Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Energy Harvesting Technique for Improved WSN Performance: Application of IOT and Deep Learning

Vishal Singh
Assistant Professor
Centre for Distance and Online Education
Punjabi University, Patiala

ARTICLE INFO

Received: 25 Dec 2023

Accepted: 22 Jan 2024

ABSTRACT

Due to technological advances, real-time automation systems using IoT-based sensor networks increasingly need faultless data transmission over wireless sensor networks (WSN). Nowadays, Wireless Multimedia Sensor Networks (WMSNs) have taken precedence over conventional scalar wireless sensors that can extract scalar sensor data together with video, audio, and image data. Such networks are expected to eventually span the whole planet in the future. These advancements with many benefits have introduced significant obstacles too, like high energy consumption, that require the deployment of optimized energy-efficient techniques. Machine learning (ML) approaches that can handle dynamic scenarios with a successful learning process have been utilized recently in WSNs as a solution to this challenge. WSNs specifically employ Deep Learning (DL) techniques, a subclass of machine learning techniques distinguished by the application of deep neural networks, to extract higher-level features from unprocessed sensor data, hence reducing computational complexity and increasing energy efficiency, etc. This paper has reviewed all such techniques based on deep learning for energy harvesting in WSN. Professionals working in this field will find this paper's review analysis extremely fascinating, as it will assist them in selecting the best methods for their particular applications.

Keyword: Wireless Sensor Networks, Multimedia Data, Energy Harvesting Technique, IOT and Deep Learning.

1. Introduction

In the modern world, WSN applications are becoming more and more common; some examples include agricultural automation, medical systems, and manufacturing control systems [1]. It has been used in all of these applications to measure, track, and store data pertaining to actual quantities including temperature, light, motion, humidity, moisture, air pressure, and vibration. Nowadays, Wireless Multimedia Sensor Networks (WMSNs) have taken precedence over conventional scalar wireless sensors networks that can extract scalar sensor data together with video, audio, and image data. The availability of inexpensive CMOS cameras and microphones, along with significant developments in distributed signal processing and multimedia source coding methods, have made WMSNs capable of delivering multimedia material.

The number of electronic devices connected to the Internet has grown at a rate never seen before in history as a result of these advancements in wireless network technologies. The World Data Corporation estimates that the number of smart devices connected to networks may have reached anywhere between tens of billions and up to one trillion by the year 2020. These include 212 billion accessible sensors, 0.110 billion integrated autos with 5.5 billion sensors, 1.2 million home automation systems with 200 million sensors, and over 0.5 billion sensor systems in American companies [2]. Over 24.1 billion IoT devices—roughly four gadgets per person—are expected to exist globally by 2030 [3]. As a result of the significant advancements in wireless sensor technologies, the issue of managing, handling protecting data and energy issues associated with WSN has grown significantly.

Real-time multimedia data is inherently complex due to its high data rate, strict latency requirements, and the need for efficient compression, transmission, and processing mechanisms, hence WSNs have different qualities and challenges. Furthermore, WSNs have a number of problems related to energy limitations and computational complexity, because of their limited memory capacity, poor processor power, short battery life, and resource constraints [4]. Particularly in

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

energy-intensive applications like multimedia processing and real-time data transmission, these limitations make it difficult to manage massive data quantities, carry out intricate calculations, and guarantee long-term network operation. On the other hand the use of multimedia data cannot be avoided, as it is a necessity in state-of-the-art technologies and the modern world [5].

An ultimate solution to this problem is a statistical or mathematical framework that establishes connections among the raw sensor data collected in the first stage and the ultimate decision adopted in the last stage. When the dynamic volatility of WSN operating conditions is within a manageable range, the successful operation of WSNs is frequently achieved by the use of a well-defined statistical or mathematical framework. These frameworks, however, fall short in offering suitable answers when the dynamic variance exceeds the acceptable threshold. Furthermore, rather than offering a trend-based link between raw sensor data and the final decision, the majority of these frameworks for modeling technical concerns in WSNs only offer the instantaneous relationship. Owing to these points of view, recent WSN applications have used machine learning (ML) approaches that could address the systematic association between the two [6].

It is an artificial intelligence (AI) algorithm, which uses example data to learn tasks automatically without explicit programming [7], [8]. Without the requirement for specialized human participation, machine learning techniques enable the creation of complicated models based only on data. This intervention-free feature makes the solutions derived from machine learning approaches more effective, affordable, and adaptable. The four main categories of machine learning approaches are semi-supervised learning, supervised learning, unsupervised learning, and reinforcement learning (RL).

Numerous WSN applications, including classification, clustering, dimensionality reduction, feature extraction, and forecasting, have effectively incorporated machine learning techniques [9], [10]. Finding the best solution, such as the best location for sensor placement, lowering computational complexity, such as the bandwidth needed to send gathered sensor data, and flexibility, such as the ability to respond to changing inputs, are just a few benefits of using machine learning techniques on WSNs. Explicit mathematical expressions can be used to characterize some machine learning algorithms that yield positive outcomes for various WSN applications. Deep Learning (DL) is another subset of AI have been used recently in a number of Wireless Sensor Network (WSN) applications and are anticipated to be essential to their future growth, especially in fields like data processing, anomaly detection, and energy optimization [11],[12],[13].

The rest of the paper is structured as follows: the research objectives are presented in Section II. Section III has given the detailed research methodology of the present work. Section IV summarized the review of the research area and methodology employed in the reported work. Section V gives an analysis of the model/technique applied in the reviewed papers. The detailed overview of results and applications of the reviewed paper is given in Section VI. Finally, the conclusion has been given in the following section VII.

2. Research Objectives

The papers primary goal was to conduct a thorough review of critical issues associated with WSN in order to use deep learning techniques for optimal energy harvesting solution. The last five years reported work was addressed in the review. Furthermore, there are two particular goals:

1. Compile and evaluate the most representative studies carried out to tackle energy issues in WSN using machine learning techniques;
2. Using ML approaches, create a critical assessment and discussion of the body of knowledge currently available in the creation of optimal solution for energy harvesting.

3. Research Methodology

Antonio Tavares, Luiz Scavarda, and Annibal Scavarda's 2016 [14] methodology is modified in this literature analysis to provide a representative and methodical examination of energy harvesting in WSN that employ DL technology. Eight parts make up this methodology: "(1) problem formulation and planning, (2) literature review search, (3) data collection, (4) quality assessment, (5) data synthesis and analysis, (6) interpretation, (7) results presentation, and (8) review updating."

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

As indicated in Table 1, different keyword combinations were utilized in the Scopus and SCI databases search in accordance with the selected approach. The methodology was used as a result. 102 documents were then chosen for in-depth examination. Last but not the least, 54 documents that improved the survey were added.

Table 1. Approach to filter papers

	Approach
Keywords	Wireless Sensor Networks, Sensors, Wireless Multimedia Sensor Networks, Internet of Things , Energy harvesting, Energy Harvesting in WSN, Energy efficiency, Machine Learning, Deep Learning, Deep Learning for Energy Optimization, IoT-based WSN Energy Management Energy-Efficient WSN using AI , Wireless Sensor Networks Power Optimization, Optimal Energy Harvesting for IoT-WSN, Adaptive Power Management in IoT Sensor Networks, Hybrid energy harvesting in IoT, Sustainability, Sustainable WSN using AI and IoT
Keyword filter	
1st filter	The last five years from 2018 to 2022
2nd filter	Paper, Conference Paper, Review, or Short Survey
3rd filter	English papers
4th filter	Focus on papers that specifically deal with WSN and energy harvesting
5th filter	The documents are filtered using abstract analysis.

Along with keyword, publication span has been selected; further a more comprehensive approach based on metadata analysis of the paper was applied for data gathering. Figure 1 illustrates the methodology the author employed to carry out a systematic literature review for this investigation. Three separate processes or stages make up the review process as shown in figure 1. In paper findings, the paper for the suggested research was chosen using paper recognition from several databases. Scopus, and SCI databases must be accessed at this point. Based on the caliber and renown of their scientific outputs, the three databases were chosen for the investigation. The chosen papers were then arranged according to the H index values. The detailed analysis for the same is presented in the table 2.

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

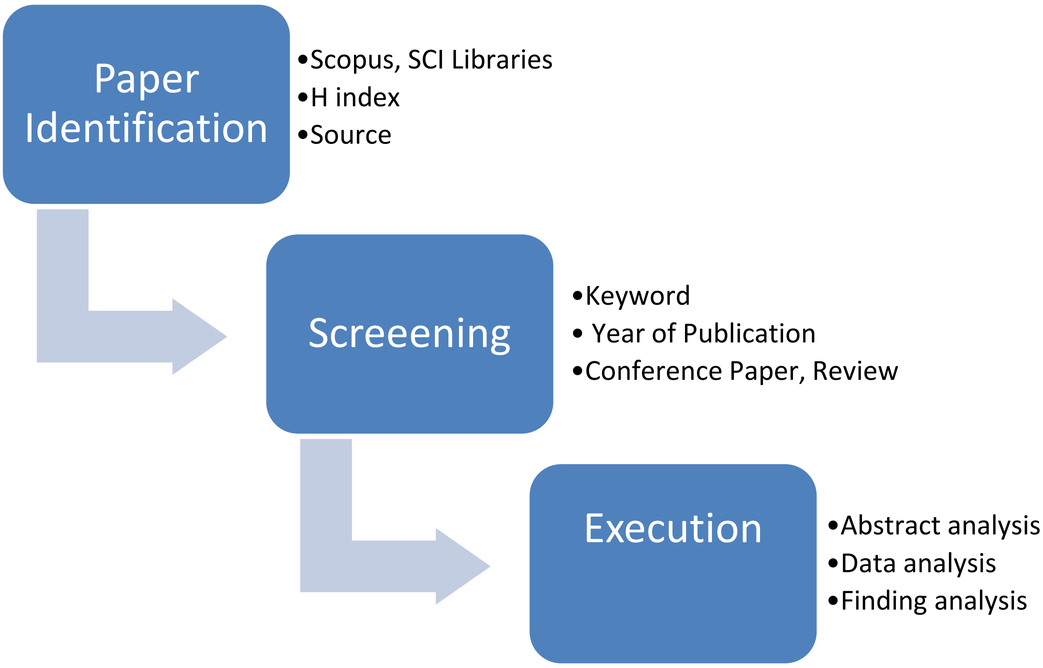

Figure 1: Systematic research methodology

Table 2: Metadata analysis of review papers

Author(s)	Year	Source	H-index	Citation Count
Rajaram & Sathiyaraj	2022	Journal of Electrical Engineering & Technology	46	74
Ijemaru et al.	2022	International Journal of Distributed Sensor Networks	73	87
Riba et al.	2022	Applied Sciences	162	35
Mysorewala et al.	2022	Renewable and Sustainable Energy Reviews	464	76
Mansura et al.	2022	Peer-to-Peer Networking and Applications	55	20
Khan et al.	2022	Journal of King Saud University-Science	77	59
Seid et al.	2022	IEEE Journal on Selected Areas in Communications	274	79
Saadane et al.	2022	Sustainable Energy Technologies and Assessments	98	91
Lv & Xu	2022	IEEE Access	290	23
Yamin & Bhat	2022	IEEE Transactions on Computer-Aided Design of Integrated Circuits & Systems	136	12
Ehlali & Sayah	2022	European Journal of Electrical Engineering and Computer Science	9	11
Elsayed et al.	2022	Journal of Sensor and Actuator Networks	47	45
Manikandan et al.	2022	ICPECTS (Conference)	7	2
Sanislav et al.	2021	IEEE Access	290	367
Ahmad et al.	2021	Measurement	160	75
Grossi	2021	Electronics	397	72
Williams et al.	2021	IEEE Access	290	149
Riaz et al.	2021	IEEE Sensors Journal	172	253
Singh et al.	2021	International Journal of Energy Research	133	188

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Ismail et al.	2021	IEEE Access	290	26
Lu et al.	2021	Sustainable Cities and Society	156	73
Chimeh et al.	2021	IEEE Sensors Journal	172	32
Zhu et al.	2021	Nano Energy	277	136
Yao & Ansari	2021	IEEE Transactions on Green Communications and Networking	54	32
Sangoleye et al.	2021	IEEE Sensors Journal	172	13
Younus et al.	2021	IEEE Internet of Things Journal	208	74
Sharma, Haque & Blaabjerg	2021	Electronics (MDPI)	110	242
Nguyen & Kim	2021	Electronics (MDPI)	110	18
Sah & Amgoth	2020	Information Fusion	179	234
Kumar et al.	2020	3rd Int. Conf. on Emerging Technologies in Computer Engineering	NA	16
Sah & Amgoth	2020	Wireless Networks	107	61
Haq et al.	2020	International Journal of Distributed Sensor Networks	73	20
Gupta & De	2020	IEEE Transactions on Signal and Information Processing over Networks	44	41
Raza & Salam	2020	Electronics (MDPI)	110	39
Gulec et al.	2020	IEEE Access	290	90
Eltresy et al.	2020	Journal of Sensors	70	35
Xu et al.	2020	Computer Communications	138	27
Zhang et al.	2020	npj Flexible Electronics	55	385
Nguyen et al.	2020	IEEE Internet of Things Journal	208	64
Ren et al.	2020	Energies	175	16
Lam et al.	2020	IEEE Access	290	50
Kim et al.	2020	IEEE Sensors Journal	172	149
Kathiriya et al.	2020	ICRITO (Conference)	7	24
Elahi et al.	2020	Energies	175	250
Wahba et al.	2020	IEEE Access	290	47
Eltresy et al.	2019	Sensors (MDPI)	273	39
Ma et al.	2019	IEEE Communications Surveys & Tutorials	287	390
Puri & Bhushan	2019	ICCCIS (Conference)	NA	29
Alsharif et al.	2019	Symmetry (MDPI)	102	135
Tang et al.	2018	Sensors (MDPI)	273	295
Chu et al.	2018	IEEE Internet of Things Journal	208	184
Fraternali et al.	2018	Workshop Proceedings	69	31
Shafique et al.	2018	IEEE Access	290	155
Sharma, Haque & Jaffery	2018	Journal of Sensor and Actuator Networks	47	122

The majority of the papers included for this review are published in reputable SCI and SCOPUS-indexed journals, as shown in Table 2. At the same time, a few relevant works are from international conferences and workshops, which were considered due to their technical contribution to the field. It is also evident that IEEE journals account for a substantial portion of the literature, reflecting their strong presence in research on energy harvesting, wireless sensor networks, and IoT applications.

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

4. Review of Research Area and Methodology Employed

The study area and methodologies used in the reviewed papers have been examined in this section. Such an analysis is valuable for classifying and selecting publications according to their focus and the methods applied to the topic under study. Together with the names of the authors and references, Table 3 displays the study findings and corresponding methodologies. To ensure fair and accurate comparisons, the evaluation of each study was carried out using consistent criteria and analytical methods.

Table 3: Analysis of Research Area and Methodology

Author(s)	Reference No.	Research Area and Methodology Analysis
Rajaram and Sathiyaraj, 2022	[13]	Optimization-based approach
Ijemaru et al., 2022	[14]	Survey of distributed sensor network techniques
Riba et al., 2022	[15]	Review-based study
Mysorewala et al., 2022	[16]	Survey of wireless sensor-based harvesting techniques
Mansura et al., 2022	[17]	Routing protocol development
Khan et al., 2022	[18]	AI-driven power forecasting and optimization
Seid et al., 2022	[19]	Multi-agent deep reinforcement learning
Saadane et al., 2022	[20]	AI-driven modeling and IoT integration
Lv & Xu 2022	[21]	Survey on deep learning in EH-IoT devices.
Yamin & Bhat 2022	[22]	Imitation learning for energy management in EH-IoT.
Ehlali & Sayah 2022	[23]	Review of EH strategies for WSN lifespan improvement.
Elsayed et al. 2022	[24]	Deep learning-based intrusion detection for clustered IoT.
Manikandan et al. 2022	[25]	ML-based techniques for energy efficiency and security in WSN.
Sanislav et al., 2021	[26]	Review-based study
Ahmad et al., 2021	[27]	Review of approaches
Grossi, 2021	[28]	Review of harvesting strategies
Williams et al., 2021	[29]	Review study
Riaz et al., 2021	[30]	Comparative analysis of energy storage technologies, efficiency, and improvements
Singh et al., 2021	[31]	Systematic survey of energy harvesting techniques
Ismail et al., 2021	[32]	Reviewed energy-efficient tracking and harvesting techniques
Lu et al., 2021	[33]	Edge-based renewable energy strategies
Chimeh et al., 2021	[34]	AI-driven parameter optimization
Zhu et al., 2021	[35]	Textile-based graphene sensors for energy-efficient monitoring
Yao & Ansari, 2021	[36]	Deep reinforcement learning-based power control
Sangoleye et al., 2021	[37]	AI-driven optimization for energy harvesting
Younus et al. 2021	[38]	Reinforcement learning for routing in SD-WSN.
Sharma et al. 2021	[39]	Survey on ML in WSNs for smart cities.
Nguyen & Kim 2021	[40]	Review of sensor types, ad hoc topologies, and EH methods.
Sah & Amgoth, 2020	[41]	Literature review on renewable energy harvesting schemes
Kumar et al., 2020	[42]	Analyzed energy conservation techniques and their network impact
Sah & Amgoth 2020	[43]	Clustering protocol for EH-WSN to improve lifetime and routing.
Haq et al., 2020	[44]	Clustering scheme validated via simulations
Gupta & De, 2020	[45]	Experimental studies on multi-sensing techniques
Raza & Salam, 2020	[46]	On-site and external energy harvesting for underground WSNs
Gulec et al., 2020	[47]	CDS algorithm for network longevity in solar energy-harvesting WSNs

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Eltresy et al., 2020	[48]	IoT integration with RF harvesting
Xu et al., 2020	[49]	AI-driven allocation strategies
Zhang et al., 2020	[50]	Deep learning-enabled wearable triboelectric sensors for IoT-based energy harvesting
Nguyen et al., 2020	[51]	Deep neural network-based relay selection for cognitive IoT with wireless power
Ren et al., 2020	[52]	Energy-efficient cellular networks with harvesting for green IoT
Lam et al., 2020	[53]	Deep learning for RF-powered food sensing IoT devices
Kim et al., 2020	[54]	Review of machine learning for advanced wireless sensor networks
Kathiriya et al., 2020	[55]	Protocols for energy-efficient self-powered WSNs in industrial IoT
Elahi et al., 2020	[56]	Comprehensive study on energy harvesting for self-powered IoT devices
Wahba et al., 2020	[57]	Predictive modeling of harvestable energy for wearable healthcare devices
Eltresy et al., 2019	[58]	RF energy harvesting system using deep learning for smart ambience control
Ma et al., 2019	[59]	Survey on sensing, computing, and communication for energy-harvesting IoT
Puri & Bhushan, 2019	[60]	Machine learning for enhancing energy efficiency and security in WSNs
Alsharif et al., 2019	[61]	Review of energy harvesting techniques for WSN and RFID systems
Tang et al., 2018	[62]	Review of self-powered WSNs for machine condition monitoring
Chu et al., 2018	[63]	RL-based multiaccess control and battery prediction for energy harvesting in IoT
Fraternali et al., 2018	[64]	Reinforcement learning for scalable configuration of EH sensors
Shafique et al., 2018	[65]	Low-cost rectenna-based energy harvesting for IoT applications
Sharma et al., 2018	[66]	Modeling and optimization of solar EH systems for WSN nodes

As shown in Table 3, energy harvesting in wireless sensor networks (WSNs) has evolved significantly to improve efficiency and sustainability, employing a variety of techniques such as mechanical, RF-based, solar, and hybrid energy harvesting. The effectiveness of these methods is influenced by numerous environmental factors, making AI-driven optimization and adaptive management techniques essential. Advances in IoT-enabled sensors, machine learning algorithms, and deep reinforcement learning have improved energy prediction, allocation, and storage efficiency.

Innovations such as wearable energy harvesters, textile-based graphene sensors, and triboelectric nanogenerators have increased power conversion rates by combining artificial intelligence with nanotechnology. Optimization approaches, including multi-agent reinforcement learning, cognitive radio clustering, and UAV-assisted energy harvesting, facilitate energy-efficient routing and decision-making in WSNs.

Comparative evaluations of energy storage innovations, such as advanced battery management systems and supercapacitors, show how AI can help extend network lifespans. Energy harvesting becomes more practical for real-world applications when edge computing, AI-driven modeling, and IoT integration are combined to enable dynamic power control. To further enhance the reliability and lifespan of self-powered WSNs, future studies are expected to focus on the seamless integration of distributed energy management techniques, AI-based optimization, and advanced material processing.

5. Analysis of model/technique applied in reviewed papers

The reviewed publications employ a wide range of models and techniques to enhance energy harvesting in wireless sensor networks (WSNs), with a strong focus on optimization, AI-driven strategies, and hybrid energy solutions. Many studies use deep reinforcement learning and machine learning to optimize power management, routing protocols, and energy distribution.

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Techniques such as cognitive radio-based clustering, UAV-assisted data transfer, and AI-driven relay optimization improve network efficiency by adapting dynamically to energy availability and environmental constraints. AI-based models are also used to forecast energy availability and optimize usage in hybrid energy harvesting systems, which combine solar, RF, thermal, and mechanical sources to maintain a constant power supply.
Comparisons of different energy storage methods, such as phase-change materials and supercapacitors, highlight the trade-offs between longevity, efficiency, and energy density. In addition, IoT-enabled frameworks often integrate AI and edge computing to improve real-time energy management.
The widespread use of AI, optimization algorithms, and multi-agent learning across these studies underlines the importance of intelligent and adaptive energy management for ensuring greater network resilience and longer operational lifespans.

Table 4: Analysis of model used

Author and Reference	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13
Rajaram and Sathiyaraj, 2022 [13]													✓
Ijemaru et al., 2022 [14]									✓				
Riba et al., 2022 [15]				✓									
Mysorewala et al., 2022 [16]													✓
Mansura et al., 2022 [17]									✓				
Khan et al., 2022 [18]	✓												
Seid et al., 2022 [19]									✓				
Saadane et al., 2022 [20]								✓					
Lv & Xu 2022 [21]													✓
Yamin & Bhat 2022 [22]								✓					
Ehlali & Sayah 2022 [23]					✓								
Elsayed et al. 2022 [24]				✓									

Manikandan et al. 2022 [25]				✓									
Sanislav et al., 2021 [26]													✓
Ahmad et al., 2021 [27]								✓					
Grossi, 2021 [28]					✓								
Williams et al., 2021 [29]				✓									
Riaz et al., 2021 [30]				✓									
Singh et al., 2021 [31]												✓	
Ismail et al., 2021 [32]								✓					
Lu et al., 2021 [33]												✓	
Chimeh et al., 2021 [34]	✓												
Zhu et al., 2021 [35]		✓											
Yao & Ansari, 2021 [36]									✓				
Sangoleye et al., 2021 [37]													✓
Younus et al. 2021 [38]												✓	
Sharma et al. 2021 [39]								✓					
Nguyen & Kim 2021 [40]												✓	
Sah & Amgoth, 2020 [41]													✓

Kumar et al., 2020 [42]													✓
Sah & Amgoth 2020 [43]								✓					
Haq et al., 2020 [44]												✓	
Gupta & De, 2020 [45]			✓										
Raza & Salam, 2020 [46]				✓									
Gulec et al., 2020 [47]								✓					
Eltresy et al., 2020 [48]												✓	
Xu et al., 2020 [49]			✓										
Zhang et al., 2020 [50]					✓								
Nguyen et al., 2020 [51]	✓												
Ren et al., 2020 [52]								✓					
Lam et al., 2020 [53]	✓												
Kim et al., 2020 [54]										✓			
Kathiriya et al., 2020 [55]	✓												
Elahi et al., 2020 [56]												✓	
Wahba et al., 2020 [57]													✓
Eltresy et al., 2019 [58]					✓								

Ma et al., 2019 [59]								✓					
Puri & Bhushan, 2019 [60]								✓					
Alsharif et al., 2019 [61]			✓										
Tang et al., 2018 [62]				✓									
Chu et al., 2018 [63]									✓				
Fraternali et al., 2018 [64]			✓										
Shafique et al., 2018 [65]													✓
Sharma et al., 2018 [66]									✓				

T1-Deep Neural Networks; T2: Machine Learning; T3: Deep Reinforcement Learning' T4: Collaborative Filtering; T5: Resource-Optimized DNNs; T6: Blockchain-enabled Task Offloading; T7: Graphene Textile-based Triboelectric Nanogenerator; T8: AI-based Smart Data Processing; T9: Optimal Status Update Model; T10: Neural Networks for Resource Allocation; T11: IoT-based Cooperative Spectrum Sharing;T12: Self-Sensing and Self-Powered System Model;T13: Smart Harvesting Protocol Models

6. Result and application analysis

Performance metrics are used to measure a model's or system's behavior, efficiency, and structure. These metrics should be presented in a structured format, providing quantitative values within defined ranges to form the basis for achieving the overall objectives of the proposed models.
The probability matrices and performance results of the models or systems proposed in the reviewed papers have been analyzed and are shown in Table 5.

Table 5: Result and application analysis of reviewed papers

Author(s)	Year	Result	Application
Rajaram and Sathiyaraj	2022	Improved power efficiency in greenhouse operations	Greenhouse Energy Management
Ijemaru et al.	2022	Enhanced sensor nodes lifetime using RF-based energy harvesting and WPT	Environmental Monitoring, Healthcare Monitoring
Riba et al.	2022	Comprehensive evaluation of harvesting methods	Power Transmission Lines

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Mysorewala et al.	2022	Enhanced sustainability of pipeline monitoring networks	Pipeline Monitoring Systems
Mansura et al.	2022	Proposed an energy-balanced and node-aware routing protocol	Energy Harvesting Wireless Sensor Networks
Khan et al.	2022	Boosted energy generation efficiency	Renewable Energy, Smart Grid
Seid et al.	2022	Optimized task scheduling in UAV networks	Unmanned Aerial Vehicles (UAV)
Saadane et al.	2022	Enhanced efficiency in smart agriculture	Smart Farming and AgriTech
Lv & Xu	2022	Surveyed deep learning approaches for EH-IoT devices	Energy Harvesting IoT Systems
Yamin & Bhat	2022	Proposed imitation learning for near-optimal energy management	Energy Harvesting IoT Devices
Ehlali & Sayah	2022	Reviewed EH strategies for improved lifespan of WSNs	Wireless Sensor Networks
Elsayed et al.	2022	Hierarchical deep learning-based intrusion detection	IoT Security Systems
Manikandan et al.	2022	Proposed ML-based energy efficiency and security methods	Wireless Sensor Networks
Sanislav et al.	2021	Comprehensive survey of energy harvesting techniques	Internet of Things (IoT)
Ahmad et al.	2021	Reviewed challenges and approaches of EH in sensor nodes for condition monitoring	Machine Condition Monitoring Systems
Grossi	2021	Comprehensive evaluation of wireless sensor networks	Wireless Sensor Networks (WSNs)
Williams et al.	2021	Comparative analysis of existing technologies	Wireless Sensor Networks (WSNs)
Riaz et al.	2021	Reviewed and compared energy storage technologies, highlighting challenges and recommendations	Micro-energy harvesting, WSNs, low-cost electronic devices
Singh et al.	2021	Classification of techniques	Sensor Network Protocols
Ismail et al.	2021	Reviews tracking methodologies	Sensor Tracking Systems
Lu et al.	2021	Optimized edge computing energy use	Smart Cities, Edge IoT

Chimeh et al.	2021	Improved low-frequency energy harvesting	MEMS, IoT Energy Harvesting
Zhu et al.	2021	IoT-based gas detection and real-time monitoring	Environmental Monitoring
Yao & Ansari	2021	Optimized wireless energy transfer	Wireless Power Transmission
Sangoleye et al.	2021	Efficient energy distribution in IoT	IoT Energy Management
Younus et al.	2021	Applied reinforcement learning to enhance routing performance	Software-defined WSN
Sharma, Haque & Blaabjerg	2021	Surveyed ML techniques in WSNs for smart city applications	Smart City Sensor Networks
Nguyen & Kim	2021	Survey of sensor types, topologies, and EH integration methods	Sensor Systems and EH Integration
Sah & Amgoth	2020	Overview of schemes	WSN Protocol Design
Kumar et al.	2020	Analysis of current methods	Wireless Sensor Networks
Sah & Amgoth	2020	Developed an efficient clustering protocol for EH WSNs	Wireless Sensor Networks
Haq et al.	2020	Proposed E2-MACH clustering scheme for energy-efficient EH WSNs	Wireless Sensor Networks
Gupta & De	2020	Improves sensing accuracy	IoT Sensor Systems
Raza & Salam	2020	Evaluates underground energy harvesting	Underground Sensor Networks
Gulec et al.	2020	Extends WSN lifetime with solar energy	Solar-Powered WSNs
Eltresy et al.	2020	Energy-efficient smart home systems	Smart Home Automation
Xu et al.	2020	Optimized energy harvesting in machine-to-machine networks	M2M Communication in IoT
Zhang et al.	2020	Developed DL-enabled triboelectric smart socks for gait and VR applications	Wearable IoT, Gait Analysis, VR
Nguyen et al.	2020	Improved wireless power transfer in cognitive IoT networks	Cognitive IoT
Ren et al.	2020	Energy-efficient IoT networking solutions	Green IoT

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Lam et al.	2020	IoT-based food monitoring using RF-powered sensors	Smart Food Supply Chain
Kim et al.	2020	Reviewed ML techniques for advanced WSN applications	Advanced Wireless Sensor Networks
Kathiriya et al.	2020	Survey of energy-efficient protocols for IIoT self-powered WSNs	Industrial IoT, Industry 4.0
Elahi et al.	2020	Overview of EH technologies for self-powered IoT	Self-powered IoT Devices
Wahba et al.	2020	Predicted energy potential for wearable healthcare devices	Wearable Healthcare Devices
Eltresy et al.	2019	RF-EH system using deep learning for museum control	IoT in Smart Museums
Ma et al.	2019	Surveyed sensing, computing, and communication in EH IoTs	Energy Harvesting IoT Systems
Puri & Bhushan	2019	Applied ML to enhance WSN security and energy efficiency	Wireless Sensor Networks
Alsharif et al.	2019	Reviewed EH techniques for WSN/RFID	Wireless Sensor Networks / RFID
Tang et al.	2018	Reviewed EH for self-powered WSNs in condition monitoring	Machine Condition Monitoring
Chu et al.	2018	Used RL for multiaccess and battery prediction in EH IoT	Energy Harvesting IoT Systems
Fraternali et al.	2018	Scaled EH sensor configurations with reinforcement learning	Energy-Neutral Sensing Systems
Shafique et al.	2018	Demonstrated low-cost rectenna for EH in IoT	Internet of Things (IoT)
Sharma, Haque & Jaffery	2018	Modeled and optimized solar EH system for WSN nodes	Wireless Sensor Networks

The analysis highlights advancements across several sectors, including Wireless Sensor Networks (WSNs), the Internet of Things (IoT), Smart Cities, Renewable Energy, Environmental Monitoring, and Wearable Electronics. A large proportion of research focuses on improving WSNs, with studies such as Mansura et al. (2022) and Younus et al. (2021) developing methods to extend network lifetime and improve energy efficiency. These improvements are particularly valuable in applications ranging from smart agriculture to environmental monitoring.

IoT-related research is also expanding rapidly, as seen in studies by Sanislav et al. (2021) and Elahi et al. (2020), which emphasize power management and harvesting techniques for IoT environments. Another growing field is the integration of multiple energy harvesting sources to support wearable electronics and IoT networks, as demonstrated by Wahba et al. (2020), which focused on energy prediction for wearable healthcare devices.

Renewable energy applications benefit from mechanical systems such as vibration-based harvesting, explored by Tang et al. (2018). Other significant topics include smart cities and sustainable infrastructure. For example, Sharma et al.

(2021) investigated machine learning-based energy optimization for urban development, while Manikandan et al. (2022) applied energy-efficient technologies in precision agriculture to improve resource use and yields.
Wearable electronics continue to evolve, with an emphasis on self-powered devices and human–machine interaction. Studies like Wahba et al. (2020) and Eltresy et al. (2019) demonstrate how AI and machine learning can improve sustainability and performance in these systems. Smart home automation and environmental monitoring also remain active research areas, with developments such as IoT-based sensors optimizing energy use in connected environments.

Conclusion

Energy harvesting methods in WSNs have been explored in this paper, with an emphasis on deep learning methods and Internet of Things-enabled solutions. It has been observed that energy management has been greatly enhanced by the combination of artificial intelligence, optimization algorithms, and multi-source energy harvesting, guaranteeing sustainability and effectiveness in WSNs. Deep learning techniques found improved decision-making in power optimization and routing. IoT frameworks use edge computing and AI-driven models for real-time energy forecast and allocation. AI-based techniques dynamically modify energy usage according to environmental conditions. The trade-offs between energy density, efficiency, and long-term performance is highlighted by comparative studies of energy storage devices in the paper. Finally, from the complete analysis of the paper it can be concluded that the integration of deep learning, IoT, and AI guarantees that future WSNs will be more intelligent, adaptable, and energy-efficient, opening the door for robust and sustainable energy harvesting solutions in a variety of applications.

References

[1] Younan, M., Khattab, S. and Bahgat, R., 2021. From the wireless sensor networks (WSNs) to the Web of Things (WoT): An overview. *J. Intell. Syst. Internet Things*, *4*(2), pp.56-68.
[2] Peixoto, M.L.M., Maia, A.H., Mota, E., Rangel, E., Costa, D.G., Turgut, D. and Villas, L.A., 2021. A traffic data clustering framework based on fog computing for VANETs. *Vehicular Communications*, *31*, p.100370.
[3] Younan, M., Khattab, S. and Bahgat, R., 2021. From the wireless sensor networks (WSNs) to the Web of Things (WoT): An overview. *J. Intell. Syst. Internet Things*, *4*(2), pp.56-68.
[4] Kennedy, M., Ksentini, A., Hadjadj-Aoul, Y. and Muntean, G.M., 2012. Adaptive energy optimization in multimedia-centric wireless devices: A survey. *IEEE communications surveys & tutorials*, *15*(2), pp.768-786.
[5] Bhatt, C.A. and Kankanhalli, M.S., 2011. Multimedia data mining: state of the art and challenges. *Multimedia Tools and Applications*, *51*, pp.35-76.
[6] Kim, T., Vecchietti, L.F., Choi, K., Lee, S. and Har, D., 2020. Machine learning for advanced wireless sensor networks: A review. *IEEE Sensors Journal*, *21*(11), pp.12379-12397.
[7] Samuel, A.L., 1959. Some studies in machine learning using the game of checkers. *IBM Journal of research and development*, *3*(3), pp.210-229.
[8] Alpaydin, E., 2020. *Introduction to machine learning*. MIT press.
[9] Alsheikh, M.A., Lin, S., Niyato, D. and Tan, H.P., 2014. Machine learning in wireless sensor networks: Algorithms, strategies, and applications. *IEEE Communications Surveys & Tutorials*, *16*(4), pp.1996-2018.
[10] Kumar, D.P., Amgoth, T. and Annavarapu, C.S.R., 2019. Machine learning algorithms for wireless sensor networks: A survey. *Information Fusion*, *49*, pp.1-25.
[11] Ye, J. and Gharavi, H., 2020. Deep reinforcement learning-assisted energy harvesting wireless networks. *IEEE transactions on green communications and networking*, *5*(2), pp.990-1002.
[12] Thomé, A.M.T., Scavarda, L.F. and Scavarda, A.J., 2016. Conducting systematic literature review in operations management. *Production Planning & Control*, *27*(5), pp.408-420.
[13] Rajaram, A., & Sathiyaraj, K. (2022). An improved optimization technique for energy harvesting system with grid connected power for green house management. *Journal of Electrical Engineering & Technology*, *17*(5), 2937-2949.
[14] Ijemaru, G. K., Ang, K. L. M., & Seng, J. K. (2022). Wireless power transfer and energy harvesting in distributed sensor networks: Survey, opportunities, and challenges. *International journal of distributed sensor networks*, *18*(3), 15501477211067740.

[15] Riba, J. R., Moreno-Eguilaz, M., & Bogarra, S. (2022). Energy harvesting methods for transmission lines: a comprehensive review. Applied Sciences, 12(21), 10699.
[16] Mysorewala, M. F., Cheded, L., & Aliyu, A. (2022). Review of energy harvesting techniques in wireless sensor-based pipeline monitoring networks. Renewable and Sustainable Energy Reviews, 157, 112046.
[17] Mansura, A., Drieberg, M., Aziz, A. A., Bassoo, V., & Sarang, S. (2022). An energy balanced and nodes aware routing protocol for energy harvesting wireless sensor networks. Peer-to-Peer Networking and Applications, 15(2), 1255-1280.
[18] Khan, Z. A., Hussain, T., & Baik, S. W. (2022). Boosting energy harvesting via deep learning-based renewable power generation prediction. Journal of King Saud University-Science, 34(3), 101815.
[19] Seid, A. M., Lu, J., Abishu, H. N., & Ayall, T. A. (2022). Blockchain-enabled task offloading with energy harvesting in multi-UAV-assisted IoT networks: A multi-agent DRL approach. IEEE Journal on Selected Areas in Communications, 40(12), 3517-3532.
[20] Saadane, R., Chehri, A., & Jeon, S. (2022). AI-based modeling and data-driven evaluation for smart farming-oriented big data architecture using IoT with energy harvesting capabilities. Sustainable Energy Technologies and Assessments, 52, 102093.
[21] Lv, M., & Xu, E. (2022). Deep learning on energy harvesting IoT devices: Survey and future challenges. IEEE Access, 10, 124999-125014.
[22] Yamin, N., & Bhat, G. (2022). Near-optimal energy management for energy harvesting IoT devices using imitation learning. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41(11), 4551-4562.
[23] Ehlali, S., & Sayah, A. (2022). Towards improved lifespan for wireless sensor networks: A review of energy harvesting technologies and strategies. European Journal of Electrical Engineering and Computer Science, 6(1), 32-38.
[24] Elsayed, R., Hamada, R., Hammoudeh, M., Abdalla, M., & Elsaid, S. A. (2022). A hierarchical deep learning-based intrusion detection architecture for clustered internet of things. Journal of Sensor and Actuator Networks, 12(1), 3.
[25] Manikandan, S., Suganthi, S., & Gayathiri, R. (2022, December). Optimal Energy Efficiency Techniques and Security Enhancement in Wireless Sensor Network Using Machine Learning. In 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS) (pp. 1-5). IEEE.
[26] Sanislav, T., Mois, G. D., Zeadally, S., & Folea, S. C. (2021). Energy harvesting techniques for internet of things (IoT). IEEE Access, 9, 39530-39549.
[27] Ahmad, I., Hee, L. M., Abdelrhman, A. M., Imam, S. A., & Leong, M. S. (2021). Scopes, challenges and approaches of energy harvesting for wireless sensor nodes in machine condition monitoring systems: A review. Measurement, 183, 109856.
[28] Grossi, M. (2021). Energy harvesting strategies for wireless sensor networks and mobile devices: A review. Electronics, 10(6), 661.
[29] Williams, A. J., Torquato, M. F., Cameron, I. M., Fahmy, A. A., & Sienz, J. (2021). Survey of energy harvesting technologies for wireless sensor networks. IEEE Access, 9, 77493-77510.
[30] Riaz, A., Sarker, M. R., Saad, M. H. M., & Mohamed, R. (2021). Review on comparison of different energy storage technologies used in micro-energy harvesting, WSNs, low-cost microelectronic devices: challenges and recommendations. Sensors, 21(15), 5041.
[31] Singh, J., Kaur, R., & Singh, D. (2021). Energy harvesting in wireless sensor networks: A taxonomic survey. International Journal of Energy Research, 45(1), 118-140.
[32] Ismail, M. I. M., Dziyauddin, R. A., Ahmad, R., Ahmad, N., Ahmad, N. A., & Hamid, A. M. A. (2021). A review of energy harvesting in localization for wireless sensor node tracking. IEEE Access, 9, 60108-60122.
[33] Lu, M., Fu, G., Osman, N. B., & Konbr, U. (2021). Green energy harvesting strategies on edge-based urban computing in sustainable internet of things. Sustainable Cities and Society, 75, 103349.
[34] Chimeh, H. E., Nabavi, S., Al Janaideh, M., & Zhang, L. (2021). Deep-learning-based optimization for a low-frequency piezoelectric MEMS energy harvester. IEEE Sensors Journal, 21(19), 21330-21341.

Journal of Information Systems Engineering and Management
2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[35] Zhu, J., Cho, M., Li, Y., He, T., Ahn, J., Park, J., ... & Park, I. (2021). Machine learning-enabled textile-based graphene gas sensing with energy harvesting-assisted IoT application. Nano Energy, 86, 106035.
[36] Yao, J., & Ansari, N. (2021). Wireless power and energy harvesting control in IoD by deep reinforcement learning. IEEE Transactions on Green Communications and Networking, 5(2), 980-989.
[37] Sangoleye, F., Irtija, N., & Tsiropoulou, E. E. (2021). Smart energy harvesting for internet of things networks. Sensors, 21(8), 2755.
[38] Younus, M. U., Khan, M. K., & Bhatti, A. R. (2021). Improving the software-defined wireless sensor networks routing performance using reinforcement learning. IEEE Internet of Things Journal, 9(5), 3495-3508.
[39] Sharma, H., Haque, A., & Blaabjerg, F. (2021). Machine learning in wireless sensor networks for smart cities: a survey. Electronics, 10(9), 1012.
[40] Nguyen, P. D., & Kim, L. W. (2021). Sensor system: a Survey of sensor Type, Ad Hoc network Topology and energy harvesting techniques. Electronics, 10(2), 219.
[41] Sah, D. K., & Amgoth, T. (2020). Renewable energy harvesting schemes in wireless sensor networks: A survey. Information Fusion, 63, 223-247.
[42] Kumar, A., Dadheech, P., & Chaudhary, U. (2020, February). Energy conservation in WSN: A review of current techniques. In 2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE) (pp. 1-8). IEEE.
[43] Sah, D. K., & Amgoth, T. (2020). A novel efficient clustering protocol for energy harvesting in wireless sensor networks. Wireless Networks, 26(6), 4723-4737.
[44] Haq, I. U., Javaid, Q., Ullah, Z., Zaheer, Z., Raza, M., Khalid, M., ... & Khan, S. (2020). E2-MACH: Energy efficient multi-attribute based clustering scheme for energy harvesting wireless sensor networks. International Journal of Distributed Sensor Networks, 16(10), 1550147720968047.
[45] Gupta, V., & De, S. (2020). Collaborative multi-sensing in energy harvesting wireless sensor networks. IEEE Transactions on Signal and Information Processing over Networks, 6, 426-441.
[46] Raza, U., & Salam, A. (2020). On-site and external energy harvesting in underground wireless. Electronics, 9(4), 681.
[47] Gulec, O., Haytaoglu, E., & Tokat, S. (2020). A novel distributed CDS algorithm for extending lifetime of WSNs with solar energy harvester nodes for smart agriculture applications. IEEE Access, 8, 58859-58873.
[48] Eltresy, N. A., Dardeer, O. M., Al-Habal, A., Elhariri, E., Abotaleb, A. M., Elsheakh, D. N., ... & Abdallah, E. A. (2020). Smart home IoT system by using RF energy harvesting. Journal of Sensors, 2020(1), 8828479.
[49] Xu, Y. H., Tian, Y. B., Searyoh, P. K., Yu, G., & Yong, Y. T. (2020). Deep reinforcement learning-based resource allocation strategy for energy harvesting-powered cognitive machine-to-machine networks. Computer Communications, 160, 706-717.
[50] Zhang, Z., He, T., Zhu, M., Sun, Z., Shi, Q., Zhu, J., ... & Lee, C. (2020). Deep learning-enabled triboelectric smart socks for IoT-based gait analysis and VR applications. npj Flexible Electronics, 4(1), 29.
[51] Nguyen, T. V., Tran, T. N., Shim, K., Huynh-The, T., & An, B. (2020). A deep-neural-network-based relay selection scheme in wireless-powered cognitive IoT networks. IEEE Internet of Things Journal, 8(9), 7423-7436.
[52] Ren, Y., Zhang, X., & Lu, G. (2020). The wireless solution to realize green IoT: Cellular networks with energy efficient and energy harvesting schemes. Energies, 13(22), 5875.
[53] Lam, M. B., Nguyen, T. H., & Chung, W. Y. (2020). Deep learning-based food quality estimation using radio frequency-powered sensor mote. IEEE Access, 8, 88360-88371.
[54] Kim, T., Vecchietti, L. F., Choi, K., Lee, S., & Har, D. (2020). Machine learning for advanced wireless sensor networks: A review. IEEE Sensors Journal, 21(11), 12379-12397.
[55] Kathiriya, H., Pandya, A., Dubay, V., & Bavarva, A. (2020, June). State of art: energy efficient protocols for self-powered wireless sensor network in IIoT to support industry 4.0. In 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 1311-1314). IEEE.
[56] Elahi, H., Munir, K., Eugeni, M., Atek, S., & Gaudenzi, P. (2020). Energy harvesting towards self-powered IoT devices. Energies, 13(21), 5528.

2024, 9(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

[57] Wahba, M. A., Ashour, A. S., & Ghannam, R. (2020). Prediction of harvestable energy for self-powered wearable healthcare devices: Filling a gap. IEEE Access, 8, 170336-170354.
[58] Eltresy, N. A., Dardeer, O. M., Al-Habal, A., Elhariri, E., Hassan, A. H., Khattab, A., ... & Abdallah, E. A. (2019). RF energy harvesting IoT system for museum ambience control with deep learning. Sensors, 19(20), 4465.
[59] Ma, D., Lan, G., Hassan, M., Hu, W., & Das, S. K. (2019). Sensing, computing, and communications for energy harvesting IoTs: A survey. IEEE Communications Surveys & Tutorials, 22(2), 1222-1250.
[60] Puri, D., & Bhushan, B. (2019, October). Enhancement of security and energy efficiency in WSNs: Machine Learning to the rescue. In 2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS) (pp. 120-125). IEEE.
[61] Alsharif, M. H., Kim, S., & Kuruoğlu, N. (2019). Energy harvesting techniques for wireless sensor networks/radio-frequency identification: A review. Symmetry, 11(7), 865.
[62] Tang, X., Wang, X., Cattley, R., Gu, F., & Ball, A. D. (2018). Energy harvesting technologies for achieving self-powered wireless sensor networks in machine condition monitoring: A review. Sensors, 18(12), 4113.
[63] Chu, M., Li, H., Liao, X., & Cui, S. (2018). Reinforcement learning-based multiaccess control and battery prediction with energy harvesting in IoT systems. IEEE Internet of Things Journal, 6(2), 2009-2020.
[64] Fraternali, F., Balaji, B., & Gupta, R. (2018, November). Scaling configuration of energy harvesting sensors with reinforcement learning. In Proceedings of the 6th international workshop on energy harvesting & energy-neutral sensing systems (pp. 7-13).
[65] Shafique, K., Khawaja, B. A., Khurram, M. D., Sibtain, S. M., Siddiqui, Y., Mustaqim, M., ... & Yang, X. (2018). Energy harvesting using a low-cost rectenna for Internet of Things (IoT) applications. IEEE Access, 6, 30932-30941.
[66] Sharma, H., Haque, A., & Jaffery, Z. A. (2018). Modeling and optimisation of a solar energy harvesting system for wireless sensor network nodes. Journal of Sensor and Actuator Networks, 7(3), 40.