International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

A Critical and Analytical Review on Energy Optimization of Industrial Internet of Thing Nodes in Industry 4.0

Miss Sunanda Balkrishna Mane[1], Dr. Pradip Chandrakant Bhaskar[2]

[1]Research Scholar, Electronic Technology, Department of Technology, Shivaji University, Kolhapur.
[2]Professor, Electronic Technology, Department of Technology, Shivaji University, Kolhapur.

Abstract

The Industrial Internet of Things (IIoT) plays a central role in Industry 4.0 by enabling intelligent automation, real-time monitoring, and data-driven industrial decision-making. However, large-scale deployment of battery-powered IIoT nodes is constrained by excessive energy consumption and limited battery lifetime, particularly in harsh and inaccessible industrial environments. Although numerous energy-efficient techniques have been reported, most existing review studies remain largely descriptive and provide limited analytical insight into practical deployment challenges.

This paper presents a critical and analytical review of energy optimization strategies for IIoT nodes, with particular focus on transmission power control, duty cycle optimization, and intelligence-driven energy management techniques. An energy-centric taxonomy is developed to classify energy consumption across hardware, communication, network, and intelligence layers. Furthermore, existing solutions are comparatively analyzed with respect to energy efficiency, latency, computational overhead, scalability, and industrial feasibility.

The analysis indicates that while deep learning and reinforcement learning–based approaches offer strong adaptability in dynamic environments, their high computational complexity and deployment constraints limit real-world applicability. Based on these findings, key research challenges are identified, and future directions emphasizing lightweight and adaptive reinforcement learning frameworks are outlined. The study aims to provide structured insights to support the design of sustainable and scalable IIoT systems in Industry 4.0.

Keywords: Industrial Internet of Things; Energy Optimization; Transmission Power Control; Duty Cycle Optimization; Edge Intelligence; Reinforcement Learning.

1. Introduction

Industry 4.0 represents a paradigm shift in manufacturing, integrating cyber–physical systems, Industrial Internet of Things (IIoT), cloud computing, and artificial intelligence to achieve flexible, efficient, and autonomous industrial operations. IIoT networks enable large-scale interconnection of sensors, actuators, machines, and control systems, generating massive volumes of industrial data. The amount of data generated by connected devices continues to grow rapidly as the IoT expands; industry analysts project that the number of IoT connections will reach approximately **21.9 billion by 2026**, underscoring the sustained acceleration in data creation and associated resource demands **[1]**. While such connectivity improves productivity and operational visibility, it also introduces critical challenges related to the energy consumption of IoT nodes.

Most IIoT nodes are battery-operated and often deployed in harsh or inaccessible industrial environments, where frequent battery replacement is costly or impractical. Communication, sensing, and local computation contribute significantly to power depletion, with wireless transmission being the dominant energy consumer. Consequently, energy optimization has become a central research problem in IIoT system design.

Despite the availability of techniques such as transmission power control, duty cycle scheduling, and learning-based resource management, existing review studies largely summarize prior work without offering systematic comparison or deployment-oriented analysis. This paper addresses this limitation by providing an analytical review that synthesizes existing approaches, identifies performance trade-offs, and highlights concrete research gaps relevant to Industry 4.0.

The remaining paper is organized as follows: Section II presents the general architecture and operational framework of Industrial Internet of Things (IIoT) networks from an energy perspective. Section III analyzes the major sources of energy consumption in IoT nodes deployed within IIoT environments, highlighting communication and computation overheads. Section IV provides an analytical discussion on the need for transmission power control and duty cycle optimization, including their impact on power consumption and computational efficiency. Section V critically reviews existing research, identifies key challenges, and outlines future research directions for energy-efficient IoT nodes in the context of big data–driven industrial applications. Finally, Section VI concludes the paper by summarizing the main findings and highlighting potential research opportunities.

1.1 Key Contributions of This Review

The major contributions of this paper are summarized as follows:

- **Energy-Centric Taxonomy for IIoT Nodes:** A structured and layered taxonomy is proposed to classify energy consumption in IIoT nodes across hardware-level, communication-level, network-level, and intelligence-level dimensions, enabling a holistic understanding of power consumption sources in Industry 4.0 environments.
- **Analytical Evaluation Beyond Descriptive Survey:** Unlike existing surveys that primarily summarize prior work, this review provides a comparative analytical assessment of energy optimization techniques by examining trade-offs among energy efficiency, latency, computational complexity, scalability, and industrial feasibility.
- **Critical Assessment of Learning-Based Techniques:** Machine learning and deep reinforcement learning–based energy optimization approaches are critically analyzed, highlighting practical challenges such as training overhead, model complexity, explainability, and suitability for resource-constrained IIoT nodes.
- **Identification of Practical Research Gaps:** Key open challenges are identified, including the lack of unified cross-layer optimization frameworks, limited use of real industrial datasets, and insufficient consideration of security–energy trade-offs.
- **Future Research Directions for Industry 4.0:** The review outlines future research directions emphasizing lightweight, adaptive, and scalable reinforcement learning–based energy management strategies that balance energy efficiency, reliability, and deployment feasibility in real-world industrial systems.

2. Architecture of IIoT Networks from an Energy Perspective

A typical IIoT architecture is composed of four logical layers: sensing, communication, data processing, and application. Each layer contributes differently to overall energy consumption and system performance.

The sensing layer includes sensors and actuators responsible for data acquisition. Energy consumption at this layer depends on sensing frequency, sensor resolution, and hardware efficiency. The communication layer is the primary energy bottleneck, as wireless data transmission and reception consume significant power. The data processing layer, often implemented at the edge or fog, reduces cloud dependency but introduces additional computational energy costs. Finally, the application layer supports industrial services such as predictive maintenance and automation, indirectly influencing energy consumption through latency and reliability requirements. From an energy optimization perspective, the communication and edge-processing layers contribute the highest power consumption, making them the primary targets for adaptive optimization techniques in industrial deployments.

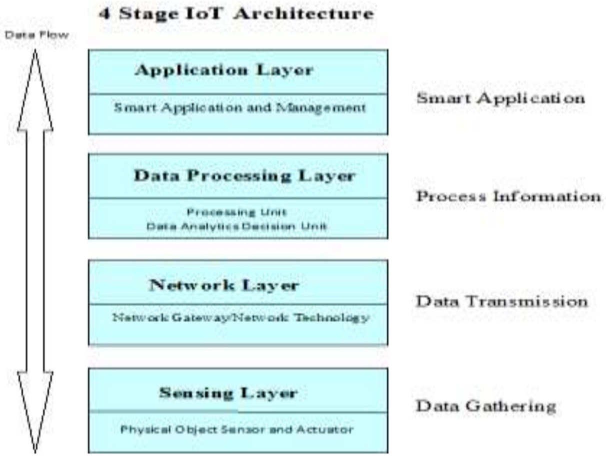

Figure 1: General architecture of IIOT

3. Taxonomy of Energy Consumption in IIoT Nodes

To enable structured analysis, energy consumption in IIoT nodes is classified into four categories: hardware-level, communication-level, network-level, and intelligence-level energy consumption. Hardware-level optimization focuses on low-power components and energy harvesting. Communication-level strategies, such as transmission power control and duty cycle optimization, yield the highest immediate energy savings. Network-level optimization addresses routing and topology management, while intelligence-level optimization employs machine learning and reinforcement learning for adaptive decision-making. This taxonomy enables a systematic comparison of optimization strategies across different system layers, which is largely missing in existing IIoT energy surveys.

4. Analytical Review of Energy Optimization Techniques

4.1. Transmission Power Control

Transmission Power Control (TPC) dynamically adjusts the transmission power of IoT nodes based on channel conditions, distance, and quality-of-service requirements. Analytical studies demonstrate that adaptive TPC can significantly extend network lifetime; however, improper tuning may increase packet loss and retransmissions.

4.2. Duty Cycle Optimization

Duty cycle control reduces energy consumption by alternating nodes between active and sleep states. While static duty cycling is simple, it is unsuitable for dynamic industrial traffic patterns. Adaptive and learning-based duty cycle mechanisms offer improved performance at the cost of higher coordination complexity.

4.3. Edge Intelligence and Learning-Based Approaches

Recent approaches employ machine learning and deep reinforcement learning to jointly optimize communication and computation parameters. These methods provide adaptability in time-varying environments but introduce challenges related to training overhead, model complexity, and real-world deployment feasibility.

5. Related Work

5.1. Literature Collection and Review Methodology

In this review, high-quality and relevant research articles were systematically collected, screened, and analyzed to ensure comprehensive coverage of energy consumption and optimization strategies in IIoT networks. Major scientific databases and digital libraries, including Google Scholar, Scopus, IEEE Xplore, Elsevier ScienceDirect, and MDPI, were explored for publications from 2015 to 2024. Keywords such as “Industrial IoT,” “Industry 4.0,” “energy consumption of IoT nodes,” “transmission power control,” and “duty cycle optimization” were employed during the search process.

The selected studies were carefully filtered based on relevance, technical contribution, and publication quality. This systematic selection process provided a reliable foundation for analyzing energy consumption challenges, optimization techniques, and open research issues related to IIoT nodes in big data–driven industrial environments.

5.2 Communication-Level Energy Optimization Techniques

Communication-level optimization remains the most dominant approach for reducing energy consumption in IIoT nodes. Transmission Power Control (TPC) and duty cycle optimization are widely adopted due to their direct impact on wireless energy usage. Sodhro et al. [3] demonstrated that TPC-based energy-efficient algorithms can achieve significant energy savings while maintaining acceptable packet loss ratios, although reliability variations were observed. Similar power control strategies using deep reinforcement learning have been explored for Device-to-Device (D2D) networks [4], achieving high energy efficiency at the expense of increased network complexity.

Duty cycle optimization approaches, such as FCDAA [7] and Q-learning-based schemes [21], effectively reduce idle listening and extend network lifetime. However, these approaches often struggle with scalability and coordination overhead in dense IIoT deployments. Studies on transmission power optimization for data and acknowledgment packets [20] further highlight that simplifying power control assumptions may lead to misleading energy estimates in industrial environments.

5.3. Edge Computing and Computation Offloading Approaches

Edge and Multi-Access Edge Computing (MEC) architectures have been widely investigated to reduce communication overhead and latency while improving energy efficiency. Zhang et al. [2] proposed a Multi-Agent System Model (MASM) with task execution allocation to balance energy-delay trade-offs across edge servers, though generalized deployment remains a challenge. Computation offloading strategies using optimization algorithms [9], deep learning [13], and deep reinforcement learning [15], [17] have demonstrated improved energy and latency performance in dynamic environments.

Despite their advantages, these approaches often introduce high computational complexity, training overhead, and security vulnerabilities. Moreover, most existing solutions rely on simulation-based evaluations, limiting their applicability in real-world IIoT systems handling continuous big data streams.

5.4. AI-Driven and Learning-Based Energy Optimization

Artificial intelligence and machine learning techniques have gained increasing attention for adaptive energy management in IIoT networks. Neural network–based approaches [8], [14], [38] enable real-time edge intelligence and anomaly detection, reducing cloud dependency and processing delay. However, such models often increase computational burden and require prior system knowledge, which may not be feasible for resource-constrained IIoT nodes.

Deep learning–based optimization frameworks [13], [17] show promising results in managing complex resource allocation problems but raise concerns regarding explainability, scalability, and energy overhead. These challenges emphasize the need for lightweight and interpretable learning models suitable for industrial deployment.

5.5 Energy Harvesting, Security, and System-Level Optimization

Energy harvesting techniques, including wireless power transfer [10], LoRaWAN-based harvesting [33], optically powered sensor nodes [34], and ambient self-powered cluster-based networks [23], provide alternative solutions to extend network lifetime. While these approaches reduce battery dependence, limited power availability and deployment cost restrict large-scale adoption.

Security and privacy-preserving mechanisms [5], [18], [22], [37] are critical for Industry 4.0 applications but often increase energy consumption due to encryption and authentication overhead. Similarly, system-level optimization approaches such as clustering [35], localization optimization [36], and cross-layer big data frameworks [31] improve operational efficiency but introduce significant computational and architectural complexity.

Table No.1: Comparison between parameters with energy saving, complexity, scalability, limitation

Technique	Energy Saving	Complexity	Scalability	Limitation
Transmission Power Control	High	Low	High	Reliability trade-off
Duty Cycle Optimization	Moderate–High	Low	Moderate	Coordination overhead
Edge Computing	Moderate	Moderate	Moderate	Infrastructure cost
Deep Learning	High	High	Low–Moderate	Training overhead
Reinforcement Learning	Very High	High	Limited	Computational burden

5.6. Summary of Challenges and Research Gaps

Based on the critical analysis of existing literature, several open challenges remain unresolved:

1. Absence of unified cross-layer optimization frameworks integrating communication and computation energy management
2. High computational overhead of deep learning and optimization algorithms
3. Limited validation using real industrial datasets
4. Inadequate consideration of **security–energy trade-offs**

5. Scalability issues in dense and heterogeneous IIoT networks

These limitations indicate the need for **lightweight, adaptive, and scalable energy optimization frameworks**, particularly reinforcement learning–based approaches that can dynamically balance energy efficiency, latency, and reliability in Industry 4.0 environments.

6. Open Research Gaps and Future Directions

Key research gaps include the lack of unified cross-layer optimization frameworks, limited availability of real industrial datasets, insufficient consideration of security and reliability, and high computational overhead of deep learning models. Future research should focus on lightweight reinforcement learning techniques and experimental validation in real industrial environments.

7. Discussion

The comparative analysis indicates that communication-level optimization techniques, particularly transmission power control and duty cycle optimization, provide the most immediate and practical energy savings with minimal computational overhead. While intelligence-driven approaches, particularly deep reinforcement learning, demonstrate superior adaptability and long-term energy efficiency, their **high computational cost and limited scalability** restrict their applicability in real-world IIoT deployments. This highlights the need for **lightweight and hybrid energy optimization frameworks** tailored to industrial constraints.

8. Conclusion

This paper presented a critical and analytical review of energy optimization techniques for IIoT nodes in Industry 4.0. By introducing a structured taxonomy and comparative analysis, the review moves beyond descriptive surveys and highlights practical limitations and research opportunities. The findings emphasize the need for adaptive, cross-layer energy management solutions to achieve sustainable and scalable IIoT deployments.

References:

1. Wireless Logic, “Five IoT trends for 2026,” Wireless Logic Blog, 2024. [Online] .Available: https://wirelesslogic.com/blog/five-iot-trends-for-2026. [Accessed: Jan. 2026].
2. W. Zhang, Z. Zhang, S. Zeadally, H. C. Chao, and V. Leung, “MASM: A multiple-algorithm service model for energy-delay optimization in edge artificial intelligence,” IEEE Trans. Ind. Informat., 2019.
3. Ali Hassan Sodhro, Snadeep Pirbhylal, Marwa Qaraqe, Sonia Lohano, Gul Hassan Sodhro, Naveed Ur Rehman Junejo and Zongwei Luo,”Power Control Algorithms for Media Transmission in Remote Healthcare Systems”, DOI 10.1109/ACCESS 2018.2859205,IEEE Access 2018.
4. Ban T-W. “A Self-Regulating Power-Control Scheme Using Reinforcement Learning for D2D Communication Networks”, Sensors. 2022; 22(13):4894. https://doi.org/10.3390/s22134894
5. Z. Kahleifeh and H. Thapliyal, "2-Phase Energy-Efficient Secure Positive Feedback Adiabatic Logic for CPA-Resistant IoT Devices," 2020 IEEE 6th World Forum on Internet of Things (WF-IoT), New Orleans, LA, USA, 2020, pp. 1-5, DOI: 10.1109/WF-IoT48130.2020.9221065.
6. M. Choi, H. Chung and I. Kim, "An Efficient Power Management Method For IoT Devices of Moving Network," 2020 International Conference on Information Networking (ICOIN), Barcelona,

Spain, 2020, pp. 29-31, DOI: 10.1109/ICOIN48656.2020.9016446.

7. A. H. Sodhro, S. Pirbhulal and V. H. C. de Albuquerque, "Artificial Intelligence-Driven Mechanism for Edge Computing-Based Industrial Applications," in IEEE Transactions on Industrial Informatics, vol. 15, no. 7, pp. 4235-4243, July 2019, DOI: 10.1109/TII.2019.2902878.
8. S. Chen, P. Gong, B. Wang, A. Anpalagan, M. Guizani and C. Yang, "EDGE AI for Heterogeneous and Massive IoT Networks," 2019 IEEE 19th International Conference on Communication Technology (ICCT), Xi'an, China, 2019, pp. 350-355, DOI: 10.1109/ICCT46805.2019.8947193.
9. Ahsan Rafiq , Wang Ping , Wei Min , Seung Ho Hong , Nteziriza Nkerabahizi Josbert A. Rafiq, W. Ping, W. Min, S. H. Hong and N. N. Josbert, "Optimizing Energy consumption and Latency based on computation offloading and cell association in MEC enabled Industrial IoT environment," 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP), Xi'an, China, 2021, pp. 10-14, DOI: 10.1109/ICSP51882.2021.9408693.
10. W. Ejaz, M. Naeem and S. Zeadally, "On-Demand Sensing and Wireless Power Transfer for Self-Sustainable Industrial Internet of Things Networks," in IEEE Transactions on Industrial Informatics, vol. 17, no. 10, pp. 7075-7084, Oct. 2021, DOI: 10.1109/TII.2020.3025510.
11. Y. Lu, X. Huang, Y. Dai, S. Maharjan and Y. Zhang, "Blockchain and Federated Learning for Privacy-Preserved Data Sharing in Industrial IoT," in IEEE Transactions on Industrial Informatics, vol. 16, no. 6, pp. 4177-4186, June 2020, DOI: 10.1109/TII.2019.2942190.
12. J. Okwuibe, J. Haavisto, E. Harjula, I. Ahmad and M. Ylianttila, "SDN Enhanced Resource Orchestration of Containerized Edge Applications for Industrial IoT," in IEEE Access, vol. 8, pp. 229117-229131, 2020, DOI: 10.1109/ACCESS.2020.3045563.
13. L. Wang, X. Sun, R. Jiang, W. Jiang, Z. Zhong and D. W. Kwan Ng, "Optimal Energy Efficiency for Multi-MEC and Blockchain Empowered IoT: a Deep Learning Approach," ICC 2021 - IEEE International Conference on Communications, Montreal, QC, Canada, 2021, pp. 1-6, DOI: 10.1109/ICC42927.2021.9500558.
14. J. Kwon and D. Park, "Efficient Sensor Processing Technique Using Kalman Filter-Based Velocity Prediction in Large-Scale Vehicle IoT Application," in IEEE Access, vol. 10, pp. 116735-116746, 2022, DOI: 10.1109/ACCESS.2022.3215166.
15. L. Ale, N. Zhang, X. Fang, X. Chen, S. Wu and L. Li, "Delay-Aware and Energy-Efficient Computation Offloading in Mobile-Edge Computing Using Deep Reinforcement Learning," in IEEE Transactions on Cognitive Communications and Networking, vol. 7, no. 3, pp. 881-892, Sept. 2021, DOI: 10.1109/TCCN.2021.3066619.
16. F. A. Jeffrey Vaz, K. Kanika, V. Padmavathi, R. Nishanthi and S. Priyadharshini, "Intelligent Battery Power Optimizer for IoT Devices," 2019 International Conference on Recent Advances in Energy-efficient Computing and Communication (ICRAECC), Nagercoil, India, 2019, pp. 1-4, DOI: 10.1109/ICRAECC43874.2019.8995054.
17. Y. Chen, Z. Liu, Y. Zhang, Y. Wu, X. Chen and L. Zhao, "Deep Reinforcement Learning-Based Dynamic Resource Management for Mobile Edge Computing in Industrial Internet of Things," in IEEE Transactions on Industrial Informatics, vol. 17, no. 7, pp. 4925-4934, July 2021, DOI: 10.1109/TII.2020.3028963.
18. M. Golec, S. S. Gill, R. Bahsoon and O. Rana, "BioSec: A Biometric Authentication Framework for Secure and Private Communication Among Edge Devices in IoT and Industry 4.0," in IEEE

Consumer Electronics Magazine, vol. 11, no. 2, pp. 51-56, 1 March 2022, DOI: 10.1109/MCE.2020.3038040.

19. L. Cui et al., "Joint Optimization of Energy Consumption and Latency in Mobile Edge Computing for Internet of Things," in IEEE Internet of Things Journal, vol. 6, no. 3, pp. 4791-4803, June 2019, DOI: 10.1109/JIOT.2018.2869226.
20. H. U. Yildiz, B. Tavli and H. Yanikomeroglu, "Transmission Power Control for Link-Level Handshaking in Wireless Sensor Networks," in IEEE Sensors Journal, vol. 16, no. 2, pp. 561-576, Jan.15, 2016, DOI: 10.1109/JSEN.2015.2486960.
21. Y. Li, K. K. Chai, Y. Chen and J. Loo, "Smart duty cycle control with reinforcement learning for machine to machine communications," 2015 IEEE International Conference on Communication Workshop (ICCW), London, UK, 2015, pp. 1458-1463, DOI: 10.1109/ICCW.2015.7247384.
22. Wang, C., Wang, D., Xu, G. et al. “Efficient privacy-preserving user authentication scheme with forward secrecy for industry 4.0”;. Sci. China Inf. Sci. **65**, 112301 (2022). https://doi.org/10.1007/s11432-020-2975-6
23. Haque, M.E., Baroudi, U. “Ambient self-powered cluster-based wireless sensor networks for industry 4.0 applications”;. Soft Comput **25**, 1859–1884 (2021). https://doi.org/10.1007/s00500-020-05259-y
24. J. Yan, Y. Meng, L. Lu and L. Li, "Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance," in IEEE Access, vol. 5, pp. 23484-23491, 2017, DOI: 10.1109/ACCESS.2017.2765544.
25. Devesh, M., Kant, A.K., Suchit, Y.R., Tanuja, P., Kumar, S.N. (2020). “Fruition of CPS and IoT in Context of Industry 4.0”. In: Choudhury, S., Mishra, R., Mishra, R., Kumar, A. (eds) Intelligent Communication, Control and Devices. Advances in Intelligent Systems and Computing, volume 989. Springer, Singapore. https://doi.org/10.1007/978-981-13-8618-3_39
26. J. Wan et al., "Software-Defined Industrial Internet of Things in the Context of Industry 4.0," in IEEE Sensors Journal, vol. 16, no. 20, pp. 7373-7380, Oct.15, 2016, DOI: 10.1109/JSEN.2016.2565621.
27. L. Leonardi, F. Battaglia, G. Patti and L. L. Bello, "Industrial LoRa: A Novel Medium Access Strategy for LoRa in Industry 4.0 Applications," IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society, Washington, DC, USA, 2018, pp. 4141-4146, DOI: 10.1109/IECON.2018.8591568.
28. Kumar, N., & Kumar, J. (2019).”Efficiency 4.0 for Industry 4.0”, Human Technology, 15(1), 55–78. https://doi.org/10.17011/ht/urn.201902201608
29. Logeshwaran, J., Kiruthiga, T., Kannadasan, R., Vijayaraja, L., Alqahtani, A., Alqahtani, N., & Alsulami, A. A. (2023). “Smart Load-Based Resource Optimization Model to Enhance the Performance of Device-to-Device Communication in 5G-WPAN”; Electronics, 12(8), 1821. https://doi.org/10.3390/electronics12081821
30. Preuveneers D, Ilie-Zudor E. “The intelligent industry of the future: A survey on emerging trends, research challenges and opportunities in Industry 4.0”,. Journal of Ambient Intelligence and Smart Environments. 2017;9(3):287-298. DOI:10.3233/AIS-170432
31. Muhammad Faheem, Rizwan Aslam Butt, Rashid Ali, Basit Raza, Md. Asri Ngadi, Vehbi Cagri Gungor,CBI4.0: “A cross-layer approach for big data gathering for active monitoring and

maintenance in the manufacturing industry 4.0”, Journal of Industrial Information Integration, Volume 24,2021,100236, ISSN 2452-414X,https://doi.org/10.1016/j.jii.2021.100236.

32. Blanco-Novoa, O., Fernandez-Carames, T. M., Fraga-Lamas, P., & Vilar-Montesinos, M. A. (2018). “A practical evaluation of commercial industrial augmented reality systems in an industry 4.0 shipyard”, IEEE Access, 6, 8201-8218.
33. H. H. R. Sherazi, M. A. Imran, G. Boggia and L. A. Grieco, "Energy Harvesting in LoRaWAN: A Cost Analysis for the Industry 4.0," in IEEE Communications Letters, vol. 22, no. 11, pp. 2358-2361, Nov. 2018, DOI: 10.1109/LCOMM.2018.2869404.
34. Souza, L. C., Neto, E. R., Lima, E. S., & Junior, A. C. S. (2022). “Optically-Powered Wireless Sensor Nodes towards Industrial Internet of Things.”; Sensors, 22(1), 57. https://doi.org/10.3390/s22010057
35. Mistarihi, M. Z., Bany Salameh, H. A., Alsaadi, M. A., Beyca, O. F., Heilat, L., & Al-Shobaki, R. (2023). “Energy-Efficient Bi-Objective Optimization Based on the Moth–Flame Algorithm for Cluster Head Selection in a Wireless Sensor Network”, Processes, 11(2),534. https://doi.org/10.3390/pr11020534
36. Alfawaz, O., Osamy, W., Saad, M. et al. “Modified Rat Swarm Optimization Based Localization Algorithm for Wireless Sensor Networks”, Wireless Pers Communication **130**, 1617–1637 (2023). https://doi.org/10.1007/s11277-023-10347-x
37. Hammad, M., Jillani, R. M., Ullah, S., Namoun, A., Tufail, A., Kim, K.-H., & Shah, H. (2023). “Security Framework for Network-Based Manufacturing Systems with Personalized Customization: An Industry 4.0 Approach”,. Sensors, 23(17),7555. https://doi.org/10.3390/s23177555
38. Lilhore, U. K., Manoharan, P., Simaiya, S., Alroobaea, R., Alsafyani, M., Baqasah, A. M., Dalal, S., Sharma, A., & Raahemifar, K. (2023). “HIDM: Hybrid Intrusion Detection Model for Industry 4.0 Networks Using an Optimized CNN-LSTM with Transfer Learning”,. Sensors 23(18),7856. https://doi.org/10.3390/s23187856/