Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 4, August 2026, pp. 3036~3046
ISSN: 2302-9285, DOI: 10.11591/eei.v15i4.10758

Hybrid long range wide area network-5G-artificial intelligence-architecture for enhanced reliable internet of things

Feriel Aouissi[1,2], Farouk Boumehrez[3,4], Abdelhakim Sahour[1,2], Mohamed Lamri[1,2], Hanane Djellab[5], Fouzia Maamri[1,2], Abdelaali Bekhouche[6]
[1]Laboratory of Systems and Applications of Information and Telecommunication Technologies (SATIT), Department of Electrical Engineering, Abbes Laghrour University, Khenchela, Algeria
[2]Department of Electrical Engineering, Faculty of Sciences and Technologies, ABBES Laghrour – Khenchela University, Khenchela, Algeria
[3]Telecommunications Institute, 8 May 1945 University, Guelma, Algeria
[4]Telecommunications Laboratory (LT), Telecommunications Institute, 8 May 1945 University, Guelma, Algeria
[5]Department of Electronics and Communication, Faculty of Sciences and Technologies, University of Tebessa, Tebessa, Algeria
[6]Department of Computer Sciences, Faculty of Sciences and Technologies, ABBES Laghrour – Khenchela University, Khenchela, Algeria

Article Info

Article history:

Received May 28, 2025
Revised May 31, 2026
Accepted Jun 19, 2026

Keywords:

5G
Artificial intelligence
Hybrid model
Internet of things
Long range wide area network

ABSTRACT

Internet of things (IoT) has made long range wide area network (LoRaWAN) a key component of low-power communication; nevertheless, its adoption in mission-critical domains is limited by its latency, throughput, and quality of service (QoS) restrictions. To bridge these gaps, this paper proposes a hybrid three-layer structure that combines LoRaWAN, fifth generation (5G), and artificial intelligence (AI) to achieve a dynamic trade-off between scalability, reliability, and energy efficiency. According to the findings, the proposed hybrid model significantly improves network performance. It is based on a random forest regressor that integrates LoRaWAN and 5G technologies. The model increases throughput to 40-80 Mbps while maintaining moderate energy consumption, and reduces latency from an average of over 300 ms to less than 150 ms. Additionally, the random forest algorithm improved the overall network performance stability and the packet delivery ratio to roughly 97%. This approach is more effective than earlier studies that relied on descriptive methods or a single technology. This work establishes the foundation for the applications of IoT in smart agriculture, healthcare, and fourth industrial revolution (Industry 4.0).

Corresponding Author:

Feriel Aouissi
Laboratory of Systems and Applications of Information and Telecommunication Technologies (SATIT)
Department of Electrical Engineering, Abbes Laghrour University
Khenchela, 40004, Algeria
Email: aouissi.feriel@univ-khenchela.dz

1. INTRODUCTION

Over the past decade, information, and communication technology has undergone a tremendous leap in development, from simple data processing to the creation of digital platforms based on computational, and machine learning (ML) technologies. Moreover, the emergence of the fourth industrial revolution (Industry 4.0) is an unparalleled expansion of interconnected devices, which engender intricate ecosystems necessitating seamless, intelligent, and efficient communication. Within this landscape, long range wide area network (LoRaWAN) technology has established itself as a fundamental and practical pillar of low-power wide-area network (LPWAN) technologies, which in turn provide long-range, and cost-effective connectivity for the deployment of the internet of things (IoT). LoRaWAN provides exceptional long-range, low-power functionalities for extensive sensor networks; this technology independently in suffices to address the diverse requirements of contemporary digital transformation comprehensively. At the same time, IoT systems are being rapidly developed, requiring low-latency, reliable communication, as well as widespread interoperability. All of this is beyond the capabilities of LoRaWAN alone. LoRaWAN risks becoming unsuitable for future IoT applications, creating an urgent need for a critical assessment of how to transform LoRaWAN from a large-scale niche technology into a robust backbone capable of advancing IoT systems. On the other hand, fifth generation (5G) technology provides rapid, low-latency connectivity, and making it ideal for bandwidth-intensive applications. This technological dichotomy has created a critical imperative for a unified connectivity framework. The integration of long range (LoRa) and 5G represents a transformative paradigm poised to redefine the landscape of wireless communication and intelligent automation. LoRa serves as the ubiquitous sensory nervous system, adeptly gathering data from millions of low-power endpoints across extensive distances. 5G constitutes the high-performance infrastructure, facilitating real-time data transmission, and high-bandwidth applications.

Furthermore, artificial intelligence (AI) is a promising tool for resource allocation and network optimization through decisions based on prediction or classification algorithms. Numerous recent studies have examined the performance and suitability of LoRaWAN in various fields. For example, study [1] verified its operational viability but neglected to discuss its scalability issues [2]. Also investigated its integration with wearable medical devices, noting that while it demonstrated excellent energy efficiency, issues with latency and jitter remained. Building on these initiatives, research [3] conducted a thorough analysis of LoRaWAN solutions based on AI and ML, finding that, compared to static adaptive data rate (ADR) setups; reinforcement learning can increase productivity by as much as 15%. Although issues with scalability and battery lifetime remained, in [4] suggested a hybrid wireless-fidelity (LoRaWAN–Wi-Fi) monitoring system in the healthcare industry that improved communication reliability and decreased energy usage and in [5] examined LPWAN, 5G, and hybrid architectures in agriculture and found that integrating LPWAN and 5G increased rural areas' reliability while lowering communication costs by about 30%. Lastly, researchers in [6] achieved significant improvements in performance and energy efficiency by using a deep learning method that utilizes long short-term memory (LSTM), artificial neural networks (ANN) models to anticipate, adjust signal-to-noise ratio (SNR), and received signal strength indicator (RSSI) parameters dynamically.

Recent studies indicate a growing trend toward integrating AI technologies with LoRaWAN networks to enhance network efficiency and connection reliability, although with variations in methods and target environments. For example, the study [7] achieved notable gains in packet delivery rate (PDR) and energy efficiency by utilizing a hybrid framework that used deep learning with TinyML to forecast optimal transmission parameters. The research [8], on the other hand, employed deep Q-network (DQN) algorithms to develop dynamic transmission policies that could adapt to changing channel conditions and interference. In challenging settings, such as subterranean applications, the study [9] demonstrates superiority in energy efficiency and convergence speed over conventional techniques using multi-agent algorithms like multi-agent dueling double deep q-network (MAD3QN) and multi-agent advantage actor-critic (MAA2C). The study [10] also examined distributed solutions, including dual lorawan (D-LoRa) and clustered dual lorawan (CD-LoRa), the latter of which demonstrated superior convergence speed under stable conditions. At the same time, the former proved suitable for dynamic environments. On the other hand, despite LoRaWAN's numerous advantages, overcoming its technical challenges requires support from advanced technologies, such as AI, to enhance energy consumption, spectrum allocation, packet routing, and device management in LoRaWAN networks. Similarly, the integration of 5G networks provides a low-latency, high-capacity backbone that LoRaWAN networks alone cannot achieve. Together, AI and 5G open up new possibilities for enhancing LoRaWAN networks, transforming them from a limited LPWAN protocol into a powerful, and future-ready tool for enabling the IoT.

This paper investigates the architectural frameworks, operational mechanisms, and pioneering applications of the LoRa-5G-AI integration. We will examine how this tripartite is not merely an incremental enhancement but a fundamental transformation, facilitating genuinely smart cities, autonomous industrial systems, and a seamlessly interconnected world where intelligence is both inherent in the infrastructure and readily accessible at scale.

2. PROPOSED ARCHITECTURE

The LoRaWAN is a network standard proposed by the LoRa alliance, based on topology presented in Figure 1. The devices communicate directly with gateways using LoRa modulation. They are embedded systems based on IoT with low-cost energy consumption that do not address a specific gateway. They transmit data to all gateways within the convergence zone, which are capable of receiving and processing the signal.

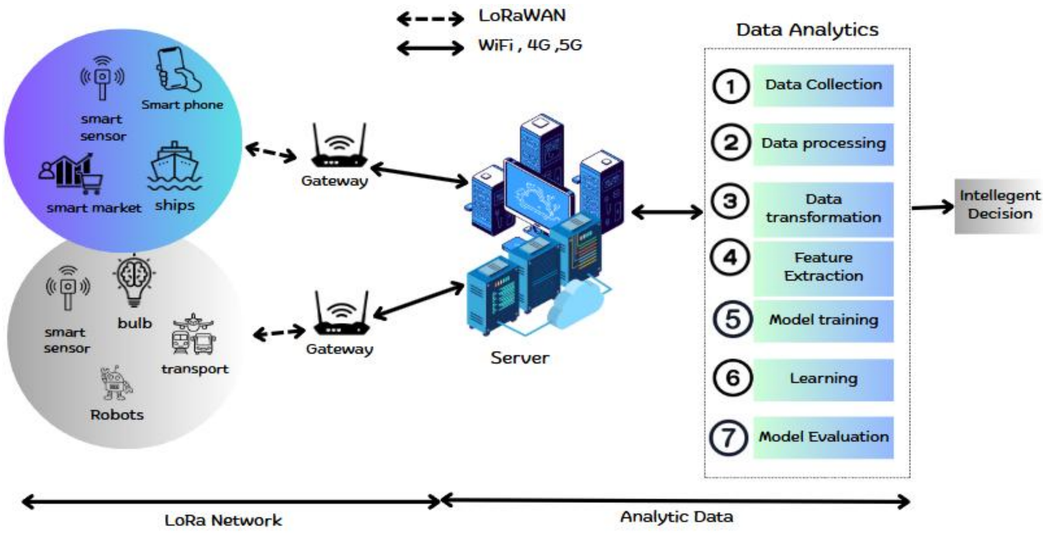


Figure 1. Architecture of LoRaWAN network

The devices maintain bidirectional communication with the gateways. When the gateway receives the LoRa frame, it is transferred to the server via Wi-Fi or a cellular network, such as 4G, 5G, or long term evolution for machines (LTE-M). It has a unique identification for activation and registration at the server level. Then the server receives and stores this data in the cloud or local databases, allowing for processing and analysis. It also provides application interfaces or control panels that help users access and interpret the data, as well as receive notifications or alerts [11].

The physical (PHY) layer defines LoRa modulation and demodulation in both directions (downlink and uplink). It uses a chip-encoded sequence called “chirp” (a high-density compressed radar pulse) that transmits the signal across a wide bandwidth with constant frequency variation. This provides flexibility against interference and multipath fading, allowing receivers to decode signals even below the noise level, and achieves a sensitivity of up to −140 dBm [12]. This process is known as chirp spread spectrum (CSS) [13]. The spread factor (SF) is one of the critical parameters that determines the number of chips per symbol, ranging from 7 to 12. As SF increases, the packet size, power, and communication distance decrease. LoRa error correction technology relies on forward error correction (FEC) with different coding rates of 4/5, 4/6, 4/7, and 4/8, where repetition improves reliability in complex and noisy environments but reduces the actual transmission rate. The ADR mechanism optimizes the trade-off between energy efficiency and network capacity by dynamically adjusting transmission parameters, such as bandwidth, transmission power, and, SF. As well, PHY layer for LoRA is well suited for low-power IoT applications due to its high sensitivity, extended range, and customizable setup. To expand its applications in complex and dense environments, however, enhancements such as adaptive transaction configuration, hybrid signal design, multiple reception techniques, and fine synchronization are required due to issues like low data rates, possible collisions, and sensitivity to frequency drifts. Moreover, in recent years, several comparative studies have been conducted between LoRaWAN and other wireless communication protocols, including Zigbee, Wi-Fi, Bluetooth, and Sigfox. Table 1 compares IoT technologies, showing LoRaWAN’s advantage in coverage and energy efficiency.

Table 1. The characteristics of each technology [14], [15]

Protocol	Zigbee	Wi-Fi	Bluetooth	Sigfox	LoRa
Standard	Zigbee 3.0 based on IEEE 802.5.2	802.1n	Bluetooth 4.2	Sigfox	LoRaWAN
Modulation	Direct sequence spread spectrum (DSSS) and quadrature phase shift keying (QPSK)	DSSS and orthogonal frequency division multiplexing (OFDM)	Gaussian frequency shift keying (GFSK)	Binary phase shift keying (BPSK)	CSS
Range	10-100 m	50 m	5-150 m	30-50 km	15 km
Frequency	2.4 GHZ	2.4-5GHz	2.4 GHz	900 MHz	433-868 MHz
Max data rate	250 kbs-2.4 GHz	Gbps	2 Mbps	100 bps	50 kbps
Energy consumption	Low	high	Low	Low	Low
Security	high	Low/high	Low/high	Low	High
Price	Medium	Low	Low	Low	Low

This comparative analysis highlights that LoRaWAN is one of the most efficient and scalable options for low power, wide-area applications, although it is not suitable for data-intensive applications. Furthermore, the 5G–LoRaWAN interaction is complementary to enhance the performance of intelligent systems, not competitive. LoRaWAN provides long-distance coverage with minimal power consumption, making it an ideal solution for networking environmental sensors in diverse environments. In contrast, 5G provides high data transfer rates, and minimal latency, making it appropriate for various applications [16]. The integrated 5G–LoRaWAN architecture is illustrated in Figure 2, where end devices send data via LoRaWAN gateways connected to edge or cloud platforms through 5G.

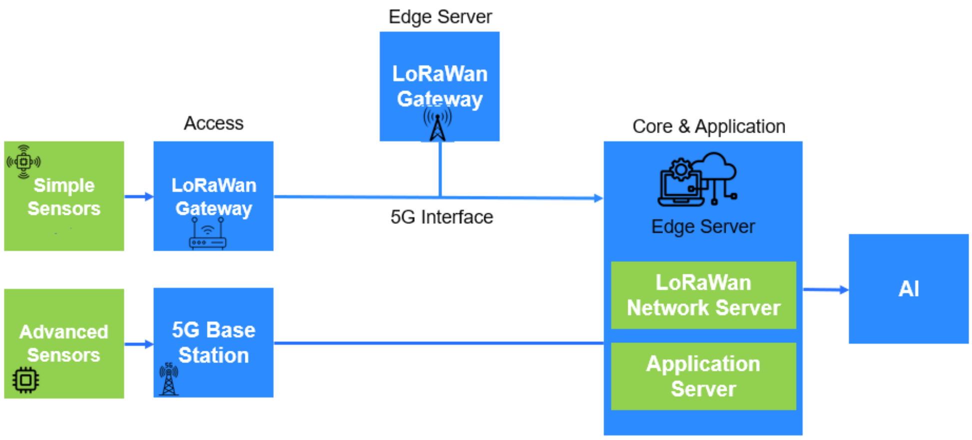


Figure 2. 5G–LoRaWAN hybrid proposed architecture

This architecture employs low-power end devices that transmit data to gateways connected through a 5G backhaul. Packets are delivered to the 5G Core using the LoRaWAN protocol with CSS modulation. The LoRaWAN network server (LNS) combined with the advanced processing and multi-access edge computing (MEC) capabilities supported by 5G network slicing, ensures efficient resource allocation based on service requirements. Subsequently, the data is transferred to the application layer, where ML and AI techniques are applied for analysis and storage, enabling diverse applications such as Industry 4.0, smart cities, and smart agriculture. Packets pass through the LoRa PHY layer, which handles channel and modulation, the LoRaWAN medium access control (MAC), which handles access control and AES-128 encryption [17], and finally the 5G network's core layer, which ensures low latency and high speed, before being encapsulated in application protocols such as MQTT or CoAP. When paired with 5G security layers, the integrity of the LoRaWAN packet is guaranteed by a message integrity code (MIC).

ML is applied to predict the performance of end nodes through their transmission patterns by developing algorithms that control bandwidth, SF, RSSI, packet size, SNR, and other parameters, thus predicting what happens at the network level as a whole and not only end nodes. Through customized models, network traffic can be expected, which in turn minimizes energy consumption, extends battery life, reduces collisions, and increases coverage capacity. All of this contributes to improving network quality of service (QoS). Many algorithms are applied, such as random forest, logistic regression, support vector machine, decision trees, and neural networks (for complex classification). Alternatively, algorithms like linear regression, ridge/lasso regression, gradient boosting, and neural networks are used in cases where regression outputs are required. These algorithms can be applied to LoRaWAN networks to predict network parameters or train them to organize packets based on the transmitted data from terminal nodes.

On the other hand, because deep learning uses multi-layer neural networks to identify intricate patterns in data, it is one of the most promising areas of ML for optimizing LoRaWAN networks used in IoT applications. Among its most well-known applications in this context are controlling smart device data transmission intervals to reduce collision rates and enhance network efficiency, enhancing signal reliability by employing optimized neural networks to eliminate noise from uplink communications, and accurately locating devices both indoors and outdoors by analyzing signal strength. An integrated communication system that mimics transmission, jamming, and reception has also been developed using the auto encoder architecture, achieving high packet success rates, and low error rates.

The random forest regressor is an algorithm designed for predicting continuous numerical values. Operating on the principle of collective intelligence, it constructs multiple decision trees during training, each built on random subsets of the data and features through bootstrap sampling and feature randomness. This approach, known as bagging (bootstrap aggregating), ensures that the model captures complex, and non-linear relationships while maintaining robustness against overfitting. For prediction, the algorithm averages the outputs of all individual trees in the forest, resulting in more accurate, and stable predictions compared to single decision trees. Key advantages include its ability to handle high-dimensional datasets, provide native feature importance rankings, and effectively manage missing values. Due to its versatility and performance, the random forest regressor finds applications across diverse domains, including energy load estimation and prediction, as well as communication and agricultural outcome analysis, making it one of the most widely used regression techniques.

The suggested solution integrates AI as a key component to manage network resources and select the best data transmission method (LoRaWAN or 5G) in real-time, in contrast to traditional models that handle these technologies independently. There are three primary modules in the architecture:

- Edge, which uses low-power sensors and TinyML for local anomaly detection and decreased data transmission.
- Fog/edge-5G, which uses gateways with an AI model (random forest) for near real-time decision-making
- Cloud/AI, uses deep learning and reinforcement learning for long-term predictive analysis.

The structure of the proposed model is shown in Figure 3. It illustrates the dynamic switching process and the three functional layers (edge, gateway/fog, and cloud), where AI selects between 5G for time-sensitive data and LoRaWAN for energy-efficient sensing. The figure also demonstrates how each layer performs specific roles: the edge layer collects data from the sensors; the gateway/fog layer performs temporary data processing and coordinates transmission between networks; and while the cloud/AI layer handles advanced analysis and decision-making. This design balances response speed and energy efficiency while enabling easy system scalability when adding new sensors.

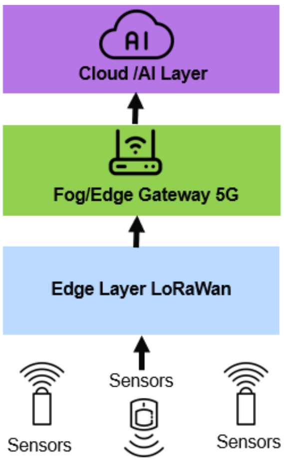


Figure 3. Dynamic switching mechanism in the proposed hybrid LoRaWAN–5G–AI architecture

3. RESULTS AND DISCUSSION

Features from 5G and LoRaWAN from two sources: the LoRaWAN traffic analysis dataset [18] and the 5G network key performance indicator (KPI) dataset [19]. Due to differences in operational and geographic conditions, the data were normalized and harmonized through resampling, and unit conversions to ensure consistency. Important parameters in the final dataset include coverage, SNR, bandwidth, latency, throughput, energy consumption, packet error rate (PER), and RSSI. By representing each technology's typical range, 0.125–0.5 MHz for LoRaWAN and 20–100 MHz for 5G, the bandwidth allotments capture the underlying spectrum differences of each technology. The random forest regressor model enabled predicting network performance metrics, such as throughput PER, latency, energy, and evaluating the efficacy of each technology across various operating scenarios.

To validate these claims, a detailed experimental evaluation is conducted. The statistical distribution of performance metrics is presented in Figure 4. In contrast, their temporal evolution across samples is illustrated in Figure 5, providing a comprehensive assessment of latency, throughput, energy consumption, and reliability over time. The proposed architecture effectively addresses each network's constraints. While AI algorithms increase PDR by reducing collisions and optimizing transmission schedules, 5G dramatically shortens response times for essential data. LoRaWAN enables low-power consumption at edge devices, the design demonstrates strong scalability, and enabling the addition of more nodes without sacrificing performance.

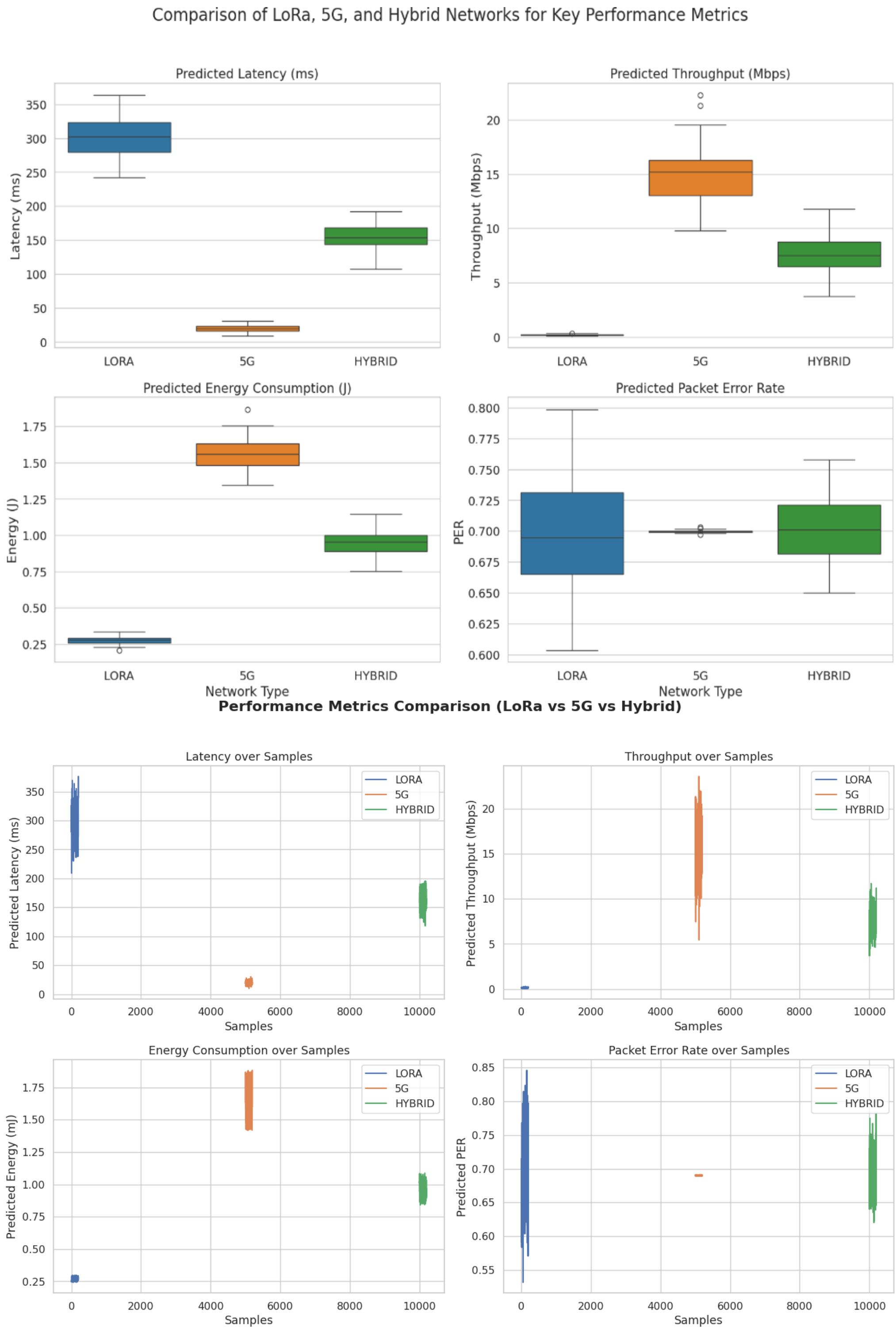


Figure 4. Comparison between LoRaWAN, 5G, and the hybrid model: performance comparison via boxplots

Moreover, the experimental findings depicted in the figures provide an accurate quantitative comparison of the three networks. LoRaWAN has the lowest throughput (less than 1 Mbps), the longest latency (averaging over 300 ms), and the lowest energy consumption (around 0.25 mJ), despite a high and fluctuating PER. 5G, on the other hand, achieves the best performance in terms of responsiveness and speed, with the fastest throughput exceeding 20 Mbps and the lowest latency around 20 ms, but at the expense of much higher energy consumption, around 1.5 mJ. By achieving balanced performance across all measures, lowering latency and energy consumption compared to LoRa, and maintaining a respectable throughput level, the hybrid system clearly strikes a balance between the two extremes incremental advancements in architecture or algorithms. For instance, it was shown in [20] that LoRaWAN could be integrated with a 5G experimental network by connecting LoRaWAN gateways to the 5G network as a backhaul.

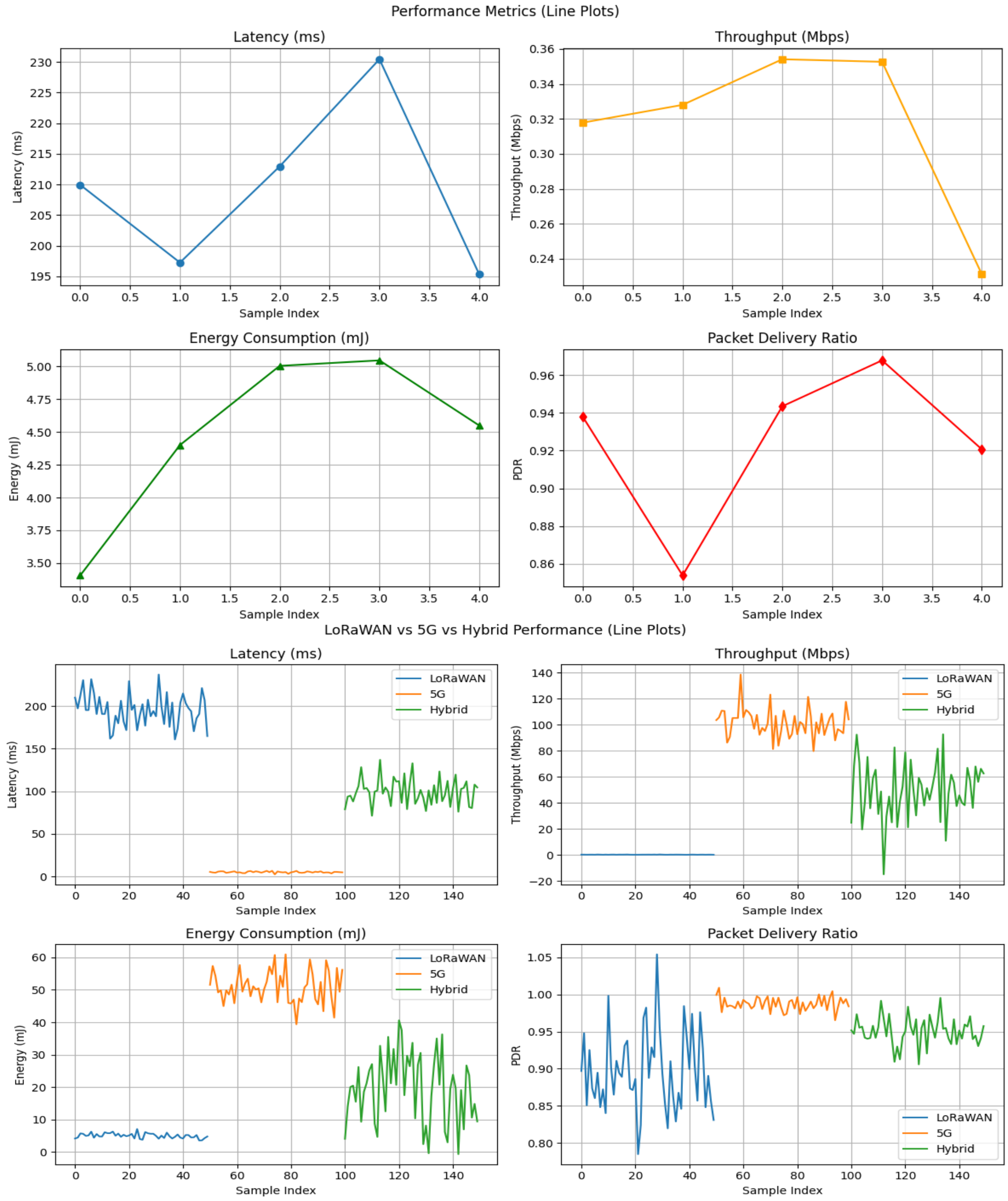


Figure 5. Comparison between LoRaWAN, 5G, and the hybrid model performance indicators over time (line plots)

In addition, this study demonstrated that structural integration was feasible but lacked intelligent resource management mechanisms. A similar concept for an integrated network was proposed in [14] via a convergent core network that incorporates a LoRaWAN server within the 5G core. This approach enhanced network management, but it ignored power consumption and dynamic load distribution policies. Applied studies such as [21] focused on the industrial use of predictive maintenance by allocating LoRaWAN for periodic data and 5G for critical data, thereby achieving improved operational efficiency, although the experiment was restricted to a single application. However, the concept of cognitive-LPWAN [22] was introduced, which uses AI to select the best technology from Sigfox, LoRa, and narrowband (NB-IoT) based on QoS requirements. Although, it lacked comprehensive field data and did not address merging LoRaWAN with 5G. This architecture is comparable to the LoRaWAN-5G-AI concept in that it employs AI to compare

LPWAN, 5G, and hybrid models in the context of smart agriculture. Table 2 presents a comparative review of previous recent studies and the proposed hybrid system, both of which involve the integration of LoRaWAN and 5G technologies, highlighting their objectives, methodologies, and findings, as well as current research gaps that still need to be addressed.

Table 2. Summary of the literature review

Ref.	Objective	Methodology	Results	Gaps
[19]	Integrating LoRaWAN with a 5G network	Connecting LoRaWAN gateways to 5GTN	Demonstrated structural integration	Absence of smart resource management
[20]	LoRaWAN–5G converged core	LoRaWAN server and collaborative RAN in 5G	Improving reliability and network management	did not discuss dynamic expansion or energy
[14]	Hybrid industrial platform	5G for crucial data and LoRa for periodic data	Improving operational efficiency	Limited scope of application
[21]	Choosing the most suitable network	AI to determine the optimal technology	Intelligent approach to QoS management	Absence of attention to field outcomes and 5G-LoRaWAN
[22]	Agricultural comparative study	Hybrid versus 5G against LPWAN	Balancing coverage and delay	Economic cost challenges

More recent studies, such as [5], have also examined reliability and cost issues. They showed that integrated networks could balance latency and coverage while highlighting the financial limitations imposed by 5G infrastructure costs. This paper demonstrates that while earlier research has provided a valuable basis for understanding the benefits and drawbacks of LoRaWAN and 5G integration, it has remained either a form of structural experimentation or a limited-scope application. On the other hand, this study proposes an integrated architectural framework that combines AI techniques with a hybrid architecture, enabling improvements in performance metrics.

Despite successfully enhancing the overall performance of IoT networks [23], the suggested hybrid model combining LoRaWAN and 5G, backed by AI algorithms, faces several technological, and legal obstacles in its real-world implementation. Integrating disparate technologies that differ in data rates, protocols, that require unified interfaces, and precise synchronization methods to ensure seamless operation, is one of the most challenging tasks. Multiple communication levels expand the attack surface, require increasingly sophisticated authentication, and key management systems, making security and privacy delicate topics as well [24]. Economically, expansion in resource-constrained regions is hampered by the high costs of infrastructure, deployment, and maintenance. Furthermore, AI systems have difficulty gathering vast volumes of data and accurately training models while preserving the energy efficiency of edge devices [25]. As the number of linked nodes increases, scalability and network coordination become more difficult, requiring flexible resource management and AI-supported predictive methods. Table 3 presents a comparative analysis between previous LoRaWAN–5G approaches and the proposed LoRaWAN–5G–AI model in terms of latency, packet delivery ratio (PDR), energy efficiency, scalability, cost, and security performance.

Table 3. Comparison of proposed model and previous literature

Index	Previous literature (LoRaWAN–5G)	Proposed model (LoRaWAN–5G–AI)
Latency	Limited improvement via 5G as a fallback	Significant decrease as a result of the intelligent guiding policy
PDR	A partial improvement in ressource allocation	Significant improvement due to fewer collisions and traffic
Energy	Relative savings via LoRaWAN	Keep your 5G contract usage low when sending many messages
Scalability	Acceptable performance at medium densities	Utilize intelligent management and load allocation to support increased density
Cost	QoS solutions that are less costly but have limitations	High service quality at a comparatively high cost
Security	Limited security processing	Need for advanced security mechanisms during integration

4. CONCLUSION

LoRaWAN is the most promising options for IoT networks. However, to design smart and sustainable hybrid networks capable of meeting the demands of the next-generation internet, this study proposes an integrated hybrid model that dynamically balances performance, power, and reliability. Since the results demonstrate that this integration enhances key performance metrics, including scalability, PDR, and latency, it has the potential to serve as an architecture for intelligent applications. Nevertheless, this technology still suffers from several limitations, including slow data transfer rates, high latency, and limited scalability, which make it less suitable for time-sensitive applications.

By combining the intelligence of AI systems, the efficiency of 5G networks, and the capabilities of LoRaWAN, this research has led to the development of a smart and sustainable hybrid network design capable of meeting the demands of next-generation IoT systems. To improve this model's readiness, future research should expand through extensive field-testing and the implementation of advanced adaptation and security measures. Finally, a roadmap for next-generation networks is proposed, with AI-enhanced hybrid LoRaWAN-5G architectures serving as the basis for smart, scalable, and energy-efficient systems.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the University of Khenchela for its support of this work.

FUNDING INFORMATION

This research did not receive any specific grant from funding agencies

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Feriel Aouissi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Farouk Boumehrez	✓	✓				✓		✓	✓	✓	✓	✓		
Abdelhakim Sahour	✓		✓	✓			✓			✓	✓		✓	✓
Mohamed Lamri		✓	✓		✓		✓	✓	✓		✓			
Hanane Djellab			✓		✓			✓	✓	✓			✓	✓
Fouzia Maamri		✓				✓			✓	✓		✓	✓	
Abdelaali Bekhouche	✓	✓	✓		✓	✓	✓			✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest among the authors.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [F. Aouissi] upon request.

REFERENCES

[1] S. K. Musonda, M. Ndiaye, H. M. Libati, and A. M. Abu-Mahfouz, "Reliability of LoRaWAN Communications in Mining Environments: A Survey on Challenges and Design Requirements," *Journal of Sensor and Actuator Networks*, vol. 13, no. 1, p. 16, 2024, doi: 10.3390/jsan13010016.

[2] N. M. Obiri and K. V. Laerhoven, "A Survey of LoRaWAN-Integrated Wearable Sensor Networks for Human Activity Recognition: Applications, Challenges and Possible Solutions," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 6713–6735, 2024, doi: 10.1109/OJCOMS.2024.3484002.

[3] G. He, C. Li, Y. Shu, and Y. Luo, "Fine-grained access control policy in blockchain-enabled edge computing," *Journal of Network and Computer Applications*, vol. 221, 2024, doi: 10.1016/j.jnca.2023.103706.

[4] S. Abdulmalek, A. Nasir, and W. A. Jabbar, "LoRaWAN-based hybrid internet of wearable things system implementation for smart healthcare," *Internet of Things*, vol. 25, p. 101124, Apr. 2024, doi: 10.1016/j.iot.2024.101124.

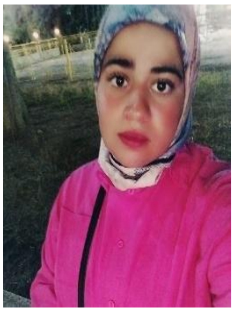
[5] W. ur Rehman *et al*., "The role of 5G network in revolutionizing agriculture for sustainable development: A comprehensive review," *Energy Nexus*, vol. 17, pp. 1-22, Mar. 2025, doi: 10.1016/j.nexus.2025.100368.

[6] M. Alkhayyal and A. M. Mostafa, "Enhancing LoRaWAN Sensor Networks: A Deep Learning Approach for Performance Optimizing and Energy Efficiency," *Computers, Materials & Continua*, vol. 83, no. 1, pp. 1079–1100, 2025, doi: 10.32604/cmc.2025.061836.

[7] M. A. Lodhi, X. Sun, K. Mahmood, A. Lodhi, Y. Park, and M. Hussain, "AI-Enhanced Resource Allocation for LPWAN-Based LoRaWAN:A Hybrid TinyML and Deep Learning Approach," *IEEE Internet of Things Journal*, vol. 12, no. 14, pp. 28950–28963, Jul. 2025, doi: 10.1109/JIOT.2025.3568445.

[8] L. Acosta-Garcia, J. Aznar-Poveda, A. J. Garcia-Sanchez, J. Garcia-Haro, and T. Fahringer, "Dynamic transmission policy for enhancing LoRa network performance: A deep reinforcement learning approach," *Internet of Things*, vol. 24, pp. 1-13, Dec. 2023, doi: 10.1016/j.iot.2023.100974.
[9] K. Mythily, S. S. Nidhi, and D. Sridharan, "Machine Learning Innovations in LoRaWAN: A Comprehensive Survey of Technology, Trends, and Applications," *International Journal of Communication Systems*, vol 38, no. 17, 2025, doi: 10.1002/dac.70285.
[10] F. Nisar, M. Amin, M. T. Irshad, H. J. Hadi, N. Ahmad, and M. Ladan, "Machine learning-based spreading factor optimization in LoRaWAN networks," *Frontiers in Computer Science*, vol. 7, Sep. 2025, doi: 10.3389/fcomp.2025.1666262.
[11] M. Ragnoli *et al.*, "A LoRaWAN Multi-Technological Architecture for Construction Site Monitoring," *Sensors*, vol. 22, no. 22, 2024, doi: 10.3390/s22228685.
[12] J. Lin, W. Yu, N. Zhang, X. Yang, H. Zhang, and W. Zhao, "A Survey on Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications," *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1125–1142, Oct. 2017, doi: 10.1109/JIOT.2017.2683200.
[13] A. Maleki, H. H. Nguyen, E. Bedeer, and R. Barton, "A Tutorial on Chirp Spread Spectrum for LoRaWAN: Basics and Key Advances," *IEEE Communications Surveys & Tutorials*, vol. 5, pp. 4578-4612, 2024, doi: 10.1109/OJCOMS.2024.3433502.
[14] Y. Chen, Y. A. Sambo, O. Onireti, S. Ansari, and M. A. Imran, "LoRaWAN-5G Integrated Network with Collaborative RAN and Converged Core Network," in *2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, Sep. 2022, pp. 1–5, doi: 10.1109/PIMRC54779.2022.9977480.
[15] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "A comparative study of LPWAN technologies for large-scale IoT deployment," *ICT Express*, vol. 5, no. 1, pp. 1–7, Mar. 2019, doi: 10.1016/j.icte.2017.12.005.
[16] E. M. Torroglosa-Garcia, J. M. A. Calero, J. B. Bernabe, and A. Skarmeta, "Enabling Roaming Across Heterogeneous IoT Wireless Networks: LoRaWAN MEETS 5G," *IEEE Access*, vol. 8, pp. 103164–103180, 2020, doi: 10.1109/ACCESS.2020.2998416.
[17] M. Eldefrawy, I. Butun, N. Pereira, and M. Gidlund, "Formal security analysis of LoRaWAN," *Computer Networks*, vol. 148, pp. 328–339, Jan. 2019, doi: 10.1016/j.comnet.2018.11.017.
[18] A. Povalac, J. Kral, H. Arthaber, O. Kolar, and M. Novak, "Exploring LoRaWAN Traffic: In-Depth Analysis of IoT Network Communications," S*ensors*, vol. 23, no. 17, pp. 1-20, Aug. 2023, doi: 10.3390/s23177333.
[19] D. Raca, D. Leahy, C. J. Sreenan, and J. J. Quinlan, "Beyond throughput, the next generation," in *Proceedings of the 11th ACM Multimedia Systems Conference*, May 2020, pp. 303–308, doi: 10.1145/3339825.3394938.
[20] R. Yasmin, J. Petajajarvi, K. Mikhaylov, and A. Pouttu, "On the integration of LoRaWAN with the 5G test network," in *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Oct. 2017, pp. 1–6, doi: 10.1109/PIMRC.2017.8292557.
[21] O.-D. D. Brito, P. Pace, and F. de Rango, "A Review on the Confluence of 5G and LoRaWAN: Architectures, Use Cases, Taxonomies, Open Issues, and Research Avenues," *IEEE Access*, vol. 13, pp. 191144–191163, 2025, doi: 10.1109/ACCESS.2025.3629386.
[22] M. Chen, Y. Miao, X. Jian, X. Wang, and I. Humar, "Cognitive-LPWAN: Towards Intelligent Wireless Services in Hybrid Low Power Wide Area Networks," *IEEE Transactions on Green Communications and Networking*, vol. 3, no. 2, pp. 409-417, Jun. 2019, doi: 10.1109/TGCN.2018.2873783.
[23] F. Boumehrez, A. H. Sahour, and N. Doghmane, "Telehealth care enhancement using the internet of things technology," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 5, pp. 2652–2660, Oct. 2021, doi: 10.11591/eei.v10i5.2968.
[24] K. Ntshabele, I. Bassey, G. Naison, and A. M. Abu-Mahfouz, "A Comprehensive Analysis of LoRaWAN Key Security Models and Possible Attack Solutions," *Mathematics*, vol. 10, no. 19, 2022, doi: 10.3390/math10193421.
[25] A. Farhad and J.-Y. Pyun, "LoRaWAN Meets ML: A Survey on Enhancing Performance with Machine Learning," *Sensors*, vol. 23, no. 15, Aug. 2023, doi: 10.3390/s23156851.

BIOGRAPHIES OF AUTHORS



Feriel Aouissi is a Ph.D. student in Networks and Wireless Communications at the Laboratory of Information and Communication Technologies Systems and Applications (SATIT). In Department of Electrical Engineering, ABBES Laghrour University, Khenchela, 40004, Algeria, earned a bachelor's degree in 2017 in Experimental Sciences and a master's degree in Networks and Wireless Communications from the Faculty of Science and Technology at the University of 8 May 1945, Guelma, Algeria. Her research interests include remote monitoring and control strategies for agricultural greenhouses, energy, and long-range communication technologies. She can be contacted at email: aouissi.feriel@univ-khenchela.dz.

Farouk Boumehrez received the Engineering degree from the University of Guelma, Algeria, in 2002, and the Magister degree in Telecommunications from the University of Annaba, Algeria, in 2008. He served as a Researcher and Associate Professor at the University of Khenchela, Algeria, from 2011 to 2025. He is currently an Associate Professor at the Institute of Telecommunications, University of Guelma, Algeria. His research interests include wireless communications, multimedia systems, the internet of things (IoT), digital communications, computer networks, video processing, and image processing. He can be contacted at email: boumfarouk@yahoo.fr.

Abdelhakim Sahour received the Engineering degree from the University of Annaba, Algeria, and the HDR degree from the University of Annaba, Algeria, in 2021. He is currently an Associate Professor and researcher at Abbès Laghrour University of Khenchela, Algeria. His research focuses on digital signal processing, FPGA-based embedded systems, the internet of things (IoT), artificial intelligence, and wireless communications. His work aims to develop innovative intelligent systems by integrating IoT technologies, fuzzy logic, and optimization techniques to address real-world engineering challenges. He can be contacted at email: hakim_sahour@yahoo.fr.

Mohamed Lamri is a Ph.D. Candidate in Automatic Control and Industrial Informatics at the University of Khenchela, Algeria, where he has been pursuing his doctoral research since March 2022 at the SATIT Laboratory. He received his Master's Degree in Electrical Engineering (Industrial Informatics) from the University Larbi Ben Mhidi in 2012, and his Bachelor's Degree in Electronics in 2010. With over 25 years of professional experience in equipment maintenance, laboratory management, and technical education, his research focuses on developing intelligent systems integrating IoT, machine learning, and deep learning for real-time wildfire risk prediction, with particular emphasis on explainable AI (XAI) techniques including LIME and SHAP. He has published multiple peer-reviewed papers in international journals and conferences on wildfire prediction and healthcare applications. He can be contacted at email: mohamed.lamri@univ-khenchela.dz.

Hanane Djellab Professor in Telecommunications, currently responsible for the Huawei ICT Academy in Tebessa and Head of the Signals and Smart Systems Laboratory. She holds a Ph.D. in Telecommunications from Badji Mokhtar University of Annaba and obtained her Habilitation à Diriger des Recherches (HDR) from Tebessa University. She earned a Magister's degree in Automation and Control in 2007 and graduated as a Communications Engineer from Tebessa University. Her professional journey began in 2003 as an engineer at the amplification center of Algérie Télécom. From 2005 to 2011, she held the positions of BSS Remote and AOR at Mobilis. She later joined the University of Khenchela as an Associate Professor before transferring to Tebessa University in 2015. Her research interests include Free Space Optical (FSO) communication, mobile networks, and wireless communication systems. She can be contacted at email: hanane.djellab@univ-tebessa.dz.

Fouzia Maamri received the Magister degree in electronics and the Ph.D. degree in electrical engineering from Larbi Ben M'Hidi University, in 2001 and 2019, respectively. She is currently a University Researcher specializing in telecommunications and chaotic systems. She is teaches with the University of Abbès Laghrour, Khenchela. Her academic work includes wireless networks, optimization algorithms, and secure systems. She also contributes to research within the SATIT Laboratory. She can be contacted at email: ma_fou@yahoo.fr.

Dr. Abdelaali Bekhouche holds a Doctorate in Computer Science, specializing in Information and Knowledge Systems, from Badji Mokhtar University in Annaba, Algeria. Since 2009, he has served as a lecturer in the Department of Computer Science at Abbes Laghrour University in Khenchela, Algeria. He is also a member of the ICOSI Laboratory in Khenchela. In 2022, he obtained his Habilitation to Direct Research (HDR). His research interests include the representation, acquisition, and utilization of meaning, with a specific focus on word sense disambiguation (WSD), natural language processing, and optimization algorithms based on swarm intelligence. He can be contacted at email: bakhouche.abdelali@univ-khenchela.dz.