IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5960~5967
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5960-5967

Long-range wide-area network for industrial monitoring: a strategic technology in industry 4.0

Hector Alejandro Alvarez-Paez[1], Mauricio Galvis-Patiño[2], Jorge Luis Nisperuza-Toledo[2], Oscar Fernando Penagos-Espinel[1], Yeison Alberto Garcés-Gómez[3]
[1]GUIAS Group, Faculty of Engineering and Basic Sciences, Fundación Universitaria Los Libertadores, Bogotá, Colombia
[2]NanoTech Group, Faculty of Engineering and Basic Sciences, Fundación Universitaria Los Libertadores, Bogotá, Colombia
[3]Faculty of Engineering and Architecture, Universidad Católica de Manizales, Manizales, Colombia

Article Info

Article history:

Received Nov 21, 2025
Revised Aug 19, 2026
Accepted Sep 20, 2026

Keywords:

Deep learning
Industrial monitoring
Industry 4.0
Internet of things
Long-range wide-area network
Low power wide area network
Machine learning

ABSTRACT

This article presents a comprehensive review regarding the deployment of long-range wide-area network (LoRaWAN) for industrial monitoring within industry 4.0 (2015–2023). Unlike generic low power wide area network (LPWAN) comparisons, this study critically analyzes the technical synergies between LoRaWAN and artificial intelligence (AI) to overcome scalability limits. The review contrasts LoRaWAN against Sigfox and narrow band internet of things (NB-IoT), highlighting its superior energy efficiency—consuming up to 75% less power during transmission than NB-IoT—and its operative range of up to 18 km in rural settings. Specific applications in precision agriculture, smart cities, and critical energy infrastructure are synthesized. Furthermore, the integration of machine learning and deep learning is examined as a catalyst for network optimization, identifying that deep learning approaches can improve packet success rates by 5% and reduce collision rates by 20% in dense environments. The results indicate that while LoRaWAN faces challenges in adaptive security and 5G interoperability, its hybridization with AI consolidates it as the most versatile enabler for sustainable and decentralized industrial internet of things ecosystems.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Yeison Alberto Garcés-Gómez
Faculty of Engineering and Architecture, Universidad Católica de Manizales
Cra 23 No 60-63, Manizales, Colombia
Email: ygarces@ucm.edu.co

1. INTRODUCTION

Industry 4.0 represents a fundamental transformation in the way industrial processes are conceived and managed. This transformation is driven by the integration of advanced technologies such as the internet of things (IoT), artificial intelligence (AI), and data analytics [1]. This industrial revolution has permeated critical sectors for sustainability, including renewable energy systems, precision agriculture, and environmental monitoring [1], [2].

In this context, the choice of communication protocol is decisive for the effectiveness of any monitoring system. Solutions based on long range (LoRa) and its implementation in long-range wide-area network (LoRaWAN) networks have emerged as ideal responses, standing out for their ability to transmit data over long distances with low power consumption [3]–[5]. These features are crucial in environments where communication infrastructure is sparse, and energy autonomy is a priority [6]. The versatility of LoRaWAN aligns perfectly with the need to establish distributed sensor networks in industrial systems, enabling connectivity in remote locations through its decentralized architecture and capacity to support

numerous nodes [6]. This review article aims to synthesize recent advances in the implementation of LoRaWAN in industry 4.0, highlighting its benefits in energy efficiency, transmission range, and adaptability in critical industrial applications.

While numerous studies have compared low power wide area network (LPWAN) technologies broadly, there is a scarcity of systematic reviews that specifically address the convergence of LoRaWAN with advanced data analytics in industrial scenarios. Most existing surveys focus on physical layer parameters but overlook the transformative potential of coupling LoRaWAN with machine learning and deep learning to solve scalability and interference issues in dense industrial networks. This review bridges that gap by correlating protocol performance with artificial intelligence (AI)-driven optimization techniques.

2. METHODS

This study employs a comprehensive search strategy focused on high-impact literature published between 2015 and 2023, coinciding with the maturation of Industry 4.0 technologies. The review process prioritized peer-reviewed articles from major scientific databases, including IEEE Xplore, ScienceDirect (Elsevier), and SpringerLink, to ensure technical rigor. The selection of sources was guided by a qualitative screening process based on three strategic intersectional criteria: i) technological comparison, selecting studies that provide empirical data contrasting LoRaWAN against Sigfox and narrow band internet of things (NB-IoT); ii) industrial applicability, focusing on research demonstrating real-world deployments in sectors such as precision agriculture and energy grids; and iii) AI integration, isolating papers that propose novel synergies between LPWAN protocols and machine learning or deep learning algorithms [7].

Technical documentation from key industry stakeholders (e.g., Semtech, AWS) was also consulted to validate architectural specifications. This thematic analysis aims to synthesize the state-of-the-art, filtering out theoretical works that lack practical validation in industrial environments. Studies before 2015, non-peer-reviewed articles, and work whose main focus was not LoRaWAN or industry 4.0 were excluded. Technical specifications from organizations such as Semtech and Amazon web services were also consulted for information on architecture and protocols.

3. DEVELOPMENT

3.1. Technical fundamentals of long-range wide-area network

The body of research shows a clear trend toward the adoption of LoRaWAN in industrial system monitoring [7]. The LoRaWAN network is structured into two main components: a frontend consisting of nodes and gateways, and a backend that manages the network and cloud data [8]. Nodes collect data via sensors, while gateways serve as access points connected to the internet [8].

LoRa physical layer utilizes chirp spread spectrum (CSS) modulation, which provides exceptional resilience against multipath fading and Doppler shifts common in industrial settings. Furthermore, the protocol employs an adaptive data rate (ADR) mechanism, allowing the network server to dynamically optimize the spreading factor (SF7 to SF12) and transmit power for each node. This feature is critical for maximizing battery life and network capacity in heterogeneous environments where static configurations would lead to spectral inefficiency.

LoRa modulation technology allows transmissions over long distances (up to 18 km in rural areas) with effective penetration of physical obstacles [7]. This is especially valuable in complex industrial environments. Its low power consumption (0.3–20 mA in transmission, <10 μA at rest, 1.2 μA in sleep mode) allows nodes to operate for prolonged periods on batteries, enabling autonomy in remote installations [9]. From a security perspective, LoRaWAN implements end-to-end encryption using AES-128, device authentication, and remote key updates, ensuring data confidentiality in critical systems [10]. Its star and tree topology facilitates scalability and efficient management of multiple nodes, supporting thousands of devices per gateway [7].

3.2. Comparison of low power wide area network technologies

LPWAN technologies—Sigfox, LoRaWAN, and NB-IoT—offer specific alternatives based on service quality, energy consumption, range, and load capacity [10]. Table 1 summarizes the relevant characteristics. Sigfox is an economic option ideal for low-frequency communications in rural and remote areas [11]. LoRaWAN stands out for its flexibility and integration capabilities in hybrid (public and private) networks, making it a versatile solution for urban and industrial monitoring [10]. NB-IoT, operating on licensed LTE bands, delivers superior service quality and low latency for critical applications, though at a higher cost [11], [12].

Research shows that the hybrid integration of technologies efficiently complements their capabilities. For example, combining ZigBee and LoRa in smart buildings meets diverse automation

requirements, improving energy efficiency and scalability [13]. Comparative studies between NB-IoT and LoRaWAN show that LoRaWAN consumes 75% less energy during transmission (30 mA vs. 120 mA), enabling up to 10 times greater battery life for low-frequency applications [13].

Table 1. Comparative characteristics of LPWAN technologies

Characteristic	LoRaWAN	Sigfox	NB-IoT
Energy consumption	Very low (1.2–20 mA TX; <10 μA standby)	Low (25 mA TX; <10 μA standby)	Moderate (100–200 mA TX; 120 mA transmission)
Range	2–18 km rural; 1–5 km urban	10–50 km rural; 3–10 km urban	Depends on LTE infrastructure
Costs	Very low (unlicensed spectrum, private networks)	Low (Sigfox subscription)	High (licenses and operator fees)
Latency	Medium (100–600 ms)	High (seconds to minutes)	Low (10–200 ms)
Security	AES-128 end-to-end encryption (AppKey & NwkKey)	No encryption by default (application layer security required)	High (LTE infrastructure). 3GPP AKA + IPsec/DTLS
Scalability	High (thousands of devices/ gateways)	Moderate	Very high (thousands/cell)
Frequency	ISM bands (868 MHz–EU; 915 MHz–US)	ISM bands (868, 902 MHz)	Licensed LTE (800–2100 MHz)

3.3. Applications in industry 4.0

The adoption of LoRaWAN in industrial sectors demonstrates robust trends in scalability and effectiveness. In precision agriculture, LoRaWAN-based intelligent irrigation systems improve agricultural productivity, reducing water and energy losses [14]–[18]. Success cases include Australian vineyards where implementation cut frost losses by 40% and increased grape quality by 15%, as well as projects in Latin America (Teleagro in Colombia) that showed a 35% reduction in operational costs for livestock [19], [20].

In smart cities, LoRaWAN networks monitor environmental variables for early risk detection [18]. In energy, advanced metering systems based on LoRaWAN optimize distribution and failure detection. In Quito (Ecuador), its application reduced the time to detect electrical failures from 45 to 8 minutes, demonstrating potential for critical infrastructures [21]–[23]. In logistics, LoRaWAN networks enable real-time asset tracking and fleet management [24]–[26]. Recent research confirms that LoRaWAN is a key solution for increasing production, efficiency, and profitability in energy, industrial, and agricultural contexts, creating social impact through improved community quality of life [27], [28].

3.4. Integration with machine learning and deep learning

The convergence of LoRaWAN with advanced learning techniques marks a major advance in performance optimization. Initial studies by Fu [29] linked control theory and machine learning, proposing data labelling and pattern recognition as key elements for adaptive control systems. Subsequent research implemented LoRaWAN-based ultrasonic sensor networks with implicit machine learning techniques for estimating volumes of granular materials [30]. Zhao *et al.* [31] addressed energy efficiency optimization in underground wireless networks using a multi-agent reinforcement learning algorithm, considering link quality, energy consumption, and collision, surpassing battery life limitations.

Farhad and Pyun [32] demonstrated that machine learning enhances LoRaWAN performance through: i) network parameter optimization (spreading factor, power, bandwidth); ii) interference mitigation; and iii) operational efficiency improvement. Real-world applications in environmental monitoring and energy optimization illustrate the positive impact of machine learning [32]. At the algorithmic level, LoRaWAN optimization using machine learning focuses on multi-agent reinforcement learning management. In these models, each node acts as an agent that seeks to maximize a reward function defined by minimizing the bit error rate and energy consumption. Specifically, Q-learning algorithms are used to dynamically adjust the spreading factor and transmission power, overcoming the limitations of standardized ADR in environments with high electromagnetic interference. On the other hand, the autoencoder architecture mentioned above uses dense encoding layers to extract features from the noisy channel, allowing the decoder at the gateway to reconstruct signals below the thermal noise threshold, which is critical in dense industrial infrastructures.

Cuomo *et al.* [33] applied clustering (k-means) and long short-term memory (LSTM) neural networks in an Italian network with 1,862 devices and 138 gateways, achieving 77% accuracy in transmission pattern prediction. This allowed identification of subgroups with specific needs and parameter tuning to avoid channel inefficiencies [33]. Deep learning shows even greater potential. Shilpa *et al.* [34] developed an autoencoder with three components (transmitter network, channel simulation, receiver network), achieving a significant reduction in bit error rate, a 20% improvement in collision rate, and a 5% increase in packet success rate, even under low signal-to-noise ratio and variable spreading factors [34].

These results confirm that deep learning increases the reliability and efficiency of LoRa networks, consolidating it as a scalable solution for dense IoT networks [34].

Advanced optimization via multi-agent reinforcement learning and deep learning supports the transition from static network management to cognitive environments is increasingly supported by multi-agent reinforcement learning frameworks, which allow LoRaWAN nodes to independently optimize their spreading factor and transmission power [35]. Recent studies demonstrate that deep learning architectures are not only effective for signal classification but also crucial for interference mitigation in industrial sectors characterized by high electromagnetic noise [36]. These advancements are fundamental for achieving the high levels of energy efficiency required in the integration of AI with IoT for smart energy management systems [37].

Transformers and attention mechanisms in industrial monitoring a significant shift in the state-of-the-art is the application of Transformers and attention mechanisms to process multi-modal sensor data in industry 4.0 [38]. Unlike traditional recurrent architectures, transformers provide superior handling of long-range dependencies in time-series data, which is essential for accurate anomaly detection and predictive maintenance [39]. By capturing complex temporal patterns, these models enable the development of high-fidelity digital twins that can simulate industrial processes with unprecedented precision [39]–[44].

4. DISCUSSION: TECHNOLOGICAL TRADE-OFFS AND CHALLENGES

4.1. Competitive advantages of long-range wide-area network

Literature analysis reveals that LoRaWAN stands out as the most versatile technology within the LPWAN ecosystem. While Sigfox and NB-IoT have specific advantages, LoRaWAN offers a unique combination of low energy consumption, LoRa (up to 18 km in rural areas), and low cost (devices at USD 15 versus USD 50 for NB-IoT) [9], [11]. Its operation in unlicensed ISM bands greatly reduces costs and allows deployment in public or private configurations, offering flexibility unavailable in technologies like NB-IoT with licensed spectrum. In terms of energy, LoRaWAN devices achieve a 15-year lifespan in low-frequency applications [9], outperforming competitors. However, NB-IoT maintains advantages in critical applications demanding ultra-low latencies (< 10 ms), such as industrial robot automation. Emerging innovations expand capabilities: integration with low earth orbit satellites reaches an 85% packet success rate in remote regions such as the Arctic [31], [45], [46]. Beyond cost reduction, the capability to deploy private LoRaWAN infrastructures grants industrial operators total data sovereignty. Unlike NB-IoT, which depends on the third-party cellular operators, LoRaWAN allows factories to keep sensitive operational data within their local intranet, mitigating cybersecurity risks associated with public cloud dependency.

4.2. Persistent challenges and future research

Despite its advantages, LoRaWAN faces critical challenges:

i) Security: although AES-128 encryption offers robust protection, vulnerabilities persist against replay attacks and weaknesses in over-the-air (OTA) updates [11], [31]. Future research must develop adaptive security mechanisms.
ii) Interoperability: integration with 5G/6G networks remains incipient, limiting convergence with emerging ecosystems [11], [31].
iii) Scalability in high density: while LoRaWAN supports thousands of devices, recent research using machine learning shows advanced optimizations are necessary in ultra-dense scenarios [32], [33].
iv) Moderate latency: in critical industrial applications requiring latency <10 ms, LoRaWAN falls short compared to NB-IoT+5G [11], [31].

Research opportunities include: i) deep integration of deep learning for adaptive prediction of parameters; ii) implementation of lightweight cryptography (LWC) and blockchain integration to ensure data integrity in resource-constrained edge devices; iii) strategic convergence with 5G/6G; and iv) evaluation of sustainability and electronic waste management. Edge AI and federated learning for low-latency operations to address the latency constraints of centralized cloud computing. Edge AI architectures have emerged to perform real-time data processing directly at the gateway or node level [47]. This decentralized approach is further enhanced by federated learning, which allows for the collaborative training of machine learning models across multiple industrial sites while preserving data privacy and minimizing bandwidth consumption [41]. These paradigms are vital for scaling LoRaWAN deployments in dense environments where data sovereignty is a critical requirement [41].

Security, blockchain, and sustainability in IoT ecosystems as industrial networks expand, security and sustainability become paramount; the integration of blockchain technology with LoRaWAN provides a decentralized ledger for immutable device authentication and secure logistics tracking [48]. Simultaneously, recent research highlights the necessity of adopting green IoT practices, focusing on the management of electronic waste and the implementation of energy-harvesting techniques to extend the lifecycle of

autonomous sensors [40]. These measures ensure that the digital transformation of Industry 4.0 remains both secure and environmentally responsible [40], [48].

Future directions: 6G, explainable artificial intelligence (XAI), and industry 5.0. Looking toward the next decade, the convergence of LoRaWAN with 6G networks and low earth orbit satellite constellations is expected to provide ubiquitous global connectivity for remote industrial assets [49]. Future frameworks will likely incorporate XAI to ensure transparency in autonomous decision-making processes, which is a cornerstone of the emerging industry 5.0 paradigm [43]. Furthermore, the development of quantum-resistant encryption and vision-based industrial inspection through vision transformers (ViT) represents the next frontier in the evolution of cognitive industrial systems [42]–[44].

5. CONCLUSION

LoRaWAN is consolidated as a strategic technology in industry 4.0, balancing energy efficiency, transmission range, and cost-effectiveness. Its transversal versatility extends to sectors as diverse as precision agriculture, smart cities, and energy management, enabling modernized industrial operations. Integration with machine learning and deep learning represents a qualitative leap, mitigating current limitations in scalability and efficiency. Studies show a 20% improvement in collision rate and a 5% increase in packet success rate through deep learning, validating its potential for complex industrial scenarios. Nonetheless, challenges in adaptive security, 5G/6G interoperability, and real-time implementation require ongoing research. Hybrid solutions combining LoRaWAN with emerging technologies expand its global applicability, as evidenced by integration with low earth orbit satellites (85% success in the Arctic). In conclusion, LoRaWAN emerges as a key enabler for the digital transformation of industry 4.0, empowering companies to respond to dynamic demands and achieve superior operational efficiency. Ultimately, the convergence of LoRaWAN with edge AI represents a paradigm shift from purely communicative nodes to cognitive sensor networks. This evolution positions LoRaWAN not merely as a connectivity option, but as the backbone of the cognitive industrial nervous system, capable of supporting the autonomous decision-making processes demanded by the next generation of Industry 5.0 frameworks.

FUNDING INFORMATION

Authors state no funding involved.

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
Hector Alejandro Alvarez-Paez	✓	✓			✓	✓	✓	✓	✓	✓		✓	✓	✓
Mauricio Galvis-Patiño	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
Jorge Luis Nisperuza-Toledo	✓				✓	✓			✓	✓			✓	
Oscar Fernando Penagos-Espinel	✓				✓	✓			✓	✓			✓	✓
Yeison Alberto Garcés-Gómez		✓	✓	✓	✓			✓	✓	✓	✓			✓

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

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [YAGG], upon reasonable request.

REFERENCES

[1] M. I. Khan *et al.*, "Integrating industry 4.0 for enhanced sustainability: pathways and prospects," *Sustainable Production and Consumption*, vol. 54, pp. 149-189, Mar. 2025, doi: 10.1016/j.spc.2024.12.012.

[2] H. Camblong, O. Curea, J. Ugartemendia, Z. Boussaada, I. Lizarralde, and G. Etxegarai, "Photovoltaic energy sharing: Implementation and tests on a real collective self-consumption system," *Heliyon*, vol. 9, no. 12, 2023, doi: 10.1016/j.heliyon.2023.e22252.

[3] M. Chiani and A. Elzanaty, "On the LoRa modulation for IoT: waveform properties and spectral analysis," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8463–8470, Oct. 2019, doi: 10.1109/JIOT.2019.2919151.

[4] H. U. Rahman, M. Ahmad, H. Ahmad, and M. A. Habib, "LoRaWAN: state of the art, challenges, protocols and research issues," in *2020 IEEE 23rd International Multitopic Conference (INMIC)*, Nov. 2020, pp. 1–6, doi: 10.1109/INMIC50486.2020.9318170.

[5] R. Islam, M. W. Rahman, R. Rubaiat, M. M. Hasan, M. M. Reza, and M. M. Rahman, "LoRa and server-based home automation using the internet of things (IoT)," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 6, pp. 3703–3712, Jun. 2022, doi: 10.1016/j.jksuci.2020.12.020.

[6] W. A. Jabbar *et al.*, "Development of LoRaWAN-based IoT system for water quality monitoring in rural areas," *Expert Systems with Applications*, vol. 242, May 2024, doi: 10.1016/j.eswa.2023.122862.

[7] H. Snyder, "Literature review as a research methodology: An overview and guidelines," *Journal of Business Research*, vol. 104, pp. 333–339, Nov. 2019, doi: 10.1016/j.jbusres.2019.07.039.

[8] M. A. Ertürk, M. A. Aydın, M. T. Büyükakkaşlar, and H. Evirgen, "A survey on LoRaWAN architecture, protocol and technologies," *Future Internet,* vol. 11, no. 10, Oct. 2019, doi: 10.3390/fi11100216.

[9] M. Ballerini, T. Polonelli, D. Brunelli, M. Magno, and L. Benini, "NB-IoT versus LoRaWAN: an experimental evaluation for industrial applications," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 12, pp. 7802–7811, Dec. 2020, doi: 10.1109/TII.2020.2987423.

[10] Semtech, "LoRa technology overview," *semtech.com*. Accessed: Nov. 23, 2023. [Online]. Available: https://www.semtech.com/lora

[11] 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.

[12] Y. Lalle, L. C. Fourati, M. Fourati, and J. P. Barraca, "A comparative study of LoRaWAN, SigFox, and NB-IoT for smart water grid," in *2019 Global Information Infrastructure and Networking Symposium (GIIS)*, Dec. 2019, pp. 1–6, doi: 10.1109/GIIS48668.2019.9044961.

[13] A. I. Ali and S. Z. Partal, "Development and performance analysis of a ZigBee and LoRa-based smart building sensor network," *Frontiers in Energy Research*, vol. 10, 2022, doi: 10.3389/fenrg.2022.933743.

[14] M. Benzaouia, B. Hajji, A. Mellit, and A. Rabhi, "Fuzzy-IoT smart irrigation system for precision scheduling and monitoring," *Computers and Electronics in Agriculture*, vol. 215, 2023, doi: 10.1016/j.compag.2023.108407.

[15] J. K. Hart and K. Martinez, "Sensor networks and geohazards," in *Treatise on Geomorphology*, Elsevier, 2022, pp. 100–120, doi: 10.1016/B978-0-12-818234-5.00037-7.

[16] P. de A. Fernández, J. L. C. Candás, and P. Arboleya, "Internet of things (IoT) for power system applications," in *Encyclopedia of Electrical and Electronic Power Engineering*, 2023, pp. 486–496, doi: 10.1016/B978-0-12-821204-2.00072-6.

[17] R. C.-Vara, A. G.-Briones, J. Prieto, and J. M. Corchado, "Smart contract for monitoring and control of logistics activities: garbage utilities case study in a smart city," in *Encyclopedia of Renewable and Sustainable Materials*, 2020, pp. 614–618, doi: 10.1016/B978-0-12-803581-8.11439-0.

[18] L. O.-Gonzalez, M. A.-Coll, G. P.-Espitia, and S. A. Butt, "Communication protocols evaluation for a wireless rainfall monitoring network in an urban area," *Heliyon*, vol. 7, no. 6, Jun. 2021, doi: 10.1016/j.heliyon.2021.e07353.

[19] J. P. Rodríguez, A. I. M.-Munoz, C. R.-Pabon, J. Hoyos, and J. C. Corrales, "IoT-Agro: a smart farming system to Colombian coffee farms," *Computers and Electronics in Agriculture*, vol. 190, Nov. 2021, doi: 10.1016/j.compag.2021.106442.

[20] W. Tao, L. Zhao, G. Wang, and R. Liang, "Review of the internet of things communication technologies in smart agriculture and challenges," *Computers and Electronics in Agriculture*, vol. 189, Oct. 2021, doi: 10.1016/j.compag.2021.106352.

[21] A. Osorio, M. Calle, J. Soto, and J. E. C.-Becerra, "Routing in LoRa for smart cities: a gossip study," *Future Generation Computer Systems*, vol. 136, pp. 84–92, Nov. 2022, doi: 10.1016/j.future.2022.05.028.

[22] A. Gabriel and F. Cruz, "Open source IoT-based collection bin applied to local plastic recycling," *HardwareX*, vol. 13, Mar. 2023, doi: 10.1016/j.ohx.2022.e00389.

[23] N. E. Guevara, Y. H. Bolaños, J. P. Diago, and J. M. Segura, "Development of a low-cost IoT system based on LoRaWAN for monitoring variables related to electrical energy consumption in low voltage networks," *HardwareX*, vol. 12, Oct. 2022, doi: 10.1016/j.ohx.2022.e00330.

[24] C. Bolaños, B. Rojas, R. S.-Cabrera, G. R.-González, Á. P. de la Cruz, and J. M. M. Molina, "Fleet management and control system for developing countries implemented with intelligent transportation systems (ITS) services," *Transportation Research Interdisciplinary Perspectives*, vol. 16, Dec. 2022, doi: 10.1016/j.trip.2022.100694.

[25] A.-C. P. Patricia *et al.*, "Teleagro's telecommunications architecture-georeferencing and detection of Bovine Cattle Zeal," *Procedia Computer Science*, vol. 170, pp. 1065–1070, 2020, doi: 10.1016/j.procs.2020.03.072.

[26] H. Li, M. B. Kaleem, Z. Liu, Y. Wu, W. Liu, and Z. Huang, "IoB: Internet-of-batteries for electric vehicles–architectures, opportunities, and challenges," *Green Energy and Intelligent Transportation*, vol. 2, no. 6, Dec. 2023, doi: 10.1016/j.geits.2023.100128.

[27] T. Ahmad *et al.*, "Energetics systems and artificial intelligence: applications of industry 4.0," *Energy Reports*, vol. 8, pp. 334–361, Nov. 2022, doi: 10.1016/j.egyr.2021.11.256.

[28] Y. A. Sukhodolov, "The notion, essence, and peculiarities of Industry 4.0 as a sphere of industry," *Studies in Systems, Decision and Control*, vol. 169, pp. 3–10, 2019, doi: 10.1007/978-3-319-94310-7_1.

[29] K. Fu, "Learning control systems and intelligent control systems: an intersection of artificial intelligence and automatic control," *IEEE Transactions on Automatic Control*, vol. 16, no. 1, pp. 70–72, Feb. 1971, doi: 10.1109/TAC.1971.1099633.

[30] A. Pozzebon, M. Benini, C. Bocci, A. Fort, S. Parrino, and F. Rapallo, "Grid-layout ultrasonic LoRaWAN-based sensor networks for the measurement of the volume of granular materials," *Measurement*, vol. 220, 2023, doi: 10.1016/j.measurement.2023.113404.

[31] G. Zhao, K. Lin, D. Chapman, N. Metje, and T. Hao, "Optimizing energy efficiency of LoRaWAN-based wireless underground sensor networks: a multi-agent reinforcement learning approach," *Internet of Things*, vol. 22, 2023, doi: 10.1016/j.iot.2023.100776.
[32] 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.
[33] F. Cuomo, D. Garlisi, A. Martino, and A. Martino, "Predicting LoRaWAN behavior: how machine learning can help," *Computers*, vol. 9, no. 3, Jul. 2020, doi: 10.3390/computers9030060.
[34] B. Shilpa, P. R. Kumar, and R. K. Jha, "LoRa DL: a deep learning model for enhancing the data transmission over LoRa using autoencoder," *Journal of Supercomputing*, vol. 79, no. 15, pp. 17079–17097, 2023, doi: 10.1007/s11227-023-05355-4.
[35] 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.
[36] P. Savvidis and G. A. Papakostas, "Edge computing for computer vision in IoT: feasibility and directions," *EAI Endorsed Transactions on Internet of Things*, vol. 11, Oct. 2025, doi: 10.4108/eetiot.9404.
[37] M. A. Lodhi *et al.*, "A contextual aware enhanced LoRaWAN adaptive data rate for mobile IoT applications," *Computer Communications*, vol. 232, Feb. 2025, doi: 10.1016/j.comcom.2024.108042.
[38] A. S. Lutakamale, H. C. Myburgh, and A. de Freitas, "A hybrid convolutional neural network-transformer method for received signal strength indicator fingerprinting localization in long-range wide-area network," *Engineering Applications of Artificial Intelligence*, vol. 133, Jul. 2024, doi: 10.1016/j.engappai.2024.108349.
[39] A. A. Zakaria, T. Amr, and A. A. Ragheb, "IoT in smart Urban planning: a comprehensive review of applications, developments, and engineering perspectives," *IEEE Access*, vol. 13, pp. 135316–135335, 2025, doi: 10.1109/ACCESS.2025.3594019.
[40] N. Bouchemal, N. Chollet, and A. R.-Cherif, "Intelligent IoT platform for agroecology: Testbed," *Journal of Sensor and Actuator Networks*, vol. 13, no. 6, Dec. 2024, doi: 10.3390/jsan13060083.
[41] A. Triantafyllou *et al.*, "Resource-efficient federated LoRaWAN architecture for far-edge IoT applications," *IEEE Access*, vol. 13, pp. 108766–108785, 2025, doi: 10.1109/ACCESS.2025.3580375.
[42] S. Wali, M. I. Khan, and M. Imran, "Semantic-aware reinforcement and ensemble learning for signal management and anomaly detection in IoT systems," *Scientific Reports*, vol. 15, no. 1, Nov. 2025, doi: 10.1038/s41598-025-26500-4.
[43] M. A. B.-Rabee, P. Mohanty, D. Al-Ibrahim, A. A. Alrasheedi, and I. Ed. Al Balaa, "Sus-Bin: sustainable battery-free smart garbage bin for solid waste management in smart city," *IEEE Access*, vol. 13, pp. 191065–191084, 2025, doi: 10.1109/ACCESS.2025.3628872.
[44] M. Chen, J. B.-Othman, L. Mokdad, and J. Ling, "Urban expressway traffic state forecast via graph neural network and LoRaWAN communication," *IEEE Internet of Things Journal*, vol. 12, no. 15, pp. 29913–29924, 2025, doi: 10.1109/JIOT.2025.3569260.
[45] T. Røste, K. Yang, and C. Wen, "Satellite to buoy IoT communications in the Arctic Ocean," *Frontiers in Marine Science*, vol. 10, 2023, doi: 10.3389/fmars.2023.1153798.
[46] A. Seferagić, J. Famaey, E. D. Poorter, and J. Hoebeke, "Survey on wireless technology trade-offs for the industrial internet of things," *Sensors,* vol. 20, no. 2, Jan. 2020, doi: 10.3390/s20020488.
[47] A. J. S.-Vergel, P. Sankaran, J. C. Velez, R. A.-Mier, and D. R.-Rios, "AtomicVAD: A tiny voice activity detection model for efficient inference in intelligent IoT systems," *Internet of Things*, vol. 35, Jan. 2026, doi: 10.1016/j.iot.2025.101822.
[48] M. Chen, Y. Zhang, Z. Ji, C. B.-Rodríguez, and K. Zhang, "AI-enhanced generalizable scheme for path loss prediction in LoRaWAN," *IEEE Internet of Things Journal*, vol. 11, no. 8, pp. 14593–14606, Apr. 2024, doi: 10.1109/JIOT.2023.3342984.
[49] X. Jin, J. Teng, and J. Chen, "IoT-edge hybrid architecture with cross-modal transformer and federated manifold learning for safety-critical gesture control in adaptive mobility platforms," *Future Internet*, vol. 17, no. 7, Jun. 2025, doi: 10.3390/fi17070271.

BIOGRAPHIES OF AUTHORS



Hector Alejandro Alvarez-Paez holds a master's degree in Engineering with an emphasis on software for intelligent systems and IoT, and a bachelor's degree in Aeronautical Engineering from Fundación Universitaria Los Libertadores. His career combines teaching experience, applied research, and technological development in areas such as data analysis, computational design, programming, and aeronautical systems. He has led academic processes within the Department of Basic Sciences, standing out for his assertive communication, responsibility, and analytical skills. His experience includes participation in aeronautical innovation projects with the Colombian air force and scientific contributions in topics related to space trajectories and IoT ecosystems. He is proficient in multiple programming languages, CAD/CAE tools, and scientific computing platforms. His profile reflects an integral and adaptable professional with strong potential for technological development and interdisciplinary research. He can be contacted at email: haalvarezp@libertadores.edu.co.



Mauricio Galvis-Patiño received his bachelor's degree in Physics Engineering from the Universidad Nacional de Colombia, and his master's degree in Sciences with Emphasis in Physics from the Universidad del Tolima, Colombia. He later pursued doctoral studies in Engineering at the Department of Physics and took part in advanced research activities within the Magnetism and Simulation Group at the Universidad de Antioquia, Medellín, Colombia. He is currently a research professor at the Fundación Universitaria Los Libertadores, Bogotá, and an active collaborator of the Magnetism and Simulation Group at Universidad de Antioquia. He can be contacted at email: mauriciogalvis@libertadores.edu.co.



Jorge Luis Nisperuza-Toledo earned his Ph.D. in Physics from Universidad Nacional de Colombia. His academic profile spans advanced research in fundamental physics alongside leadership in engineering education and innovation. As dean of the Faculty of Engineering and Basic Sciences at Fundación Universitaria Los Libertadores, he has championed interdisciplinary curricula that bridge physical sciences, intelligent systems, and applied technologies. His research contributions include studies on dark matter candidates and scalar-sector extensions to the Standard Model of particle physics. With expertise in computational modelling, simulation and data-driven research methods, he fosters the development of engineers and scientists equipped to tackle complex scientific and technological challenges. He can be contacted at email: jorge.nisperuza@libertadores.edu.co.



Oscar Fernando Penagos-Espinel his bachelor's degree in Electronic Engineering from Fundación Universitaria Los Libertadores and later earned a master's degree in Electronic Engineering from the Universidad Nacional de Colombia. His professional experience spans teaching, research, and academic leadership in areas such as machine learning, control systems, automation, robotics, and embedded systems. He has served as a full-time professor at multiple institutions, teaching courses in artificial intelligence, digital communications, signal processing, and systems engineering. His research includes contributions to mobile robotics, image analysis, and intelligent navigation methods. He currently serves as program director for Electronic Engineering and Mechatronics, demonstrating strong analytical skills, ethical commitment, and a proactive approach to technological development and innovation. He can be contacted at email: ofpenagose@libertadores.edu.co.



Yeison Alberto Garcés-Gómez received bachelor's degree in electronic engineering, and master's degrees and Ph.D. in Engineering from the Department of Electrical, Electronic and Computer Engineering, Universidad Nacional de Colombia, Manizales, Colombia, in 2009, 2011 and 2015, respectively. He is full professor at the Academic Unit for Training in Natural Sciences and Mathematics, Universidad Católica de Manizales, and teaches several courses such as experimental design, statistics, and physics. His main research focus is on applied technologies, embedded systems, power electronics, and power quality, but also many other areas of electronics, signal processing and didactics. He has published more than 30 scientific and research publications, among them more than 10 journal papers. He can be contacted at email: ygarcesg@ucm.edu.co.