

A Novel Path Recovery Framework to Accurate Data Transmission in Web Sensor Networks

B. Harish Goud¹, Raju Anitha²

Submitted: 28/11/2023

Revised: 27/12/2023

Accepted: 09/01/2024

Abstract: Wireless Sensor Networks (WSNs) represent a groundbreaking paradigm in the field of distributed sensing and data acquisition. These networks consist of numerous tiny, battery-powered sensor nodes equipped with sensors for measuring physical or environmental parameters. The nodes communicate wirelessly to form a self-organizing and ad-hoc network, enabling real-time data collection and transmission. WSNs find applications in various domains, encompassing smart cities, healthcare, industrial automation, and environmental monitoring. They offer advantages such as flexibility, scalability, and cost-effectiveness. This abstract explores the fundamental principles, challenges, and applications of WSNs, highlighting their crucial role in enabling data-driven decision-making and enhancing our understanding of the physical. In most cases, the network is organized into small clusters to make affordable sensors that collect valuable data from their surroundings. The Cluster Head (CH) node takes responsibility for receiving data from the sensor node forward to Base Station (BS). This existing model uses more energy and causes network data collisions. To solve the issues in traditional networks **Harish Goud et al** proposed Energy Optimization in Path Arbitrary Wireless Sensor Network. The PAWSN model avoids the traditional CH selection and data transmission to CH. In PAWSN data transmission through the optimal path selection, achieved better performance. The PAWSN network senses a huge amount of data from source to destination and its leads bottleneck the network at a single node. The network bottleneck is called path failure in WSN. To deal with the constraints of previous research, in this paper proposed a framework called **Novel Path Recovery in WSN (NPR-WSN)**. The implementation of the suggested model by making using NS2 simulator. The scientific results demonstrate that the suggested NPR-WSN structure improves data performance transmission in WSN. The PDR, throughput, latency, and energy metrics are used to gauge performance.

Keywords: *Wireless Sensor Networks, Optimal Path, Node Interference, Path Recovery*

1. Introduction

A network of wireless sensors (WSN) is a specialized the kind of system that consists of small, autonomous sensor nodes equipped with various sensors and wireless communication capabilities. These nodes work together to monitor and collect data from the surrounding environment. In our modern, interconnected world, the demand for real-time data

collection and monitoring is greater than ever before. From environmental conservation to industrial automation and healthcare, the need to acquire precise information from diverse and often challenging locations has spurred the development of a revolutionary technology known as Wireless Sensor Networks (WSNs). At its core, a WSN is a network of autonomous sensor nodes equipped with sensors that can detect and measure a wide range of physical parameters, such as temperature, humidity, light, motion, and more. These sensor nodes communicate wirelessly with each other and, in many cases, with a central data collection point, enabling the seamless transmission of data from the field to the user. WSNs have garnered immense attention due to their versatility, scalability, and potential to revolutionize data acquisition in numerous domains. Whether it's monitoring climate changes in remote forests, optimizing manufacturing processes in factories, or enhancing patient care in healthcare settings, WSNs offer a powerful means of gathering data in real time,

*1Research Scholar in Dept of CSE, Koneru
Lakshmaiah Education*

*Foundation, Vaddeswaram, Andhra Pradesh
522502, India*

e-mail: bhg120109@gmail.com

*2Dept of CSE, Koneru Lakshmaiah Education
Foundation, Vaddeswaram, Andhra Pradesh
522502, India*

Corresponding Author Email e-mail:

bhg120109@gmail.com

e-mail: anitharaju@kluniversity.in

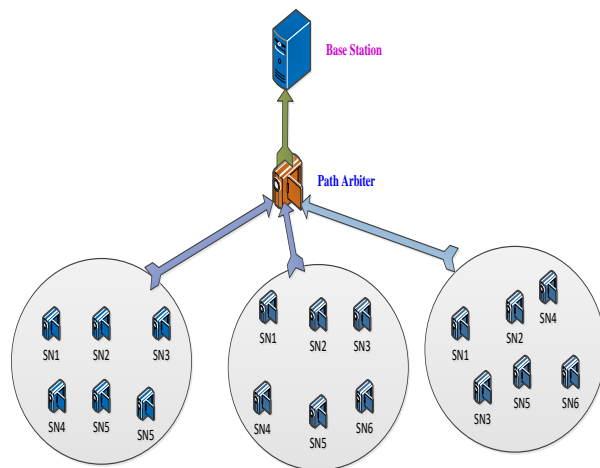
** Corresponding Author Email:*

bhg120109@gmail.com

often in locations that were previously inaccessible or costly to monitor.

The WSN system senses signals and collects physical information. The sensor nodes are deployed in the form of random or uniform to collect the information. Even though the sensor nodes are applied in different applications, the nodes have different performance limitations such as battery power, transmission delay and delivery ratio. Many limitations of wireless networks are reduced due to the unique infrastructure of WSN, such as self-configuration, deployment and easy management. The multi hop data transmission from sensor node to base station is also helpful to overcome traditional network limitations.

Later various solutions are proposed by dividing the network into dissimilar cluster boundaries. Each cluster declared a cluster head for an amount of time. It seeks to gather and transmit data from sensor nodes to BS. The quantity of sensor nodes expands as the area of WSN increases. The network scalability and efficient routing essential for data distribution. The routing mechanism is implemented in two methods like dynamic and static methods. The static mechanism maintains manual routing information. In a dynamic mechanism the routing information reconstitutes immediately then when a new event or change in network topologies happens. Especially the mobility routing mechanism is favored compared to static mechanisms.



The WSN preferred dynamic mechanism, which is easy to transmit routing status Routing is the process of moving from one protocol to another. redistribution. The dynamic routing has different challenges in WSN due to node interference and unreliable data transmission. Many researchers proposed different routing mechanisms to improve the performance of WSN in data transmission. Even

though many research constraints need significant improvements such as node failure, improved throughput and reduced energy efficiency in WSN. In previous research work introduced Path Arbitrary Wireless Sensor Networks (PA-WSN) using machine learning algorithms. Fig 1 shows the model architecture of PAWSN. The PAWSN model avoids the traditional CH selection and data transmission to CH. In PAWSN data transmission through the optimal path selection, achieved better performance. However, PA-WSN network significantly improved throughput performance and reduced energy consumption. The PAWSN network senses a huge amount of data from source to destination and its leads bottleneck the network at a single node. The network bottleneck is called path failure in WSN. To deal with the shortcomings of previous research, in this work proposed a framework called Novel Path Recovery in WSN(NPR-WSN).

The research paper is described in various sections, with Every segment covered the following. In Section II, an extensive a critique of current affirm mechanisms for energy efficiency in WSN is provided. Section III outlines the suggested approach to improving NPRWSN's energy efficiency. Section IV focuses on presenting observations regarding the suggested mechanism and conducting a comparative analysis. Finally, in Section V, the paper concludes by highlighting the strengths of the proposed mechanism and discussing potential avenues for future research.

2.Related Works

This section described various research works based on WSN for data transmission. Also given description of various frameworks with enhancements and limitations.

B.Harish Goud et al [Ref 1,Ref 12] When choosing the optimal path from the sender sensor node to the destination sensor node, the way arbitrary is an important factor. The method of defining the optimized primary path and alternate routes between sources and destinations at random. The link node's energy level and node distance determine the path from source to destination

Xiaobin Xu et al [Ref 2] proposed a hybrid model for additional data transmission and control delay. The redundant data transmission reduces network life time and increases network delay. Many approaches are proposed to avoid redundant data transmission. Data prediction models are divided into two categories.

First one, reconstruct data from the past and propose reactionary classes that have uncontrollable delay. Next one mainly focuses on data prediction and additional transmissions. To address the limitations in hybrid models, implement two algorithms for real-world WSNs. The network model outcomes stated it was projected model achieved high execution in principles of energy but also pause. However, the hybrid model cannot resolve node interference and node failure problems in WSN.

Hosein Azarhava et al [Ref 5] proposed Wireless Energy Harvesting Sensor Network based on TDMA to increase during period in WSN. The node determines the network lifetime harvest

energy. So reducing usage of energy by wireless sensors nodes has an impact on the lifetime of wireless networks. The proposed WEHSN had two time intervals for data transmission in WSN. First interval for energy management and second interval for transmitting sensor data. Time scheduling criteria and transmission power consumption are included in the WEHSN limitations for energy-efficient resource allocation. The numerical results show energy efficiency using Dinkelbach method. The WEHSN also solved Conditions for Karush-Kuhn-Tucker. Even so, the WEHSN solved many problems in WSN data transmission and improved network lifetime. But the system is unable to focus on the node error and node recovery problems.

BANTENG LIU et al [Ref 6] a 3D-based Data Collecting was suggested Algorithm for data transmission in WSN. The DCA_3D weights node coverage and improves network lifetime. The DCA_3D improves data collection optimization from source node to sink node with calculation of energy consumption and link transmission. Also calculates a sink node-based data gathering optimisation model. Finally, an artificial bee colony algorithm applied for optimal path selection for fair data transmission. The simulation results showed that the proposed model achieved better performance in terms of network coverage and data transmission. Even though the DCA_3D model outperforms with comparison of different approaches such as ANT, RAND, GREED, EDG 3D. But the system is unable to reduce node error and node interference in WSN. use of sensor networks that are wireless has been on the rise in recent years, thanks to Internet of Things is advancing quickly. (IoT). WSN enables the acquisition of large volumes of diverse data from different environments, which can help us better understand the world we live in.

However, wireless links are often unreliable and error-prone, which hinders the level of transmitting and the usefulness of the data obtained from WSN.

WEI XIN et al [Ref 7], et al proposed a hybrid transmission control and data access control mechanism for WSN. The proposed mechanism is Using mathematical representations of the two control operations, which help formulate a challenge in optimization that considers various factors such as network stability, data loss rate, data utility, and energy consumption. Because of the difficulty and intransigence of original Using a Nonlinear feature topology optimization theory, the problem is divided into three very straightforward sub-problems. A The architecture of the Based on the solutions, the Stochastic Data Scheduling Mechanism (SDSM) to these sub- problems. The effectiveness and feasibility of Moreover, the SDSM are examined, At last the effectiveness of the proposed mechanism is proved by in-depth analyses. Utilizing a portable washbasin for sensor data collecting is a promising approach to increase the wireless sensor networks' lifetime. In previous studies, to mitigate long delays and non-fresh data, All other sensors sent their data in a multi-hop fashion to the nearest data collection points (CP) after a set of data collection points (CPs) was chosen.. The path length and time needed to gather data from all sensors would be decreased when the mobile sink went to and collected data from the chosen CPs.

Zhang Lin et al [Ref 8] et al propose a DDCF, a data gathering mechanism, which utilizes a portable washbasin for data collection in a diverse with the goal of prolonging length of the network while expanding surveillance coverage. DDCF as proposed involves two phases in each round: creation of the tree topology and CP selection. Several factors, such as remaining energy, coverage contribution, and the degree of data fusion, are taken into account during the CP selection phase to dynamically choose CPs in each cycle, balancing the lifespan of CPs and improving surveillance quality. Each sensor chooses its parent during the phase of creating a tree topology by taking into account the amount of energy remaining, the level of data fusion, and the transmission success ratio in order to further balance and lower the sensor nodes' energy usage. Performance evaluations show that the suggested DDCF performs better than earlier studies in terms of surveillance quality, fairness, and network longevity..

GUOZHI LI et al [Ref 10] In wireless sensor networks (WSNs) with limited resources, it might be

difficult to transmit and analyze non-redundant perceptual data. The incorporation of edge computing technologies in wireless sensor networks has, however, opened up new possibilities. Despite this, maintaining a balance between link bandwidth and node energy resources and ensuring reliable data dissemination in edge computing-enabled wireless sensor networks (EWSN) remains a difficult problem. Various perceptual data are efficiently distributed to different sensor nodes in the EWSN using the joint bandwidth allocation and energy consumption (JBAEC) algorithm, which is proposed in this article. Under the assumption of early perceived energy, this method considers the available transmission lines between the source sensor and destination nodes. To that purpose, we create a model that accounts for the expenses associated with various types of data packets and energy detection

3. Methodology being proposed

3.1 Status of the Problem

A new path arbitrary wireless sensor network using machine learning (PA-WSN) was introduced in previous research. The PAWSN model avoid the conventional CH determination and information transmission to CH. Performance was improved in PAWSN data transmission by selecting the best path. The PAWSN network's leads delay the network at a single sensor node because it senses a large amount of data from source to destination. Every data transmission is affected by network interference, which uses a lot of energy in the network. Network delay and high energy consumption are the system's primary issues, according to current technology. Node Path Recovery for WSN (NPRWSN) was proposed as a means of overcoming the system's limitations.

3.2 Interference Model

The NPR-WSN framework, as proposed, establishes optimal paths between source and destination nodes in a WSN. In essence, a wireless network has several paths that connect its source and destination. However, the inference model uses the NPR-WSN framework to choose the best paths from the multiple paths. Every source node initially transmits RREQ to sensor nodes, while the destination node responds with RREP. Here, the source node uses the chosen path to transmit a clearance signal to other sensor nodes in the network without causing any interference. In WSN, the source node now starts the multimedia data

transfer. The interference model enhances network functionality.

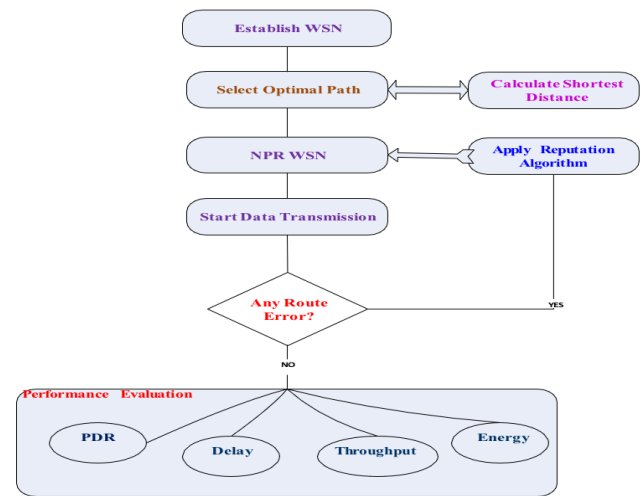


Fig 2 Proposed NPRWSN architecture

3.3 Node/Link Recovery Model

Improving the performance of multimedia distribution in wireless sensor networks (WSN) requires addressing the behavior of failure nodes. To address this issue, a proposed framework called NPRWSN aims to transform the behavior of failed nodes to normal. This transformation is accomplished through the implementation of a reputation sensing framework that is applied to the failed nodes within the network.

Reputation algorithm

Transmit Signal after Input

State of the output node

1. Initiate
2. Take a look. Source Node SN, Indicator of Reputation IR, Signal Out Reputation SOR, Send Time, Send Signal SS, defective Node DN.
3. Source node delivers Send Signal to defective Node
4. If(Send signal received by defective Node)
5. {
6. Indicator of Reputation = Indicator of Reputation + one
7. }
8. If(DN forward SS)
9. {
10. Signal Out Reputation = Signal Out Reputation + one
11. }
12. Total Node Reputation TNR calculation
13. $TNR = \frac{\text{Indicator of Reputation} + \text{Signal Out Reputation}}{\text{Simulation Time}}$
14. If(THRESHOLD = TNR)
15. {
16. Convert to Normal Node with FN
17. }
18. Finish

4.Results

The Node Interference and Failure Recovery (NPR) framework for wireless sensor networks(WSN) was Version 2.35 of Network Simulation.

4.1 Realtime Simulation

Table 1 Investigative studies

| S NO | Define Variable | Parameter Value |
|------|--------------------------|-------------------|
| 1 | The Channel's Type | Wireless Channel |
| 2 | Station | Dissemination |
| 3 | Input/Output Network | Wireless Phy |
| 4 | Queue Type for Interface | DropTail |
| 5 | sample of Antenna | isotropic antenna |
| 6 | Length of Queue | 50 |
| 7 | Protocol for routing | AODV |
| 8 | Number of devices | 50 |
| 9 | Data Rate | 3MB |
| 10 | Basic Rate | 2MB |
| 11 | Total Simulation Time | 50 |

Table 1 shows the deployment of WSN utilizes two-ray ground radio propagation, and proposed processes

$$\text{Throughput} = \frac{\text{Total No. of Bytes Recieved.....Eq(2)}}{\text{Simulation Time Interval}}$$

are assessed using performance criteria that are compared. Throughput, packet delivery ratio, latency, and energy usage are indicators of the enhanced performance.

4.2 Performance Metrics

Table 2 The PDR results of performance comparisons

| Simulation Time | PDR Performance | | | |
|-----------------|-----------------|------|--------|------|
| | NRPWSN | LBSO | DCBSRP | EBAR |
| 0 | 0 | 0 | 0 | 0 |
| 10 | 12 | 5 | 4 | 3 |
| 20 | 32 | 16 | 14 | 10 |
| 30 | 54 | 36 | 29 | 22 |
| 40 | 78 | 62 | 45 | 42 |
| 50 | 98 | 83 | 75 | 58 |

4.2.1 PDR Performance show the correlation consequences of PDR execution of NRPWSN. The performance graph on PDR with the appropriate simulation period in Figure 3. The findings of comparing the suggested mechanism with the current mechanism were displayed.

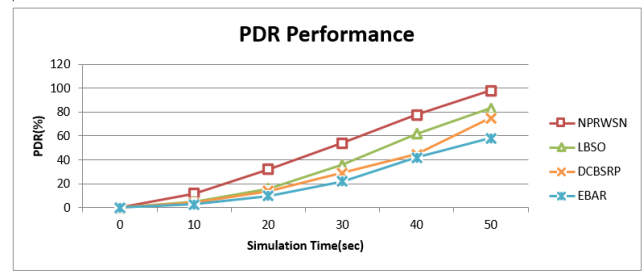


Fig 3 Performance evaluation of PDR

Figure 3 shows the empirical findings from the previously used LBSO, DCBSRP, and EBAR methods as well as the suggested NPRWSN mechanism. An X-axis represents the simulation time of 50 seconds, while the Y-axis indicates the percentage of packet delivery ratio (PDR). As depicted in the figure, the proposed NPRWSN mechanism exhibits a gradual increase in PDR with increasing simulation time. Despite the fact that the existing mechanisms also follow a similar pattern, NPRWSN outperforms LBSO, DCBSRP, and EBAR in terms of performance.

4.2.2 Throughput Performance

TABLE 3 Demonstrate the performance throughput comparison results of NPRWSN.

| Simulation Time | Throughput Performance | | | |
|-----------------|------------------------|-------|--------|-------|
| | NRPWSN | LBSO | DCBSRP | EBAR |
| 0 | 0 | 0 | 0 | 0 |
| 10 | 76608 | 49786 | 40145 | 39458 |
| 20 | 78096 | 43698 | 35148 | 32458 |
| 30 | 76352 | 40258 | 29487 | 22546 |
| 40 | 80306 | 38147 | 24986 | 19258 |
| 50 | 84376 | 35457 | 22458 | 17963 |

$$\text{PDR} = \frac{\sum \text{Number of Received Packets}}{\text{Number of Sent Packets}} \quad \dots \quad \text{Eq(1)}$$

depicts the proposed mechanism's throughput performance

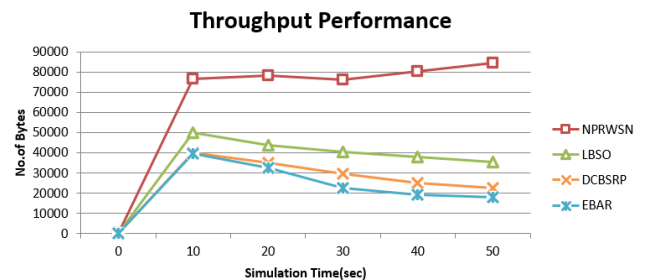


Fig 4 Comparison on Throughput performance

Figure 4 shows the throughput and effectiveness of the suggested NRPWSN method. The X-axis indicates the

simulation duration from 0 to 50 seconds, while the Y-axis represents the volume of bytes delivered to the final node. As shown in the figure, the proposed NPRWSN mechanism significantly improves the throughput performance, achieving 83476 bytes compared to the current systems, including EBAR, LBSO, and DCBSRP, which achieve 51456, 44158, and 40256 bytes.

4.2.3 Delay Performance

TABLE 4 provide the comparison findings for NRP WSN's delay performance.

| Simulation Time | Delay Performance | | | |
|-----------------|-------------------|-------|--------|-------|
| | NRPWSN | LBSO | DCBSRP | EBAR |
| 0 | 0 | 0 | 0 | 0 |
| 10 | 0.112 | 0.321 | 0.428 | 0.496 |
| 20 | 0.0706 | 0.205 | 0.298 | 0.386 |
| 30 | 0.0492 | 0.175 | 0.225 | 0.362 |
| 40 | 0.0422 | 0.135 | 0.195 | 0.279 |
| 50 | 0.0405 | 0.098 | 0.141 | 0.22 |

Figure 5 depicts the proposed mechanism's delay performance in relation to the simulation era. The results' putative mechanism is contrasted with the system's existing state of the art.

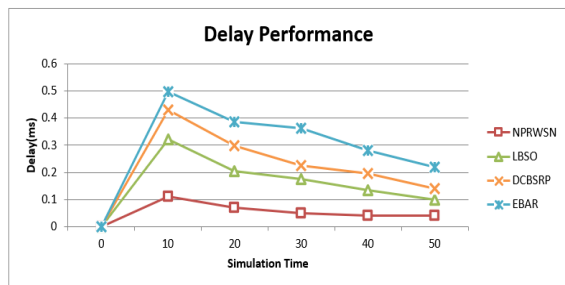


Fig 5 Delay Performance Comparison Results

Figure 5 illustrates the comparative performance of the proposed mechanism's network delay. The Y-axis represents the network delay in milliseconds, while the X-axis represents the simulation time in seconds. The experimental findings demonstrate that, in terms of network delay, the suggested mechanism performs better than the existing approach. The performance of the suggested method significantly improves between 0 and 50 seconds, gradually reducing and minimizing the network latency, despite its high starting point.

4.2.4 Energy Performance

$$R.E = \sum (\text{Nodes Initial Energy} - \text{Nodes Consumed Energy}) \dots \text{Eq(4)}$$

The energy performance comparison results for NPRWSN are shown in Table 5.

Table 5

| Simulation Time | Energy Performance | | | |
|-----------------|--------------------|------|--------|------|
| | NRPWSN | LBSO | DCBSRP | EBAR |
| 0 | 100 | 100 | 100 | 100 |
| 10 | 96 | 85 | 82 | 76 |
| 20 | 93 | 71 | 66 | 57 |
| 30 | 91 | 62 | 51 | 34 |
| 40 | 89 | 52 | 40 | 24 |
| 50 | 85 | 50 | 34 | 18 |

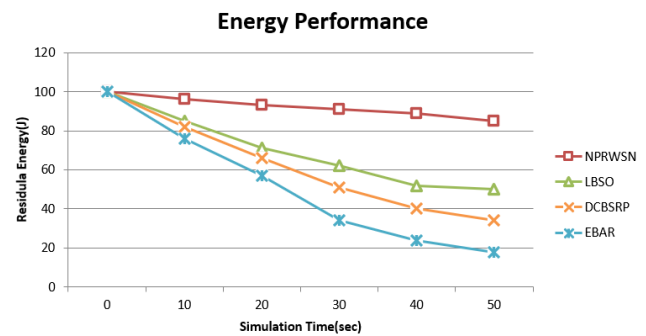


Fig 6 Energy Performance

The duration of the simulation and its energy usage are displayed in Figure 5. The total amount of energy used for each time interval was displayed on this graph. The simulation runs between 0 and 50 seconds. Each sensor node in the NPRWSN network gets 100 Joules of energy. The amount of energy used gradually increases with simulation time. Be that as it may, with correlations of existing systems the proposed components consume low energy. The proposed instrument NPRWSN consumes 35 J at end of reenactment, while the current component LBSO, DCBSRP and EBAR [9][10][11] consumed is 50J, 66J and 85J separately

5. Conclusions

In this journal article, we have navigated the intricate landscape of Wireless Sensor Network (WSN) path recovery, a fundamental aspect that underpins the reliability and resilience of these networks in dynamic and challenging environments. As we conclude our exploration, several key insights emerge, shedding light on the significance of path recovery within the context of WSNs. WSNs represent a technological marvel, enabling the collection of real-time data from diverse and often inaccessible locations. However, the effectiveness of these networks hinges on their ability to maintain connectivity and data flow even when

faced with node failures, environmental changes, or interference. Path recovery mechanisms serve as the vital link in this process, ensuring that data reaches its intended destination despite disruptions. The WSN is used to send data very effectively. The real-time environments serve as the foundation for the functionalities of sensor nodes in operation. Due to the nature of WSN, the sensor nodes are severely limited in terms of resources. There are numerous issues that need to be resolved with the current WSN, but efficient performance and network delay are crucial. Path Arbitrary Wireless Sensor Networks (PA-WSN) based on machine learning were developed to address issues in conventional networks. The PAWSN model dodges the conventional CH determination and information transmission to CH. Performance was improved in PAWSN data transmission by selecting the best path. The PAWSN network senses a significant amount of data from source to destination, and one node's leads create a bottleneck in the network. In WSN, the bottleneck in the network is called path failure. A framework referred to as Novel Path Recovery in WSN (NPR-WSN) was proposed in this paper to address the limitations of previous research. NS2 simulation is used to put the proposed framework into action. The empirical findings demonstrate that the proposed NPR-WSN framework enhances WSN data transmission performance. NS2 simulations are used to carry out the implementation. The empirical results showing that the suggested approach works better than the established system

Acknowledgements

Availability of data and material: The datasets used in this study are taken from public domain and the appropriate URLs have been cited in the text.

Author contributions

Authors contribution statement: All authors are contributed equally. In particular, B.Harish Goud– Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation.

Supervision:

Raju Anitha - Conceptualization, Methodology, Formal analysis and investigation, Writing - review and

editing, Supervision.

Acknowledgments

A preliminary version of this work appears in this paper is extension research work of my previously

published paper in expert systems journal title “Energy optimization in path arbitrary wireless sensor network.”

Conflicts of interest

Conflict of interests: All the authors declare that they have no competing interests.

References

- [1] B.Harish Goud–T.N.Shankar., Basant Sah.,Rajanikanth Aluvalu., 2023. Energy Optimization in Path Arbitrary Wireless Sensor Network. Expert Systems, DOI: [10.1111/exsy.13282](https://doi.org/10.1111/exsy.13282).
- [2] Xu, X. and Zhang, G., 2017. A hybrid model for data prediction in real-world wireless sensor networks. IEEE Communications Letters, 25(5), pp.1712-1715.
- [3] Xu, Y.H., Yu, G. and Yong, Y.T., 2020. Deep reinforcement learning-based resource scheduling strategy for reliability-oriented wireless body area networks. IEEE Sensors Letters, 5(1), pp.1-4.
- [4] Bin, K., Luo, S., Zhang, X., Lin, J. and Tong, X., 2020. Compressive data gathering with generative adversarial networks for wireless geophone networks. IEEE Geoscience and Remote Sensing Letters, 18(3), pp.558-562.
- [5] Azarhava, H. and Niya, J.M., 2020. Energy efficient resource allocation in wireless energy harvesting sensor networks. IEEE Wireless Communications Letters, 9(7), pp.1000-1003.
- [6] Liu, B., Chen, Y., Wan, J., Sun, P., Wang, Z., Ren, T., Yin, Z. and Zhang, R., 2020. Data collection algorithm of a 3D wireless sensor network that weighs node coverage rate and lifetime. IEEE Access, 8, pp.214978-214991.
- [7] Xin, W., Jiang, Z., Lin, G. and Yu, D., 2020. Stochastic optimization of data access and hybrid transmission in wireless sensor network. IEEE Access, 8, pp.62273-62285.
- [8] Lin, Z., Keh, H.C., Wu, R. and Roy, D.S., 2020. Joint data collection and fusion using mobile sink in heterogeneous wireless sensor networks. IEEE Sensors Journal, 21(2), pp.2364-2376.
- [9] Haseeb, K., Almustafa, K.M., Jan, Z., Saba, T. and Tariq, U., 2020. Secure and energy - aware heuristic routing protocol for wireless sensor network. IEEE Access, 8, pp.163962-163974.

- [10] Li, G. and Song, X., 2020. Data distribution optimization strategy in wireless sensor networks with edge computing. *IEEE Access*, 8, pp.214332-214345.
- [11] Chang, C.Y., Chen, S.Y., Chang, I.H., Yu, G.J. and Roy, D.S., 2020. Multirate data collection using mobile sink in wireless sensor networks. *IEEE Sensors Journal*, 20(14), pp.8173-8185.
- [12] Goud, B. ., & Anitha, R. . (2023). Emerging Routing Method Using Path Arbitrator in Web Sensor Networks. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(4), 232–237. <https://doi.org/10.17762/ijritcc.v11i4.6444>