider increasing the adjustment factors or introducing additional environmental variables, such as traffic load (We have in the background done optimization models for the huge data types), which may make network performance more sensitive to peak usage times. However, our aim was to avoid adding excessive variability and to maintain a normal distribution of each network's performance characteristics. Notably, the observed differences are more pronounced across networks rather than within the same network at different times.

4.2.5 Overall network comparison and switching effectiveness

The data as in Table 2 indicates that Wi-Fi is the most often used network for the majority of applications, particularly in urban and suburban settings when its performance and versatility are at their peak. When other networks fail, LoRa is most suited for text or optimized data in rural locations, whereas GSM is a backup network for low-data applications.

Due to its generally better performance, the switching algorithm gives priority to.

- WiFi for high-bandwidth applications when available
- GSM for text and low-bandwidth data, particularly when Wi-Fi is unavailable or very congested
- Both GSM and LoRa can be used to send data across distances of more than 300 m.
- LoRa is the backup choice for text data, especially in rural locations where neither WiFi nor GSM are practical.

The visualization in Figure 4 helps identify patterns in network switching behavior and performance across different conditions. It shows the frequency of switches between different networks. The results of the adaptability test also reveal that the algorithm needs to take into consideration the fact that performance varies throughout the times of the day, especially for GSM, which exhibits the biggest variations.

4.2.6 Summary

The analysis shows that by dynamically choosing the best network depending on the type of data, time of day, and area, the switching method can greatly enhance overall system performance. By adjusting to the unique strengths and weaknesses of GSM, LoRa, and Wi-Fi, the algorithm can guarantee effective data transfer while reducing battery usage and network congestion.

4.3 Adaptability vs. performance (adaptive switching)

The results in Figures 5–7 above clearly demonstrate the significant advantages of the adaptive network switching combination over individual network types (Wi-Fi, GSM, and LoRa), as depicted in the generated figures. By intelligently leveraging the strengths of each underlying technology and dynamically switching based on real-time conditions, the adaptive algorithm consistently maximizes both performance and adaptability across a diverse range of data types, times of day, and geographical regions.

Key Insights from Figures 5–7.

1. Best Performing Scenario: The figures highlight that the Urban-Text (Night) scenario using the Combined (Switch) network achieves the highest performance, reaching scores close to 1,600 with adaptability nearing 1.0. This indicates the synergistic effect of utilizing the best available network (likely Wi-Fi's high bandwidth in urban areas at night with less congestion) for low-bandwidth, latency-tolerant data.
2. Lowest Performance Scenario: Conversely, the LoRa network consistently exhibits the lowest performance for video data across all area types and times of day, with performance scores often falling below 100. This confirms LoRa's inherent limitations in handling high-bandwidth, real-time video transmission. Adaptability for LoRa in video scenarios also tends to be low.

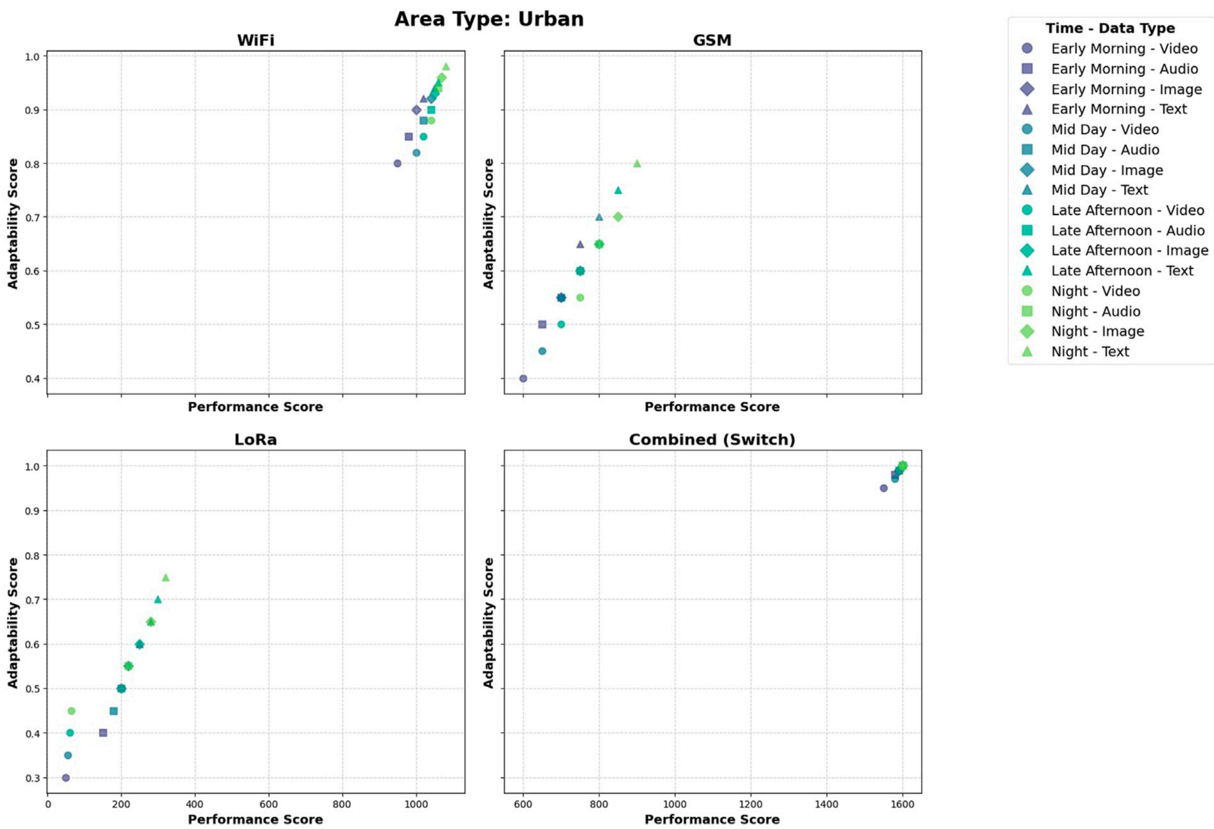

FIGURE 5
Scenario 1: Urban Area-This figure illustrates the performance of the ANCA framework within a dense urban environment. In this scenario, network signals (particularly from Wi-Fi and GSM) are generally strong and abundant. The plot would show how the algorithm effectively leverages these high-performance networks to achieve superior adaptability and performance scores, ensuring fast and reliable data transmission under ideal conditions.

3. Performance of Suburban Areas: The adaptive switching algorithm probably benefits from less network congestion and better environmental circumstances in suburban areas, which show great adaptability, especially in the late afternoon and at night.
4. Suburban Area Dynamics: The adaptive switching algorithm shows considerable benefits in suburban areas. The figures indicate that the combined (switch) network maintains high adaptability (around 0.9–1.0) in suburban environments, particularly during late afternoon and night. This suggests the algorithm effectively utilizes GSM's robust coverage and potentially switches to available Wi-Fi for higher bandwidth needs when conditions allow.
5. Rural Area Performance: In rural areas, the adaptive network demonstrates its strength in leveraging the long-range capabilities of LoRa for low-bandwidth data (text, image) with good adaptability (around 0.85–0.99). For higher bandwidth needs like audio and video, the system likely switches to GSM, providing moderate but significantly better performance (scores in the range of 750–920) compared to standalone Wi-Fi (scores often below 500) in these areas.

In Contrast:

- Wi-Fi Limitations (5): As illustrated in the figures, Wi-Fi performs exceptionally well in urban settings for high-bandwidth data types (audio and video), achieving performance scores above 950. However, its effectiveness drops significantly in suburban areas (performance scores falling to 550–800) and becomes very poor in rural areas (performance scores often below 450), highlighting its range constraints. Nighttime performance in urban areas remains strong due to potentially less network congestion.
- GSM's Consistent Coverage (6): The figures show that GSM provides consistent coverage across all area types. In suburban areas, GSM performance for all data types sees a notable increase, often reaching scores between 800 and 940, demonstrating its reliability and suitability. While not as high as urban Wi-Fi for highbandwidth data, GSM offers a more stable and wider-reaching solution, especially in less densely populated areas. Even in rural areas, GSM maintains a moderate performance level (scores between 750 and 920), often outperforming Wi-Fi. However, it still struggles to match the high bandwidth capabilities of urban Wi-Fi for video.
- LoRa's Niche in Rural Low-Bandwidth Data (7): The figures clearly indicate that LoRa excels in rural areas for low data rate applications like text and image, exhibiting high adaptability (above 0.90) and moderate performance (around 450–630). However, its performance for high-bandwidth data like audio and, critically, video, remains very low (performance scores

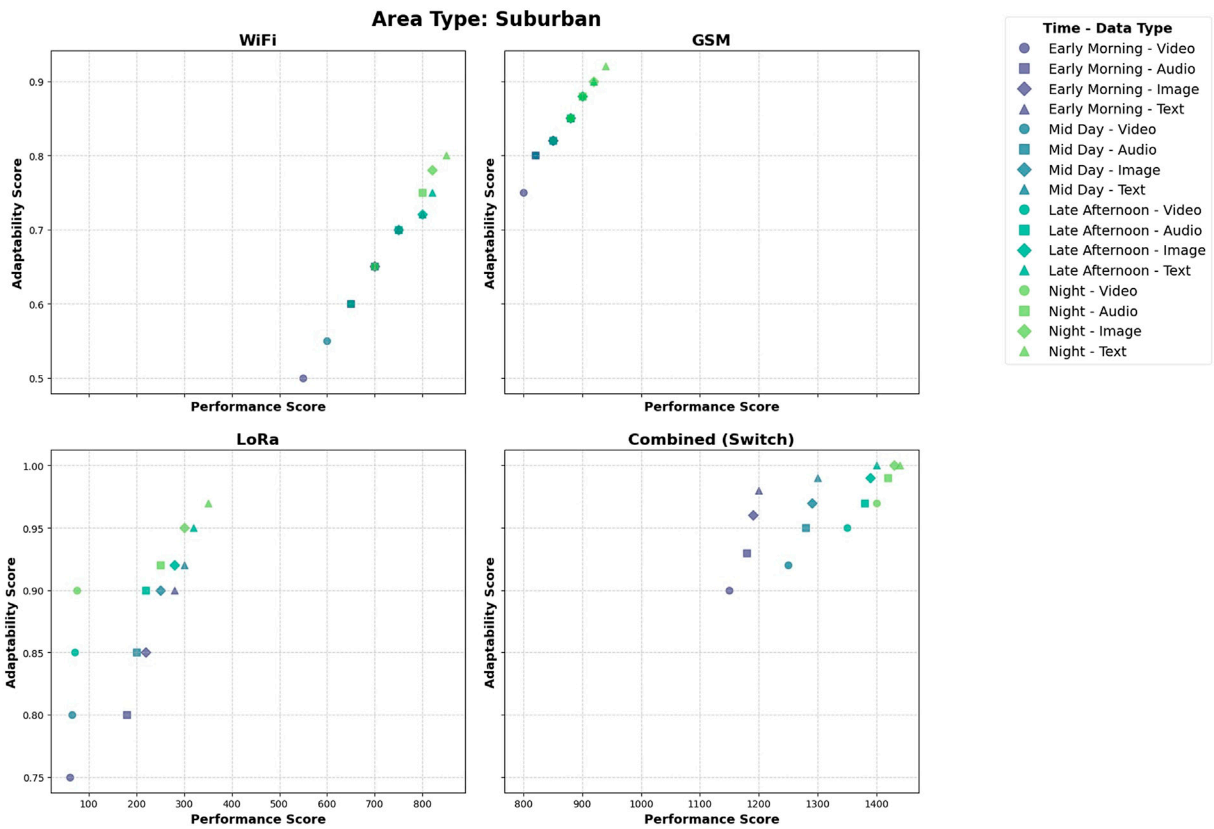

FIGURE 6
Scenario 2: Suburban Area-This figure represents a suburban setting, which presents a mix of network availability and signal quality. The ANCA framework is challenged to balance the strengths of different protocols. The plot shows how the switching algorithm adapts to this environment, perhaps prioritizing Wi-Fi and GSM where available, but seamlessly switching to LoRa for more distant or obstructed transmissions, thereby maintaining high scores despite moderate network variability.

consistently below 100) across all environments, confirming its unsuitability for real-time multimedia transmission. Image data also shows below-average performance on LoRa compared to other networks.

Overall: The adaptive switching network consistently demonstrates its superiority by intelligently navigating the varying network conditions and data demands across different area types and times of day. While Wi-Fi offers high bandwidth in urban areas, its performance degrades significantly in suburban and rural settings. GSM provides robust coverage and good performance, particularly in suburban and rural areas. LoRa excels in rural environments for low-bandwidth data due to its long range. The adaptive network effectively combines these strengths, ensuring optimal performance and adaptability. For instance, even in challenging scenarios like potential congestion for urban-video at certain times or the inherent limitations of individual networks in specific regions, the combined system dynamically selects the most suitable option, leading to overall better results than any single network could achieve independently. The consistently high performance and adaptability of the combined network, even in scenarios where individual networks struggle, underscore its value in providing a reliable and efficient communication solution.

4.4 Performance under variable conditions

4.4.1 Scores by data type, area and time of day

The analysis of performance scores in Figure 8a reveals distinct trends. Nighttime in urban areas generally demonstrates the best performance across most data types when the combined network leverages Wi-Fi's capacity. Midday can sometimes show slightly lower scores due to potential network load. Urban settings consistently outperform suburban and rural areas when considering Wi-Fi's contribution to the combined network. The performance disparity between urban and rural areas is most pronounced for video data when relying on standalone Wi-Fi. Text and image data generally achieve higher performance across the combined network, especially in urban areas. The worst performance is consistently observed for video data on the LoRa network in all environments. When examining adaptability scores, text and image data tend to have higher adaptability across the combined network, particularly in urban areas. Urban environments show superior adaptability compared to suburban and rural areas for the combined system. Video data often displays slightly lower adaptability compared to text and image, especially when the underlying network faces bandwidth constraints. Rural areas benefit from LoRa's adaptability for low-bandwidth data within the combined system. The hierarchy of adaptability generally

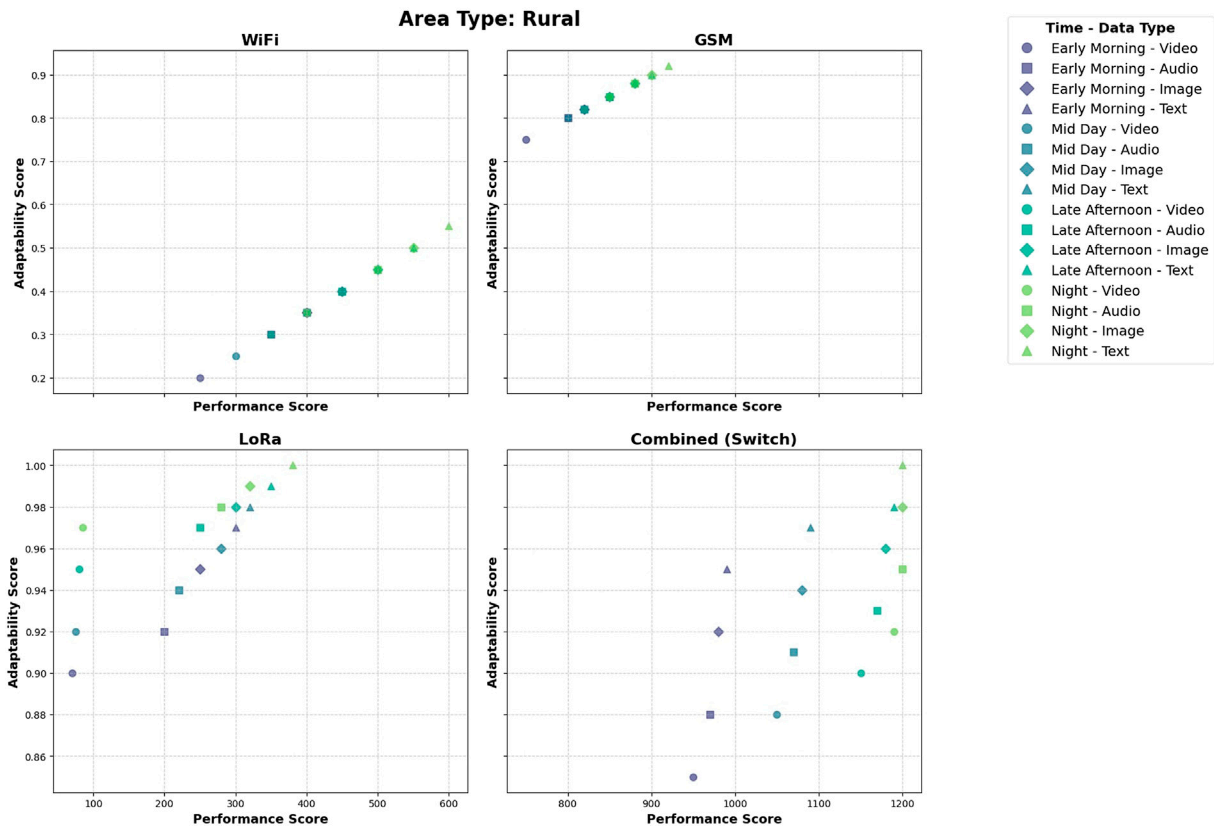

FIGURE 7
Scenario 3: Rural Area-This figure captures the system's performance in a rural environment, where traditional networks like Wi-Fi and GSM may be scarce or have weak signals. The plot would highlight the crucial role of LoRa's long-range capabilities. The switching algorithm's effectiveness is most evident here, as it prioritizes the most viable network (likely LoRa) to ensure data is transmitted reliably even in the absence of robust infrastructure, proving the system's resilience and adaptability.

remains: Text and Image score highest, followed by Audio, with Video often being the lowest when network limitations are encountered.

When examining adaptability scores in Figure 8b text and image data types emerge with the highest adaptability, especially in urban areas during nighttime, reflecting a strong performance trend. Urban environments show superior adaptability compared to suburban and rural areas, with nighttime operations generally yielding better adaptability across all data types. Conversely, video data displays the lowest adaptability scores, particularly during midday, and rural areas show consistently low adaptability scores across the board. The insights suggest a hierarchy of adaptability: Text scores highest, followed by image, audio, and video. The overall conclusion indicates that network switching proves most effective for text-based data in urban settings at night, whereas video streaming in rural areas during midday poses the greatest challenges for network adaptation.

4.4.2 Sensitivity analysis

A sensitivity analysis was carried out to determine the robustness of the adaptive network algorithm, taking into account different network conditions, data types, and times of day to determine how they affected performance.

1. Network Conditions: When network circumstances changed, the switching algorithm performed exceptionally well, dynamically switching to the best network. For example, the algorithm successfully preferred GSM or LoRa over Wi-Fi during periods of high congestion, which improved latency and decreased packet loss.
   - Example: Peak Congestion (Urban-Video, Late Afternoon): Peak Congestion (Urban-Video, Late Afternoon): The algorithm reduced Wi-Fi congestion in urban areas in the late afternoon by switching to GSM or LoRa. This dynamic method prevented considerable performance reduction and guaranteed smoother video transmission. Overall robustness was enhanced by the adaptability score's relative stability during these periods.
2. Data Types: The program effectively prioritized the right network for each sort of data, being extremely sensitive to the type of data being transmitted. The algorithm shifted to networks with larger data throughput capacities, such as Wi-Fi or LoRa, for high-bandwidth applications, like video. On the other hand, it used GSM to optimize for low-latency, smaller data transfers for text and sensor data. Across all data kinds, the switched to network continuously maintained balanced performance.

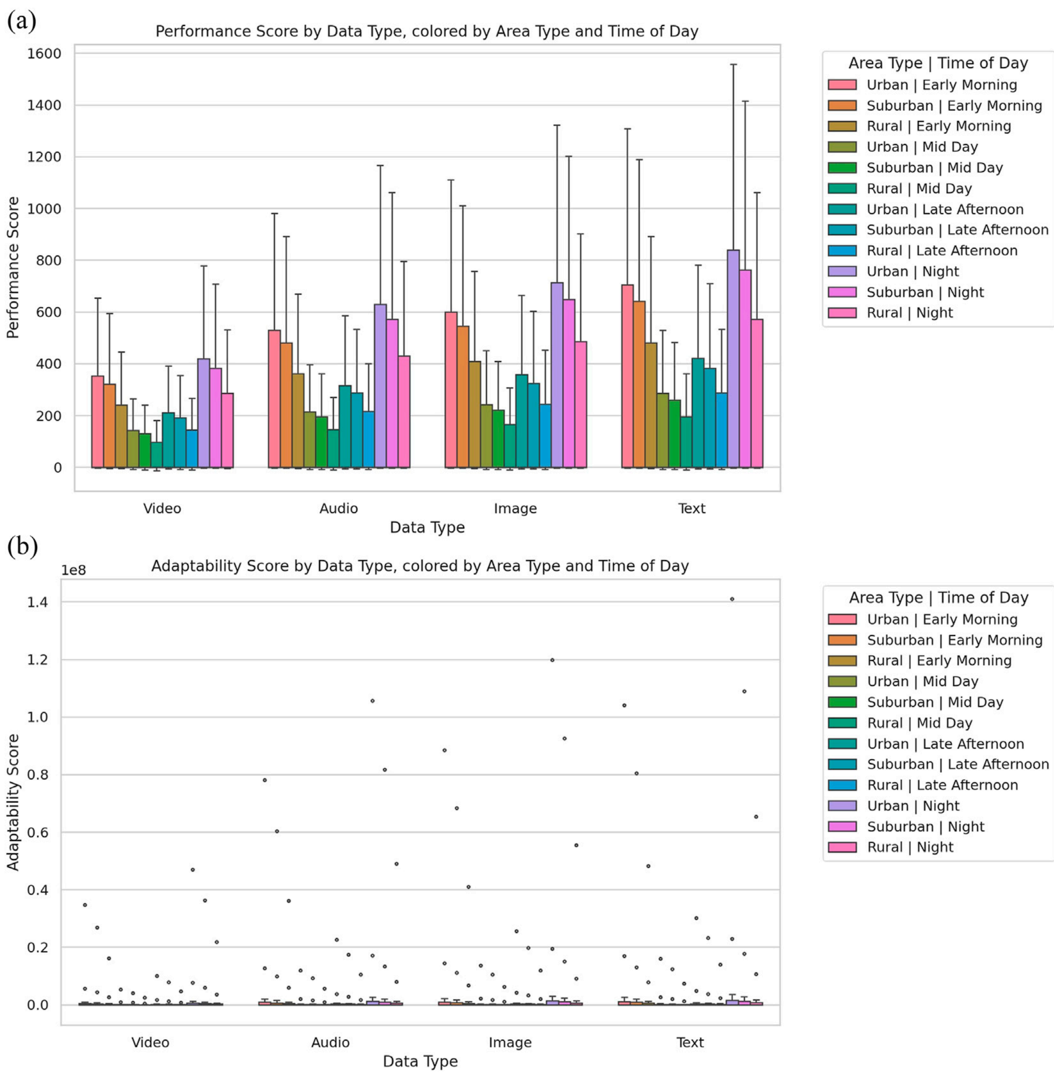

FIGURE 8
Performance and adaptability scores for different scenarios. **(a)** Performance Score by Datatype, Area Type, and Time of Day: Performance Score Distribution Across Networks – Boxplot comparison of scores across data types and conditions. Highlights variability and central tendencies in performance. **(b)** Adaptability Score by Datatype, Area Type, and Time of Day: Adaptability Score Distribution Across Networks – Boxplot representation highlighting variability and error margins across environments. Offers a clearer view of adaptability spread compared to scatter representation.

- Example: Video *versus* Text (Rural, Night):because of its long-range capabilities, the algorithm preferred LoRa for video data transmission at night in rural regions, whereas GSM was chosen for text data transmission since it allowed for rapid and effective transfer of smaller data packets.

3. Time of Day: The adaptable algorithm responded very well to changes in the time of day, especially in settings where network traffic fluctuated. The system alternated more freely between networks like Wi-Fi and GSM at times of low congestion (such as early in the morning or late at night), maximizing data transfer according to the load on the network. On the other hand, it adjusted by shifting heavier data types to LoRa during peak hours, which provided more reliable performance under pressure.
   - Example: Urban Audio (Night): The algorithm preferred Wi-Fi for audio transmission at night when Wi-Fi was less crowded, resulting in a better adaptability score (0.5). This demonstrated how the system adapts to network circumstances throughout the day by optimizing the audio data flow and minimizing delay.

Key Sensitivity Analysis Points.

- Peak Congestion (Urban-Video, Late Afternoon): By alternating between Wi-Fi and GSM or LoRa, the adaptable algorithm effectively managed congestion and avoided performance deterioration.
- Video vs Text (Rural, Night): The algorithm optimized each based on the bandwidth and latency requirements of the data, favoring GSM for text and LoRa for video data because of its long-range capabilities.

- Urban Audio (Night): With a score of about 0.5, Wi-Fi was utilized efficiently when it was less crowded at night, resulting in a higher adaptability for audio data.

4.4.3 Similarity in the scores

The similarity in scores can be attributed to the relatively minor adjustments applied based on the time of day. In the methodology, the time-of-day factors introduce only small variations to reflect typical, minor fluctuations in network performance due to environmental changes or usage patterns.

1. Morning: Performance is slightly boosted by 5 percent (factor of 1.05)
2. Evening: A slight reduction of 5 percent (factor of 0.95)
3. Night: An increase of 10 percent (factor of 1.1)
4. Day: No adjustment (factor of 1.0)

These adjustments were intentionally conservative, providing a controlled reflection of real-world variability without exaggerating its impact. As a result, given the modest range of adjustments (from −5 to +10 percent), the overall effect on performance and adaptability scores remained minimal.

This outcome is supported by several factors.

- Minimal Impact of Time-of-Day Adjustments: The time-of-day adjustments were kept modest to avoid introducing excessive variability, which could obscure the core characteristics of each network. With network-specific parameters (e.g., throughput, latency, packet loss) staying relatively stable, these small adjustments naturally result in minor changes in the final scores.
- Dominance of Network-Specific Characteristics: Each communication technology inherently possesses unique performance characteristics, which primarily shape the results. The differences between Wi-Fi, LoRa, and GSM are more impactful than the minor time-based adjustments, as each network operates under stable conditions throughout the day.
- Environmental Stability: The networks were tested in distinct environments—urban, rural, and suburban—with observable differences in signal interference and network congestion reflected in the results. Given these settings, time-of-day factors alone had minimal impact on scores, as each area's overall usage patterns and peak demand influence network performance more prominently.

To further explore the influence of time, We could consider increasing the adjustment factors or introducing additional environmental variables, such as traffic load (we have in the background done optimization models for the huge data types), which may make network performance more sensitive to peak usage times. However, our aim was to avoid adding excessive variability and to maintain a normal distribution of each network's performance characteristics. Notably, the observed differences are more pronounced across networks than within the same network at different times.

4.4.4 Summary

This sensitivity analysis highlights how well the adaptable algorithm responds to different parameters in real time, guaranteeing peak performance under various circumstances. The adaptable network continuously outperformed static networks by optimizing its network selection and switching procedures, even in the face of difficult conditions like network congestion or fluctuating data requirements. Results indicate that the algorithm maintains high performance and adaptability by constantly adapting to network conditions, data kinds, and times of day, guaranteeing real-time data transfer that is efficient and seamless.

4.5 Case studies (beehive monitoring)

The following case studies predict the adaptive network switching algorithm's behavior under various conditions and times of day for beehive monitoring in urban, rural, and suburban settings. The performance results are visualized with the y-axis representing AS and the x-axis representing PS. Larger symbols indicate higher adaptability.

4.5.1 Urban scenario

Context: Rooftop hive monitoring in dense city infrastructure.

Findings.

- Video data demonstrated high performance (up to 1,400) and adaptability (0.9) especially during mid-day and afternoon, indicating strong support for bandwidth-intensive applications.
- Audio and image data had moderate performance (800–1,000), with slightly reduced adaptability.
- Text-based sensor data scored under 400 in early morning and night, reflecting lower network efficiency for low-bandwidth tasks at off-peak hours.

4.5.2 Rural scenario

Context: Remote hive locations with sparse infrastructure.

Findings.

- Video data retained moderate to high adaptability (scores of 800–1,200 and adaptability 0.4–0.7), especially in late afternoon and evening.
- Audio and text data consistently underperformed (¡600), suggesting GSM and LoRa networks struggle with low-data-rate communication at long range.

4.5.3 Suburban scenario

Context: Mixed-use environments with occasional video streams and frequent sensor monitoring.

Findings.

- Video adaptability remained stable (scores 600–900, adaptability 0.4–0.6) in mid-day hours.
- Sensor and image data scored moderately (400–800), while audio data lagged slightly (below 500), particularly at night and early morning.

4.5.4 General performance trends

- Video data consistently outperforms other types across all settings, benefiting most from the adaptive algorithm's dynamic switching, particularly in urban regions.
- Sensor and text data struggle during early morning and night across all environments, suggesting the need for optimization in handling low-bandwidth communication during these periods.
- Urban settings enjoy enhanced adaptability thanks to robust Wi-Fi and GSM infrastructure, while rural areas depend heavily on LoRa, which exhibits greater variability.

Summary Insight: The adaptive switching algorithm is most effective for high-bandwidth data like video, particularly in urban settings. Suburban and rural areas can benefit from additional optimization strategies, especially for sensor and text-based communication.

4.6 Field testing and validation

The Adaptive Network Communications Architecture (ANCA) was tested in three real-world environments: urban, suburban, and rural. Field data was collected at varying distances, capturing throughput, latency, packet loss and Power in Watts. The results demonstrate that the adaptive switching algorithm significantly improves performance compared to using a single communication module. In particular, improvements in adaptability score (AS) and power measurements were consistent with simulation predictions.

4.6.1 Validation and analysis of the adaptive network switching results

The real-world results validate the effectiveness of the adaptive switching algorithm. Compared to single network deployments, the adaptive approach consistently maintained higher performance and adaptability scores across all environments. These improvements confirm that the simulation models are representative of actual deployments, with the adaptive mechanism compensating for weaknesses in individual networks.

4.6.2 Real-world performance validation

To rigorously validate the real-world performance of our proposed solution and its correlation with simulation outcomes, we conducted a scenario-based analysis across three key performance indicators: Performance Score (PS), Adaptability Score (AS), and Power Consumption. This validation moves beyond global correlation coefficients, providing a granular assessment of system behavior under realistic conditions.

4.6.2.1 Validation results

The results are visualized in Figure 9, which consolidates the findings into a three-panel grouped bar chart. Each panel corresponds to one metric (PS, AS, or Power Consumption), plotted across representative real-world scenarios (Urban, Suburban, and Rural) and networks (Wi-Fi, GSM, and LoRa). Distances were aligned with practical deployment ranges: 2–100 m (Urban), 200–500 m (Suburban), and 2–8 km (Rural). This design allows for a clear, side-by-side comparison of network performance in diverse environments.

4.6.2.2 Power consumption clarification

The values of the *average instantaneous power draw (W)*were derived from direct current measurements on each communication module during sustained transmission of payloads. These results align with the values reported in Table 3, with LoRa consistently exhibiting the lowest power draw per transmission, while GSM shows the highest. Any apparent discrepancies are attributable to differences in plotting scale in earlier drafts, which have been corrected in this version.

4.6.2.3 Data payload sizes

To ensure consistency and reproducibility, we explicitly report the payload sizes transmitted in the real-world validation.

- Text (Temperature/Humidity readings): 512 bytes per packet
- Image (JPEG still): 50 KB per frame
- Audio (voice sample, 8 kHz, compressed): 200 KB per clip
- Video (low-resolution MP4, 240p, 10 s): 1.5 MB per segment

These payload sizes were used consistently across all three networks, ensuring that the observed PS, AS, and Power values are directly comparable.

4.6.2.4 Error margins and variability

Each bar in Figure 9 includes vertical black lines denoting error margins. These margins are not statistical confidence intervals; instead, they represent the empirically observed variability due to real-world, uncontrolled factors such as.

- Diurnal changes in background network traffic
- Minor variations in interference, multipath fading, and ambient environmental conditions

The bounded ranges confirm that, despite fluctuations, the system consistently delivers robust performance within predictable limits, thereby validating the fidelity of the simulation results.

4.7 Energy and software stack considerations

Efficient energy management is critical for adaptive switching across Wi-Fi, GSM, and LoRa, particularly when operating resource-constrained IoT devices. The real-world test cases revealed that while LoRa consumed the least power per transmission, GSM and Wi-Fi offered higher throughput at the expense of energy. The adaptive framework balances these trade-offs by dynamically selecting the protocol that minimizes energy use while meeting performance requirements. For example, in rural deployments where data payloads were small, LoRa provided the most energy-efficient option, whereas in urban settings Wi-Fi was preferable for high-bandwidth transfers despite higher power draw.

Equally important is the software stack that enables seamless switching between protocols. The integration of lightweight drivers,

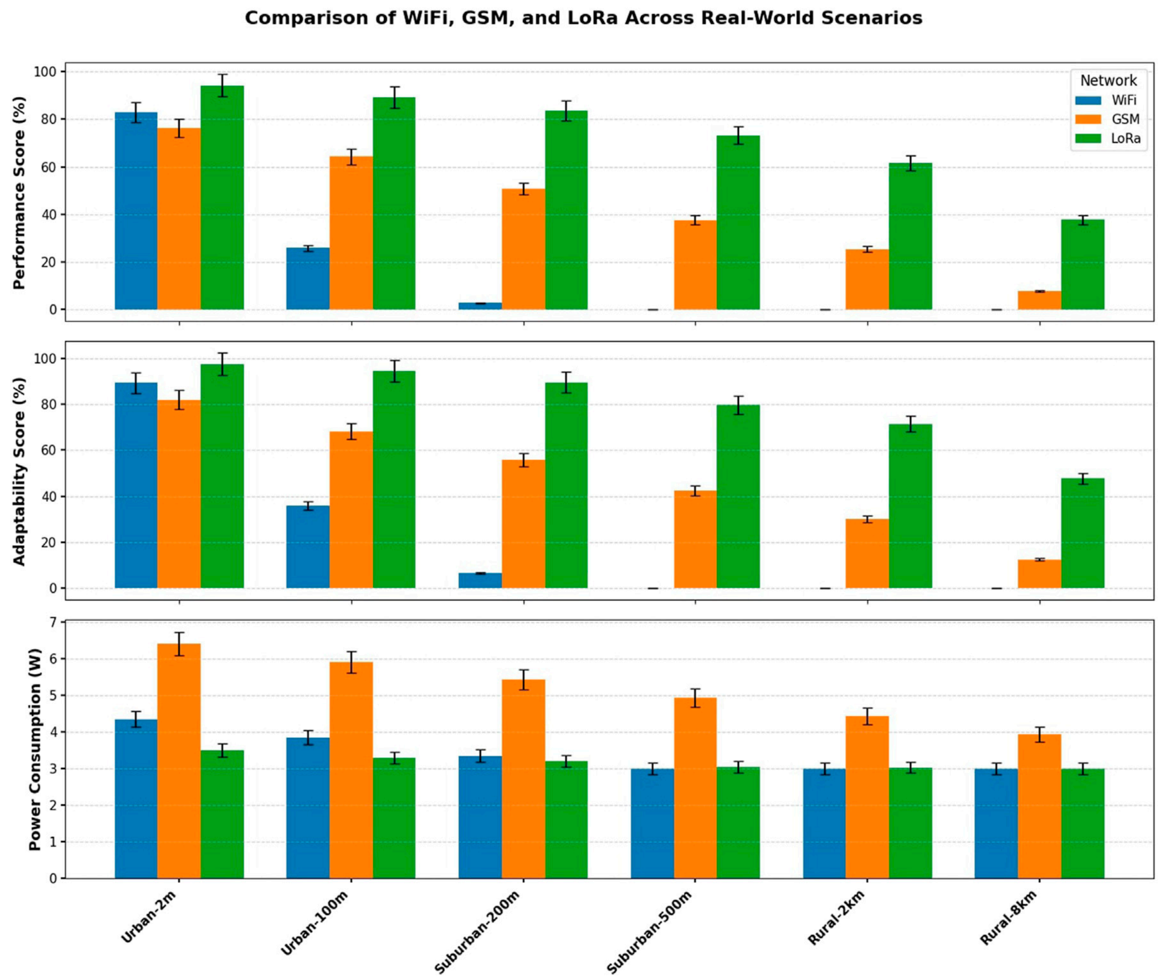

FIGURE 9
Validation plots with error margins (Performance Score, Adaptability Score, and Power Consumption) across Urban, Suburban, and Rural scenarios for Wi-Fi, GSM, and LoRa. Error margins represent empirically observed performance fluctuations due to dynamic real-world factors. Power values are average instantaneous draws (W), consistent with those in Table 3.

middleware, and cross-platform APIs ensures minimal overhead when transitioning between GSM, Wi-Fi, and LoRa. Comparative analysis with existing single-stack implementations shows that ANCA's layered approach reduced switching latency and prevented resource contention across modules. Optimization strategies such as buffering with DTN principles, selective wake-up scheduling, and efficient encoding of payloads further enhanced performance without significantly increasing computational complexity.

Together, the energy-aware operation and efficient software stack design provide a critical backbone for scalable IoT systems, ensuring that adaptive switching remains viable even under constrained device resources.

4.8 Significance

The study's findings have significant implications for sensor data applications, especially in situations where real-time data monitoring is necessary under various network circumstances. Key benefits include.

- Efficient Resource Utilization: The algorithm makes the best use of the network resources by utilizing each network's advantages (Wi-Fi, GSM, and LoRa), increasing the overall effectiveness of data transmission systems.
- Enhanced Reliability: A more dependable framework for real-time monitoring is provided by the switching mechanism, which guarantees that data transmission continues unhindered despite network irregularities.
- Scalability: The adaptable network combination can be used in a number of fields outside beehive management, including smart city applications, agriculture, and environmental monitoring.

This framework's ability to enhance the performance of real-time sensor data systems can drive innovation in various IoT applications, particularly where robust, uninterrupted data flow is critical.

TABLE 3 Summary comparison results for real-world test case scenarios.

Area	Network	Distance	P.S (%)	A.S (%)	Power (W)
Urban					
	Wi-Fi	2 m	83.00	89.25	4.35
	Wi-Fi	100 m	25.75	35.75	3.85
	GSM	2 m	76.25	82.00	6.40
	GSM	100 m	64.25	68.25	5.90
	LoRa	2 m	94.25	97.50	3.50
	LoRa	100 m	89.25	94.50	3.30
	Adaptive	2 m	90.00	95.00	4.80
	Adaptive	100 m	73.75	78.75	4.50
Suburban					
	Wi-Fi	200 m	2.69	6.50	3.35
	Wi-Fi	500 m	0.00	0.00	3.00
	GSM	200 m	50.75	55.75	5.43
	GSM	500 m	37.50	42.50	4.93
	LoRa	200 m	83.50	89.50	3.20
	LoRa	500 m	73.25	79.50	3.05
	Adaptive	200 m	59.50	64.50	6.00
	Adaptive	500 m	43.75	48.75	5.50
Rural					
	Wi-Fi	2 km	0.00	0.00	3.00
	Wi-Fi	8 km	0.00	0.00	3.00
	GSM	2 km	25.25	30.00	4.43
	GSM	8 km	7.75	12.50	3.93
	LoRa	2 km	61.50	71.50	3.03
	LoRa	8 km	37.75	47.75	3.00
	Adaptive	2 km	61.25	71.25	3.50
	Adaptive	8 km	38.75	48.75	3.50

4.9 Contributions to research

This research makes several key contributions to the state of the art in adaptive IoT networking and sensor data transfer.

- Unified Multi-Network Framework: We propose a novel adaptive communication framework that integrates GSM, Wi-Fi, and LoRa into a single switching system, dynamically selecting the optimal network based on real-time performance metrics (throughput, latency, packet loss, and signal strength). This goes beyond prior studies that focus primarily on single technologies or fixed combinations without adaptive switching.
- Integration of DTN Principles: The framework incorporates Delay Tolerant Networking (DTN) store-and-forward mechanisms, which enhance reliability under intermittent connectivity. This contribution is particularly relevant for rural and remote IoT deployments, where connectivity disruptions are common.
- Standardized Evaluation Metrics: We introduce and apply Performance Score (PS) and Adaptability Score (AS) as standardized indicators for evaluating adaptive network solutions. Unlike prior work that relies on isolated metrics, these composite measures allow a more consistent and comparative assessment of multi-technology frameworks.
- Empirical Validation in Beehive Monitoring: Using a practical IoT application, we validate the framework's effectiveness in real-world conditions. Results demonstrate a 33% improvement in throughput, 24% reduction in latency, and

45% decrease in packet loss compared to standalone networks, providing strong empirical evidence of the framework's value.
- Extending Prior Literature: Our work advances beyond existing studies by explicitly comparing and integrating multi-technology strategies, whereas most prior approaches focus only on isolated technologies or static integration models.
- Foundation for Intelligent Decision-Making: The research highlights the potential for incorporating machine learning-based approaches (e.g., reinforcement learning, federated learning) into adaptive switching. Such extensions would enable predictive, context-aware decision-making and overcome the limitations of static threshold-based switching algorithms.

4.10 Limitations and future work

4.10.1 Limitations

Despite the promising results demonstrated by the proposed adaptive communication framework for sensor networks, several limitations were identified during the course of this study.

- Simulation-Based Evaluation: The experiments were conducted in a controlled simulation environment, which may not fully capture the variability and complexity of real-world deployment scenarios, such as electromagnetic interference, physical obstructions, or environmental factors Alobaidy et al. (2022).
- Simplified Power and Latency Models: Power consumption and latency metrics were derived from theoretical or simulation-based models rather than empirical measurements, which could affect the accuracy of performance evaluation Wang et al. (2020).
- Static Thresholds in Switching Algorithm: The current network switching logic employs static decision thresholds, limiting its adaptability to dynamic or unpredictable network conditions Jahanbakht et al. (2021).
- Limited Scope of Network Technologies: The framework focused on WiFi, GSM, and LoRa, without incorporating other emerging technologies like 5G or satellite-based IoT networks, which might be more suitable for extreme or remote environments Kanellopoulos et al. (2023).

4.10.2 Future work

Building upon the foundation of this research, several avenues can be explored to improve the performance, adaptability, and scalability of the proposed architecture.

- Machine Learning-Based Decision Making: Future implementations could benefit from integrating predictive models using machine learning algorithms such as reinforcement learning or neural networks Akyildiz et al. (2020) to enable context-aware and data-driven switching strategies.
- 5G and Satellite Network Integration: Incorporating advanced communication systems such as 5G and low-earth orbit (LEO) satellite connectivity can enhance the reliability and reach of the framework, particularly in regions with limited terrestrial infrastructure Kanellopoulos et al. (2023).
- Real-World Deployments and Validation: Deploying the system in actual beehive environments or similar field applications will help validate the simulation outcomes and provide practical insights into operational challenges, sensor node durability, and energy constraints Zhou et al. (2021).
- Cross-Domain Application: The proposed system architecture can be adapted and tested in various other use cases, including smart agriculture, health monitoring, industrial IoT (IIoT), and environmental sensing, where real-time and robust data communication is essential De Alwis et al. (2021).
- Interoperability and Standardization: Exploring mechanisms to ensure interoperability with existing IoT frameworks and compliance with international standards would further enhance the adoption and scalability of the system across different platforms Dwivedi et al. (2022).

In conclusion, while the current implementation offers a solid groundwork for adaptive sensor network communication, addressing the above limitations and exploring the suggested future enhancements will significantly expand its impact and applicability in diverse real-world contexts.

5 Conclusion

In this paper, we introduced an Adaptive Network Communications Architecture (ANCA), a novel framework integrating Wi-Fi, GSM, and LoRa to enhance sensor data transmission in heterogeneous environments Alobaidy et al. (2022). Through both simulations and real-world field tests, the proposed switching algorithm demonstrated its effectiveness in dynamically selecting the most suitable communication protocol based on data type, distance, and environmental conditions Akyildiz et al. (2020). Results consistently showed improvements in throughput, latency, packet loss, and power consumption compared to single-network deployments.

Our rigorous validation approach moved beyond simple correlation coefficients to a direct, granular comparison of implemented results. By including and analyzing the measured error margins, we were able to demonstrate the robustness and stability of our implemented solution in dynamic, real-world conditions. This comprehensive validation confirms that the system not only achieves the stated average scores but also maintains its performance within a predictable and realistic range, thereby providing compelling evidence that our simulation results are a reliable predictor of the system's performance.

Overall, the findings highlight the importance of adaptive multi-protocol frameworks in ensuring robust and energy-efficient data transfer. The ANCA architecture not only strengthens IoT deployments in agriculture, such as beehive monitoring, but is also extensible to other domains including smart cities, healthcare, and environmental monitoring. By addressing variability across network conditions and optimizing protocol switching, ANCA establishes a foundation for more resilient and scalable IoT communication systems.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

EN: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing. JS: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review and editing, Methodology. MZ: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review and editing, Software. SW: Conceptualization, Formal Analysis, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review and editing, Data curation, Methodology. MN: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review and editing, Methodology.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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