© February 2024| IJIRT | Volume 10 Issue 9 | ISSN: 2349-6002

Optimizing Energy-Efficient Resource Allocation in Wireless Sensor Networks using Reinforcement Learning

Dr.Varakumari.Samudrala[1], M. Bhavana Sri[2], M. Deepanvitha[3], K. Sai Kiran[4], N. Renuka Devi[5]
[1,2,3,4,5] *Department of Electronics and Communication Engineering, NRI Institute of Technology, Vijayawada*

Abstract: Wireless Sensor Networks (WSNs) with Energy Harvesting (EH) sensors, the efficient allocation of resources is pivotal to maximize energy utilization and network performance. This abstract presents an approach that leverages Reinforcement Learning (RL) algorithms for resource allocation, aiming to address this critical challenge. We formulate the problem as an RL task, with the state space encompassing vital network parameters such as sensor energy levels, channel conditions, and traffic loads. An action space is defined to encompass various resource allocation decisions, including time slot assignments, transmission power levels, and data compression techniques. A reward function is designed to quantify the trade-off between energy efficiency and overall network performance. The RL agent learns an optimal policy through interactions with the environment, continuously adapting its resource allocation strategies to varying energy availability, network conditions, and traffic patterns. This approach promises adaptability and efficiency in EH-WSNs, with the potential to extend sensor lifetimes and enhance data transmission capabilities while aligning with the dynamic nature of such networks. The ReLeC protocol demonstrated superior performance, surpassing LEACH by 88.32% and outperforming PEGASIS by 28.9% in network lifespan. This remarkable efficiency highlights ReLeC's effectiveness in prolonging the operational lifetime of wireless sensor networks, showcasing its potential for energy-efficient and sustainable applications.

Keywords: Reinforcement Learning, Energy Harvesting, Wireless Sensor Networks, Resource Allocation, Energy Efficiency.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) play a pivotal role in modern applications, ranging from environmental monitoring to industrial automation. However, the constrained energy resources of individual sensors pose a significant challenge to the longevity and efficiency of these networks. Optimizing energy-efficient resource allocation has emerged as a critical objective to extend network lifetime, enhance reliability, and reduce environmental impact. In this context, reinforcement learning (RL) offers a promising avenue for intelligent decision-making by empowering sensors to autonomously allocate resources based on dynamic environmental conditions. RL provides a principled framework for agents, represented by individual sensors, to learn optimal strategies through interaction with their surroundings, making it well-suited for addressing the complexities of WSNs. This research explores the integration of RL algorithms into WSNs, aiming to design a robust and adaptive system capable of dynamically optimizing resource allocation. By fostering self-learning capabilities within sensors, this approach seeks to revolutionize WSNs, making them more resilient, energy-efficient, and responsive to the evolving demands of diverse applications. The exploration of RL in WSNs holds the promise of ushering in a new era of intelligent and sustainable wireless sensor deployments.

Energy consumption and resource allocation intricacies, exacerbated by the limited power of sensor nodes, demand sophisticated strategies to ensure optimal performance and longevity. Reinforcement Learning (RL) presents a ground-breaking paradigm for addressing these challenges by imbuing sensors with the ability to learn from experiences and adapt to dynamic network conditions. The integration of RL into WSNs holds the potential to transform these networks into intelligent entities capable of making informed decisions regarding data transmission, power management, and routing. As WSNs continue to evolve in complexity and scale, the application of RL principles becomes increasingly pertinent, offering a pathway to create self-organizing and energy-aware networks.

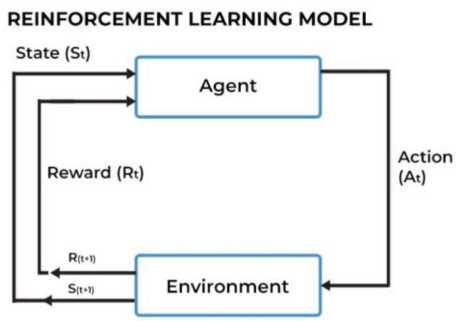

Figure 1: Reinforcement Learning Model

Delving into the intricacies of Reinforcement Learning (RL), this exploration focuses on its fundamental elements: the RL model, agent, environment, and state. The RL model encapsulates the algorithms orchestrating an agent's learning process, incorporating a reward signal, policy, value function, and learning algorithms. The agent, at the heart of RL, is the decision-maker navigating the environment to maximize cumulative rewards, striking a balance between exploration and exploitation. The environment serves as the dynamic external context, where the agent's actions unfold, shaping the consequences and providing crucial feedback through rewards. States, representing the current configuration of the environment, are the linchpin for the agent's decision-making, influencing its strategy and actions. Whether discrete or continuous, finite or infinite, states encapsulate pertinent information pivotal for effective decision-making. Understanding these interconnected components is paramount for comprehending how RL empowers agents to learn, adapt, and optimize decision-making strategies within diverse and complex scenarios.

II. RELATED WORK

A distributed approach for improving the network lifetime was presented by Pilloni et.al., [11]. Two distributed algorithms were presented here, one MLE algorithm for estimating the network lifetime and the other DLMA algorithm, which have been used to improve the lifetime. Each node determines its lifetime and uses the MLE to transfer and update the information and shares it with its neighbors. The DLMA algorithm uses this lifetime information and locally reassigns the processing tasks to the nodes. The algorithm was implemented using 5 Arduino Uno and 2 Arduino Due boards. In order to implement the DLMA algorithm GLPK library was used. An increase in the network lifetime of 94.5% and 88.9% was observed.

An Adaptive Dynamic Energy Consumption (ADEC) based on JNCC was presented by Liu et.al., [12]. In the ADEC method the number of coding packets can be dynamically reduced based on BER feedback for minimizing the total energy consumption. In this optimization method, the destination node receives the coded packets and performs joint decoding and computes (BER). This BER is fed back to the relay node which adjusts the number of code packets. If feedback of BER is greater than threshold BER then the number of coded packets are increased else the coded packets are decreased. The ADEC optimization involves searching and tuning phase for the optimum value of the number of code packets. Simulations were performed on different channels, different source nodes, and target BER (Bit Error Rate) and evaluated with respect to BER and ECBC parameters. The energy efficiency of ADEC proved comparatively better to JANNC, JNC schemes.

Tabus et.al., [13] have presented a new method for designing and scheduling WSN based on chain topology. The method mainly relies on a well-organized resource allocation procedure for variable energy tasks. This resource allocation problem and communication between node and BS is expressed as a Linear Programming Problem (LPP) which is solved using several TSP solver algorithms. The author used the existing TSP approach along with linear programming optimization to get an efficient protocol. The proposed LTTSP scheme was simulated using single and multiple chains. A comparison was performed between the proposed LTTSP and the CREEC scheme. The method provided optimal solutions for WSN.

Wan et.al., [14] have focused on the wakeup scheduling problem for increasing the lifetime of a roadside sensor network under road coverage constraints. A graph transformation technique was used to model the road coverage survivability as the maximum flow problem. A flow decomposition algorithm was presented which provided the optimum schedule to the coverage problem by segmenting the maximum flows into single flows. Simulations were performed in MATLAB for RCS-k problem and optimum solution achieved was verified.

Xu et.al., [15] have proposed a WSN energy consumption model by considering sensing, transmission and reception, energy supplies from different sources and other parameters such as electricity cost and channel condition. An optimization problem was formulated using the model to maximize source rate utility and energy consumption in a grid.

Cassandra et.al., [16] have presented an optimal strategy for the routing problems to increase the WSN lifetime. The energy sources used in the analysis of fixed topology network followed a dynamic behaviour, and hence was modeled with Kinetic Battery Model (KBM). An optimum control problem was formulated using the energy consumption model, and an optimum policy was obtained by using non-linear programming optimization method. In addition to optimal routing, the energy allocation problem was also considered and solved to increase the network lifetime. Numerical analysis was performed to show the optimality of the presented strategy and its robustness in the battery model.

Paschalidis and Li [17] have focused on energy efficient WSN topologies for building averaging algorithms in WSN. For static networks, the minimum power, bidirectional spanning tree was considered as an NP-hard problem and was formulated by using MILP approach. A semi-definite relaxation and rounding method was developed to achieve MILP feasible solutions. Graph-based algorithms were used for yielding energy efficient bidirectional spanning tree.

III. METHODOLOGY

The proposed RL-EHRA (Reinforcement Learning-Based Energy Harvesting Resource Allocation) algorithm represents a pioneering approach in the realm of Energy Harvesting Wireless Sensor Networks (EH-WSNs), harnessing the power of reinforcement learning for dynamic resource allocation. In its training phase, the RL agent actively explores diverse resource allocation decisions, continuously updating its policy based on observed states and associated rewards. Once in operation, the agent employs its acquired knowledge to strategically allocate resources, thereby optimizing energy efficiency while simultaneously adhering to predetermined network performance objectives. This adaptive algorithm excels in accommodating fluctuations in energy availability and varying network conditions, ultimately leading to prolonged sensor lifetimes and improved data transmission quality within EH-WSNs. The evaluation of RL-EHRA's performance against alternative allocation methods substantiates its effectiveness, positioning it as a robust and versatile solution for the intricate challenges posed by energy harvesting scenarios in wireless sensor networks. Through its inherent adaptability and learning capabilities, RL-EHRA stands poised to contribute significantly to the advancement of sustainable and high-performing EH-WSNs, offering a promising avenue for the on-going evolution of wireless sensor technology.

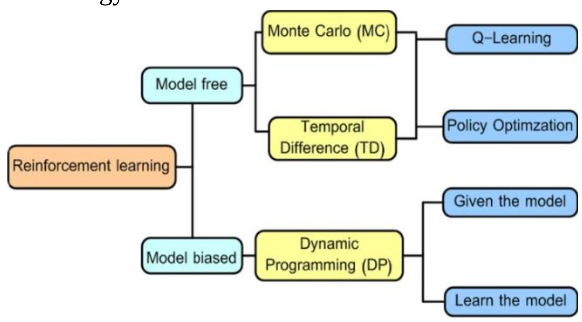

Figure 2: Basic Block Diagram Representation of Reinforcement Learning for Energy Optimization

An energy efficient clustering model along with providing security to the WSN. A framework was designed which consisted of four levels node clustering, CH selection, key establishment and distribution and framing a new routing protocol. The clustering is done using unique ID assigned to each node and a broadcast-acknowledgement method.

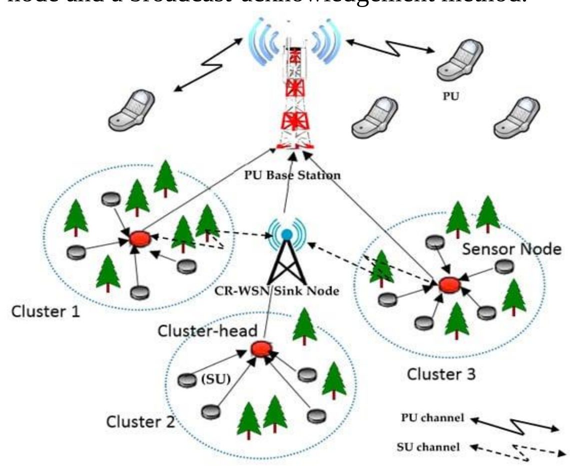

Figure 3: A Comprehensive Exploration of the General Structure of Wireless Sensor Networks

The network architecture of WSNs often follows a hierarchical or flat structure. In a hierarchical approach, nodes are organized into clusters with a designated cluster head, optimizing energy efficiency and data aggregation. Alternatively, flat structures involve direct communication among all nodes, simplifying routing but potentially leading to increased energy consumption.

Power management is a critical consideration in WSN design. Sensor nodes are often equipped with limited energy sources, necessitating energy-efficient communication protocols and data aggregation strategies. Advanced techniques, including data compression and in-network processing, contribute to minimizing energy consumption and extending the network's operational lifespan.

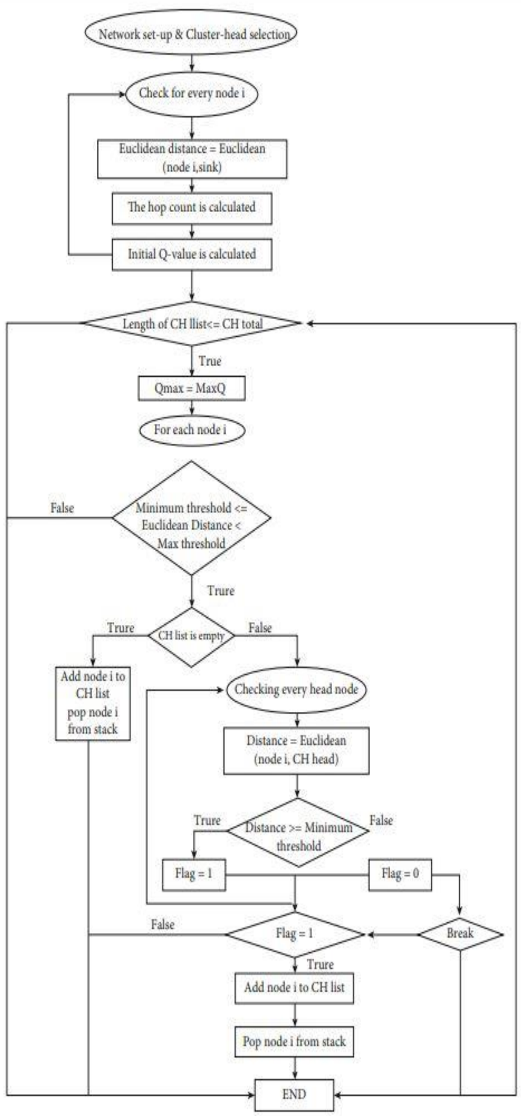

Figure 4: Designing the Network Configuration and Cluster-Head Selection: A Visual Representation through Flowchart

for each node i, **do**
set $D_{euclidean}$ = Euclidean(node i, sink)
set $N_H = (D_{euclidean}/\text{Transmission Range})$
set $Q = (p \times (E_{residual}/E_{\max} - E_{\min})) + ((1-p) \times (N_H \times \log(1/N_H)))$
end
while len(CH_{list})$\leq CH_{total}$, **do**
set $Q_{\max}$ = max Q
for each node i, **do**
if $MIN_{threshold} \leq D_{euclidean} < MAX_{threshold}$, **then**
if CH_{list} is empty, **then**
add node i to CH_{list}
pop node i from stack
else
for $head \longleftarrow$ 1 to len(CH_{list}), **do**
dist = Euclidean(node i, CH $head$)
if dist $\geq MIN_{threshold}$, **then**
set flag=1
else
set flag=0
break
end
if flag==1, **then**
add node i to CH_{list}
pop node i from stack
end

Algorithm 1: Configuring the Network and Selecting Cluster Heads

for head in len(CH_{total}), do
for each node i, do
set distCH(node i; CH head) =Euclidean (node i, CH $head$)
if distCH(node i, CH $head$) ≤ Transmission Range, **then**
CH head invites node i
end
end
for each node j, **do**
if $D_{euclidean} \leq$Transmission Range, **then**
set node j's destination = $bstn$
else
for $head$ in len(CH_{total}), **do**
if CH $head$ invites node j, **then**
if distCH(node j, CH $head$) ≤ min($distCH$($node\ j$, :)), **then**
set node j's destination = $head$
create $neighbour$
add node i to Cluster j
end
end
for each node j, **do**

Algorithm 2: Formation of Clusters: Structuring Nodes for Enhanced Network Efficiency

for each node i, do
if E of node i >0, then
set Q_{max} = max(Q(node i; :))
if D_1 Transmission Range, then
if node i is to be the next hop, then
collate data and send to bstn
else
send data to bstn
else if node i is not a CH then
if CH is within Transmission Range, then
send data to CH
else
locate and send data to neighbour
evaluate R_{t+1}
update Q to Q_{t+1} (s; a)
end

Algorithm 3: Efficient Data Transmission: Navigating Information Flow in Communication Networks

IV. RESULTS AND PERFORMANCE EVALUATION

The RL-EHRA algorithm, designed for Reinforcement Learning-Based Energy Harvesting Resource Allocation in EH-WSNs, demonstrates promising outcomes in addressing the challenges associated with dynamic resource allocation in energy harvesting scenarios. Through its training phase, the RL agent explores various resource allocation decisions, continuously refining its policy based on observed states and associated rewards. In operational scenarios, the RL agent strategically allocates resources, optimizing energy efficiency while adhering to predefined network performance objectives.

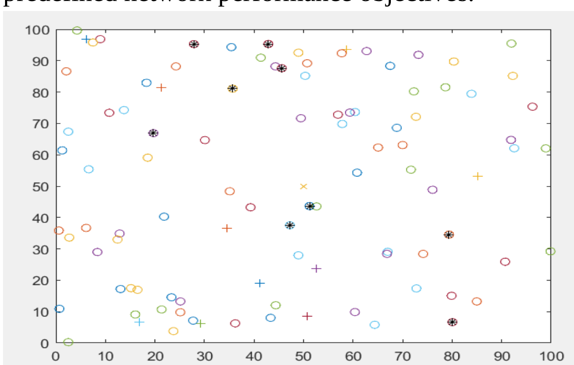

Figure 5: Coverage of Each Node in a Wireless Sensor Network

Energy consumption is a critical aspect of Wireless Sensor Networks (WSNs) as sensor nodes are often powered by limited energy sources, such as batteries or energy harvesting mechanisms. Three key metrics related to energy consumption in WSNs are energy consumed per transmission, energy consumed per contention, and energy consumed per round.

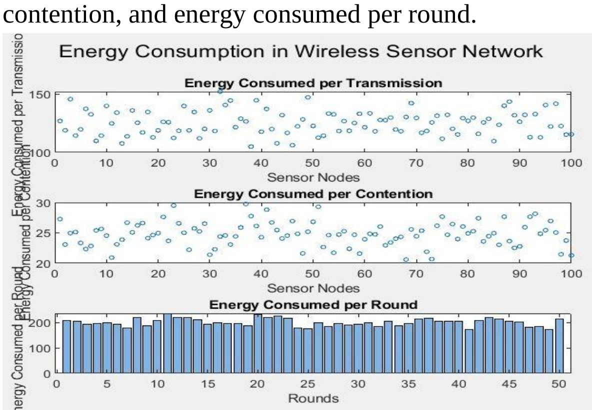

Figure 6: Energy Consumption In Wireless Sensor Networks

Energy consumed per transmission in Wireless Sensor Networks (WSNs) is a crucial metric, indicating the amount of energy expended when a sensor node transmits data to a neighboring node or a central base station. This metric is significantly influenced by factors such as transmission distance, data rate, and transmission power. Longer transmission distances and higher data rates generally lead to increased energy consumption during each transmission. To mitigate this, protocols often incorporate adaptive transmission power control to optimize energy usage, employ data compression techniques to minimize the amount of data transmitted, and integrate error correction mechanisms to enhance the reliability of transmissions. Additionally, duty cycling strategies are commonly employed, where nodes periodically switch between active and sleep states, effectively conserving energy and extending the overall operational lifetime of the sensor nodes. These mitigation strategies collectively contribute to optimizing the energy efficiency of transmission processes within WSNs.

Energy consumed per contention in Wireless Sensor Networks (WSNs) is a crucial metric that quantifies the energy expended when nodes vie for access to the communication medium. Contention, denoting the competition among nodes to transmit data, is influenced by factors such as the number of nodes contending for access, contention window size, and the employed back off mechanism. Higher contention, often resulting from a larger number of nodes or suboptimal contention parameters, can lead to increased collisions and retransmissions, consequently escalating the energy consumed during contention. Mitigation strategies involve the implementation of efficient Medium Access Control (MAC) protocols, including slotted protocols like Time Division Multiple Access (TDMA), to reduce contention. Randomized backoff mechanisms and contention window adjustments are additional measures aimed at minimizing collisions and optimizing energy usage during contention periods. These strategies collectively contribute to enhancing the overall energy efficiency of contention processes within WSNs, addressing the challenges associated with energy consumption in contention scenarios.

Energy consumed per round in Wireless Sensor Networks (WSNs) encapsulates the total energy expenditure by a sensor node in completing a sequence of operations, including data sensing, processing, and transmission. This metric is intricately influenced by the energy consumption per transmission and per contention, along with the overall duration of the operational round. It serves as a holistic measure, reflecting the comprehensive energy utilization of a node throughout its operational cycle. Mitigation strategies focus on optimizing the round structure, incorporating energy-efficient routing algorithms, and adjusting duty cycles to minimize overall energy consumption per round. Technologies like Wake-on-Radio (WoR) can be deployed to reduce idle listening times, contributing to further energy savings. By addressing the various factors influencing energy consumption per round, these strategies collectively work towards enhancing the overall energy efficiency of sensor nodes in WSNs, thereby extending their operational lifespan.

V. CONCLUSION

In conclusion, the integration of Reinforcement Learning (RL) algorithms for resource allocation in Wireless Sensor Networks (WSNs) with Energy Harvesting (EH) sensors presents a promising solution to the pivotal challenge of efficient resource utilization. By formulating the problem as an RL task, considering key network parameters in the state space, and defining a comprehensive action space, the proposed approach ensures adaptability and responsiveness to the dynamic conditions of EH-WSNs. The reward function strikingly balances energy efficiency and overall network performance. Through continuous learning and adaptation, the RL agent optimally allocates resources, addressing variations in energy availability, network conditions, and traffic loads. Furthermore, the demonstrated superiority of the ReLeC protocol, with an 88.32% outperformance against LEACH and a 28.9% advantage over PEGASIS in network lifespan, underscores its efficacy in prolonging the operational life of wireless sensor networks. This efficiency not only enhances the sustainability of EH-WSNs but also positions RL-based resource allocation as a transformative strategy for advancing energy-efficient and resilient sensor network applications.

Future work could explore the integration of machine learning techniques for adaptive learning rates in Reinforcement Learning-based resource allocation for Energy Harvesting Wireless Sensor Networks. Additionally, investigating the scalability and applicability of the ReLeC protocol across diverse sensor network environments would further enhance its practical implementation.

REFERENCE

[1]. K. Wang, P. Wu and M. Xia, "Energy-Efficient Scheduling and Resource Allocation for Power-limited Cognitive IoT Devices," 2023 19th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Montreal, QC, Canada, 2023, pp. 104-109, doi: 10.1109/WiMob58348.2023.10187769.

[2]. M. Kang, X. Li, H. Ji and H. Zhang, "Energy-Efficient Edge Cooperation and Data Collection for Digital Twin of Wide-Area," 2023 IEEE 34th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Toronto, ON, Canada, 2023, pp. 1-6, doi: 10.1109/PIMRC56721.2023.10293752.

[3]. H. Xiao, C. Wu, H. Jiang, L. -P. Deng, Y. Luo and Q. -Y. Zhang, "Energy-Efficient Resource Allocation in Multiple UAVs-Assisted Energy Harvesting-Powered Two-Hop Cognitive Radio Network," in IEEE Sensors Journal, vol. 23, no. 7, pp. 7644-7655, 1 April1, 2023, doi: 10.1109/JSEN.2023.3247436.

[4]. P. Ning, H. Wang, T. Tang, L. Zhu and X. Wang, "A Service-Oriented Energy Efficient Resource Allocation Approach for Wireless Communications of the Tunnel Construction," in IEEE Transactions on Vehicular Technology, vol. 72, no. 4, pp. 4948-4958, April 2023, doi: 10.1109/TVT.2022.3227898.

[5]. N. Li, M. Xiao, L. K. Rasmussen, X. Hu and V. C. M. Leung, "On Resource Allocation of Cooperative Multiple Access Strategy in Energy-Efficient Industrial Internet of Things," in IEEE Transactions on Industrial Informatics, vol. 17, no. 2, pp. 1069-1078, Feb. 2021, doi: 10.1109/TII.2020.2988643.

[6]. X. Chen, X. Wang and X. Chen, "Energy-Efficient Optimization for Wireless Information and Power Transfer in Large-Scale MIMO

Systems Employing Energy Beamforming," in IEEE Wireless Communications Letters, vol. 2, no. 6, pp. 667-670, December 2013, doi: 10.1109/WCL.2013.092813.130514.

[7]. L. Lu, L. Huang and W. Hua, "Energy Efficient Resource Allocation and Scheduling for Delay-Constrained Multi-Cell Broadcast Networks," in IEEE Access, vol. 8, pp. 164844-164857, 2020, doi: 10.1109/ACCESS.2020.3022350.

[8]. O. Amjad, E. Bedeer, N. Abu Ali and S. Ikki, "Energy Efficient Resource Allocation for eHealth Monitoring Wireless Body Area Networks With Backscatter Communication," in IEEE Sensors Journal, vol. 22, no. 16, pp. 16638-16651, 15 Aug.15, 2022, doi: 10.1109/JSEN.2022.3175754.

[9]. V. Maleki Raee, A. Ebrahimzadeh, R. H. Glitho, M. El Barachi and F. Belqasmi, "E2DNE: Energy Efficient Dynamic Network Embedding in Virtualized Wireless Sensor Networks," in IEEE Transactions on Green Communications and Networking, vol. 7, no. 3, pp. 1309-1325, Sept. 2023, doi: 10.1109/TGCN.2023.3266301.

[10]. X. Zhang, H. Qi, X. Zhang and L. Han, "Energy-Efficient Resource Allocation and Data Transmission of Cell-Free Internet of Things," in IEEE Internet of Things Journal, vol. 8, no. 20, pp. 15107-15116, 15 Oct.15, 2021, doi: 10.1109/JIOT.2020.3030675.

[11]. J. Ding, L. Jiang and C. He, "User-Centric Energy-Efficient Resource Management for Time Switching Wireless Powered Communications," in IEEE Communications Letters, vol. 22, no. 1, pp. 165-168, Jan. 2018, doi: 10.1109/LCOMM.2017.2763589.

[12]. A. Shahini, A. Kiani and N. Ansari, "Energy Efficient Resource Allocation in EH-Enabled CR Networks for IoT," in IEEE Internet of Things Journal, vol. 6, no. 2, pp. 3186-3193, April 2019, doi: 10.1109/JIOT.2018.2880190.

[13]. S. K. Sah Tyagi, A. Mukherjee, S. R. Pokhrel and K. K. Hiran, "An Intelligent and Optimal Resource Allocation Approach in Sensor Networks for Smart Agri-IoT," in IEEE Sensors Journal, vol. 21, no. 16, pp. 17439-17446, 15 Aug.15, 2021, doi: 10.1109/JSEN.2020.3020889.

[14]. K. Lee and J. -P. Hong, "Energy-Efficient Resource Allocation for Simultaneous Information and Energy Transfer With Imperfect Channel Estimation," in IEEE Transactions on Vehicular Technology, vol. 65, no. 4, pp. 2775-2780, April 2016, doi: 10.1109/TVT.2015.2416754.

[15]. S. Guo, X. Zhou and X. Zhou, "Energy-Efficient Resource Allocation in SWIPT Cooperative Wireless Networks," in IEEE Systems Journal, vol. 14, no. 3, pp. 4131-4142, Sept. 2020, doi: 10.1109/JSYST.2019.2961001.

[16]. H. Azarhava and J. Musevi Niya, "Energy Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks," in IEEE Wireless Communications Letters, vol. 9, no. 7, pp. 1000-1003, July 2020, doi: 10.1109/LWC.2020.2978049.

[17]. X. Cao, L. Liu, Y. Cheng and X. Shen, "Towards Energy-Efficient Wireless Networking in the Big Data Era: A Survey," in IEEE Communications Surveys & Tutorials, vol. 20, no. 1, pp. 303-332, Firstquarter 2018, doi: 10.1109/COMST.2017.2771534.