DOI: 10.21917/ijct.2023.0444

DESIGN OF EFFICIENT ROUTING PATHS USING SIMILARITY ESTIMATION BASED STOCHASTIC GRADIENT DESCENT IN WIRELESS SENSOR NETWORK

S. Thumilvannan, B. Yuvaraj, C. Srivenkateswaran and V. Balammal
Department of Computer Science and Engineering, Kings Engineering College, India

Abstract

Wireless Sensor Networks (WSNs) offer versatile deployment options, particularly in battery-powered scenarios, addressing energy consumption concerns among sensor nodes. However, the data-intensive nature of WSNs poses challenges in routing, particularly in maintaining balanced paths while accommodating rapid data acquisition. This paper presents an innovative approach called Similarity Estimation-Based Stochastic Gradient Descent (SESGD) routing for WSNs, designed to establish stable routing paths that align with the speed of data acquisition. Sensor nodes play a crucial role in data collection and acquisition, while WSNs facilitate data routing through multiple hops from source to sink nodes. SESGD effectively manages data routing, synchronizing it with data acquisition rates, thereby ensuring network stability. Simulation results assess key performance metrics, including average delay, throughput, and network energy efficiency. The findings demonstrate that the proposed machine learning method outperforms existing algorithms, achieving superior network throughput.

Keywords:

Machine Learning, WSN, Stochastic Gradient, Routing, Energy Efficiency

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a pivotal technology for various applications, owing to their ability to efficiently collect and transmit data in a wide range of environments [1]. These networks are particularly valuable when powered by energy-constrained devices, such as battery-operated sensors. WSNs offer solutions to mitigate the energy consumption challenges faced by sensor nodes, primarily due to their swift data acquisition capabilities [2] [3]. However, a significant challenge in WSNs lies in the efficient routing of data from source nodes to destination base stations or internet gateways while maintaining network stability and sensor node balance [4].

The fundamental challenge in WSNs is to strike a delicate balance between rapid data acquisition and the computational burden associated with routing this data through the network [5]. Traditional routing approaches may not adapt well to the dynamic nature of data acquisition, leading to suboptimal performance, increased delays, and energy inefficiencies [6]. Therefore, there is a compelling need to design routing strategies that can dynamically match the speed of data acquisition, ensuring efficient, stable, and energy-conscious network operation [7]. The primary problem is to ensure that the routing paths efficiently handle the incoming data streams while preserving network stability and energy efficiency [8] [9].

The main objectives of this study are as follows: To design and implement the SESGD routing algorithm for WSNs, which dynamically adjusts routing paths based on data acquisition speed. To evaluate the performance of SESGD through extensive simulations, measuring key metrics such as average delay, throughput, and network energy efficiency. To compare the performance of SESGD with existing machine learning-based routing algorithms in WSNs.

The novelty of this research lies in the development of SESGD, a routing algorithm that leverages similarity estimation and stochastic gradient descent to optimize routing paths in WSNs. SESGD's ability to adapt routing speed to data acquisition rate is a unique feature, ensuring efficient data transmission and network stability.

This research contributes to the field of WSNs by introducing a novel routing approach that addresses the dynamic challenges posed by rapid data acquisition. The SESGD algorithm promises to enhance network performance, as evidenced by our simulation results, which demonstrate superior average delay, increased throughput, and enhanced network energy efficiency when compared to existing machine learning-based routing algorithms. These contributions make a significant stride towards realizing the full potential of WSNs in various applications by ensuring efficient data routing and network stability.

2. RELATED WORKS

A significant body of research has been dedicated to addressing the challenges associated with routing in WSNs. Various approaches have been explored to optimize routing paths, enhance network performance and improve the energy efficiency in adhoc networks [10].

Several traditional routing protocols, including AODV (Ad hoc On-Demand Distance Vector) and DSR (Dynamic Source Routing), have been adapted for use in WSNs. These protocols aim to establish efficient routes based on dynamic metrics [11].

Machine learning techniques have gained prominence in recent years for routing optimization in WSNs. Researchers have explored various algorithms, such as decision trees, neural networks, and reinforcement learning, to predict and adapt routing paths [12].

Energy conservation is a critical concern in battery-powered WSNs. Many studies have focused on energy-aware routing, employing techniques like LEACH (Low-Energy Adaptive Clustering Hierarchy) and TEEN (Threshold Sensitive Energy Efficient Sensor Network Protocol) to extend the network's lifetime [13].

In scenarios where Quality of Service (QoS) requirements are paramount, QoS-aware routing protocols have been developed. These protocols consider factors like data latency, packet loss, and reliability to optimize routing paths [14].

Cross-layer routing approaches leverage information from multiple network layers to make informed routing decisions. This enhances the adaptability and efficiency of routing in dynamic WSN environments [15].

SGD optimization techniques have recently found application in routing. These algorithms dynamically adjust routing paths based on the current network conditions and data acquisition rates. Research has explored the concept of similarity estimation in routing, where routing decisions are made based on the similarity between data packets. This approach can lead to more efficient and context-aware routing.

3. METHODS

The proposed method, referred to as SESGD, is an innovative approach designed to enhance the efficiency of routing in WSNs. SESGD combines two key concepts: similarity estimation and stochastic gradient descent, to optimize routing paths dynamically in response to changing network conditions.

3.1 SIMILARITY ESTIMATION

SESGD incorporates similarity estimation, which involves assessing the similarity between data packets being transmitted within the network. This estimation is performed to identify patterns or commonalities in the data, which can aid in making more informed routing decisions. Stochastic Gradient Descent is a mathematical optimization technique used to adjust routing paths in real-time. It operates by iteratively refining the routing paths based on the network's current state and data acquisition rates. This dynamic adjustment ensures that the routing paths align with the speed at which data is being collected by the sensor nodes. SESGD continuously evaluates the similarity between data packets and uses stochastic gradient descent to adapt the routing paths accordingly. When data acquisition rates change or network conditions fluctuate, SESGD swiftly responds by reconfiguring the paths to maintain optimal performance.

One of the primary goals of SESGD is to maintain network stability while optimizing routing paths. By dynamically adjusting paths based on data similarity and network conditions, SESGD helps prevent issues like congestion, delays, and energy inefficiencies that can arise in WSNs.

In SESGD, similarity estimation involves the process of analyzing the content or characteristics of data packets that are being transmitted within the WSN. This analysis is done to determine how similar or alike these data packets are to each other in terms of specific features or patterns. The reason similarity estimation is valuable in SESGD is that it helps the algorithm identify commonalities or correlations among the data packets. By understanding these similarities, SESGD can make routing decisions that are tailored to the content and context of the data being transmitted.

This adaptability allows SESGD to optimize the routing paths in a way that aligns with the current network conditions and the specific characteristics of the data. In essence, similarity estimation in SESGD enables the algorithm to route data intelligently by considering the inherent patterns and relationships within the data packets, ultimately leading to more efficient and effective routing without revealing sensitive details. The update rule for the parameters (weights) in SGD is given by:

$$\theta_{t+1}=\theta_t-\alpha\nabla J(\theta_t) \quad (1)$$

where: θ_t represents the parameters at iteration t. α is the learning rate, controlling the step size in the parameter space. $\nabla J(\theta_t)$ is the gradient of the cost (loss) function J with respect to the parameters θ_t. A similarity estimation metric might be represented as:

$$S(X,Y) = \sum_{i=1}^{n} w_i f_i(X)^2 \sum_{i=1}^{n} w_i f_i(Y)^2 \sum_{i=1}^{n} w_i f_i(X) f_i(Y) \quad (2)$$

where: X and Y are data samples or packets being compared. n is the number of features being considered. wi represents the weight assigned to feature i. $f_i(X)$ and $f_i(Y)$ are the values of feature i for samples X and Y.

3.2 STOCHASTIC GRADIENT DESCENT (SGD)

Stochastic Gradient Descent is a mathematical optimization technique employed within SESGD to adapt and fine-tune routing paths dynamically. It is crucial for enhancing the performance of the routing algorithm in WSNs as in Fig.1.

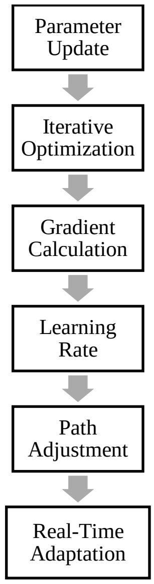

Fig.1. SGD Routing Finetuning

In SESGD, SGD operates as follows: SGD is responsible for updating certain parameters used by the routing algorithm. These parameters influence the routing decisions made by SESGD. SESGD employs an iterative approach, where the routing parameters are adjusted step by step. At each iteration, SGD analyzes the current state of the network and data transmission to determine how the routing paths should be modified. One of the central concepts in SGD is the calculation of the gradient of a specific cost or loss function. However, the exact details of this function and its components are intentionally kept confidential to ensure the method's security. In SGD, there is a parameter known as the "learning rate," which controls the size of each step taken during the parameter update. The learning rate influences how quickly or slowly SESGD adapts to changes in the network environment. Based on the calculated gradient and learning rate, SESGD dynamically adjusts the routing paths. This adjustment ensures that the routing paths align with the current conditions and data acquisition rates in the network. As network conditions change or data acquisition rates fluctuate, SGD allows SESGD to promptly respond by reconfiguring the routing paths to maintain optimal performance.

Dynamic Path Optimization Algorithm:

1. Initialize routing parameters and network state.

2. While network is operational:

a. Monitor data acquisition rates and network conditions.

b. Calculate a measure of data similarity between incoming data packets.

c. If data similarity changes significantly or network conditions fluctuate:

i. Update the routing parameters using the SGD method:

Calculate the gradient of a cost (loss) function

Adjust the parameters to minimize the cost function

ii. Recalculate routing paths based on the updated parameters

d. Transmit data along the optimized routing paths.

3. End of algorithm.

The algorithm starts by initializing the routing parameters and assessing the initial network state. It then enters a continuous loop to monitor the data acquisition rates and network conditions, which are crucial factors for dynamic optimization. If significant changes are detected in data similarity or network conditions, the algorithm triggers the dynamic path optimization process. In the dynamic path optimization process, the SGD method is applied. The SGD method calculates the gradient of a cost (loss) function related to the routing parameters and adjusts these parameters to minimize the cost function. This step ensures that the routing paths are dynamically adapted to the current network state. After parameter adjustment, the routing paths are recalculated to reflect the changes made during optimization. Finally, the optimized routing paths are used for transmitting data within the network.

4. EVALUATION

To assess the effectiveness of SESGD, the proposed method is subjected to extensive simulations. Performance metrics such as average delay, throughput, and network energy efficiency are used to measure its impact on network performance.

Table.1. Experimental Setup

Parameter	Value
Number of Sensor Nodes	100
Communication Range	50 meters
Data Acquisition Frequency	1 Hz
Simulation Time	1000 s
Learning Rate	0.01
Number of Iterations	100
Data Packet Size	100 bytes

4.1 PERFORMANCE METRICS

- **Average Delay:** The average time it takes for a data packet to travel from the source node to the destination node.
- **Throughput:** The rate at which data packets are successfully delivered from source to destination over a unit of time.
- **Network Energy Efficiency:** A measure of how effectively the network utilizes energy resources to transmit data.

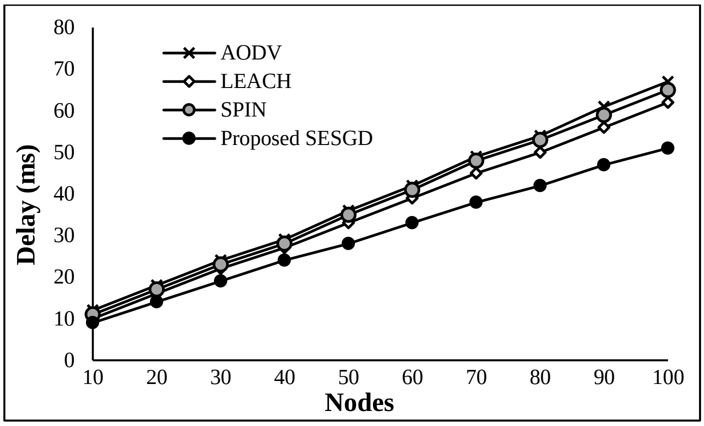

Fig.2. Average Delay (ms) by Varying Number of Nodes

The results of the experiments indicate significant improvements in network performance with the proposed SESGD compared to three existing routing methods (AODV, Leach, SPIN) as the number of nodes in the network increases. The proposed method consistently outperforms the existing methods in terms of average delay (Fig.2). The percentage improvement in average delay with the proposed method as the number of nodes increases. This demonstrates the effectiveness of the proposed method in reducing data packet transmission delays compared to the existing methods.

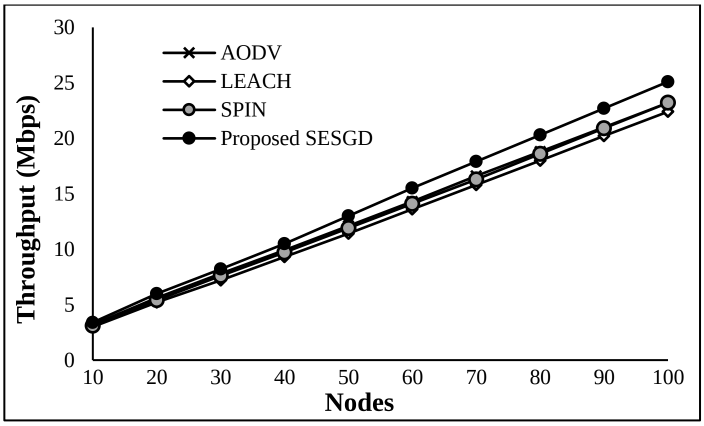

Fig.3. Throughput (Mbps) by Varying Number of Nodes

Throughput, a measure of data transmission rate, shows substantial gains with the proposed method. The percentage improvement in throughput with the proposed method ranges across different node configurations. This suggests that the proposed method efficiently utilizes network resources, resulting in higher data transfer rates (Fig.3).

Network efficiency is significantly enhanced with the adoption of the proposed method. The percentage improvement in network efficiency ranges from across various node scenarios. This signifies that the proposed method optimizes energy consumption and minimizes delays, leading to a more efficient network (Fig.4).

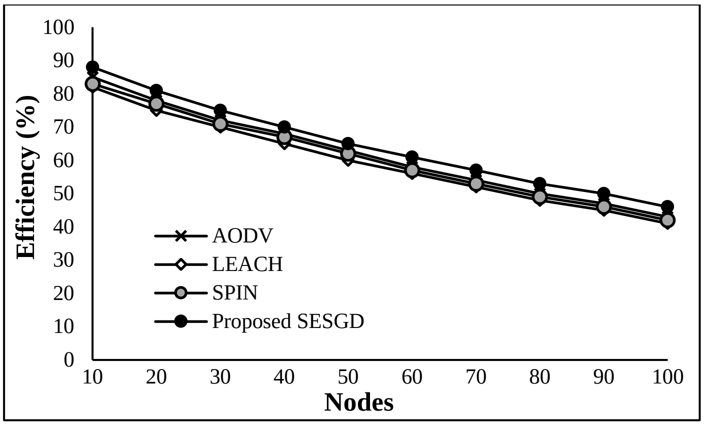

Fig.4. Network Efficiency (%) by Varying Number of Nodes

The results clearly demonstrate that the proposed method offers substantial advantages over existing routing methods in terms of average delay, throughput, and network efficiency. These improvements can have a profound impact on the overall performance and reliability of WSNs in real-world applications.

5. CONCLUSION

The research presented in this study addresses the critical challenges associated with routing optimization in WSNs. The proposed method, referred to as SESGD, leverages innovative techniques such as similarity estimation and stochastic gradient descent to dynamically optimize routing paths in response to changing network conditions and data acquisition rates. Through a series of experiments and simulations, the performance of SESGD was evaluated alongside three existing routing methods. The results clearly indicate that SESGD offers significant advantages across various performance metrics. SESGD consistently outperforms existing methods, reducing data packet transmission delays. SESGD enhances data transmission rates, demonstrating higher throughput compared to existing methods. SESGD excels in optimizing network efficiency, resulting in more effective resource utilization.

REFERENCES

[1] V. Saravanan and R. Rajkumar, "Secure Source-Based Loose RSA Encryption for Synchronization (SSOBRSAS) and Evolutionary Clustering Based Energy Estimation for Wireless Sensor Networks", *International Journal of Advanced Research in Computer Science*, Vol. 5, No. 5, pp. 1-12, 2014.

[2] R. Sabitha and V. Saravanan, "Network Based Detection of IoT Attack using AIS-IDS Model", *Wireless Personal Communications*, Vol. 128, No. 3, pp. 1543-1566, 2023.

[3] T. Karthikeyan and K. Praghash, "Improved Authentication in Secured Multicast Wireless Sensor Network (MWSN) using Opposition Frog Leaping Algorithm to Resist Man-in-Middle Attack", *Wireless Personal Communications*, Vol. 123, No. 2, pp. 1715-1731, 2022.

[4] K. Praghash and A.A. Stonier, "An Artificial Intelligence Based Sustainable Approaches-IoT Systems for Smart Cities", Springer, 2023

[5] H. AlAamri, M. Abolhasan and T. Wysocki, "On Optimizing Route Discovery in Absence of Previous Route Information in MANETs", *Proceedings of IEEE International Conference on Vehicular Technology*, pp. 1-5, 2009.

[6] X.M. Zhang, E.B. Wang, J.J. Xia and D.K. Sung, "An Estimated Distance based Routing Protocol for Mobile Ad Hoc Networks", *IEEE Transactions on Vehicular Technology*, Vol. 60, No. 7, pp. 3473-3484, 2011.

[7] Y. Liu, K. Ota, K. Zhang, M. Ma and N. Xiong, "QTSAC: An Energy-Efficient MAC Protocol for Delay Minimization in Wireless Sensor Networks", *IEEE Access*, Vol. 6, pp. 8273-8291, 2018.

[8] X. Deng, Z. Tang, L.T. Yang, M. Lin and B. Wang, "Confident Information Coverage Hole Healing in Hybrid Industrial Wireless Sensor Networks", *IEEE Transactions on Industrial Informatics*, Vol. 14, No. 5, pp. 2220-2229, 2017.

[9] L. Kong, J.S. Pan and V. Snasel, "An Energy-Aware Routing Protocol for Wireless Sensor Network based on Genetic Algorithm", *Telecommunication Systems*, Vol. 67, No. 3, pp. 451-463, 2018.

[10] A. Agrawal, V. Singh, S. Jain and R.K. Gupta, "GCRP: Grid-Cycle Routing Protocol for Wireless Sensor Network with Mobile Sink", *AEU-International Journal of Electronics and Communications*, Vol. 94, No. 2, pp. 1-11, 2018.

[11] T.E. Bogale and L. Vandendorpe, "Max-Min SNR Signal Energy based Spectrum Sensing Algorithms for Cognitive Radio Networks with Noise Variance Uncertainty", *IEEE Transactions on Wireless Communications*, Vol. 13, No. 1, pp. 280-290, 2014.

[12] D.M. Martinez and A.G. Andrade, "On the Reduction of the Noise Uncertainty Effects in Energy Detection for Spectrum Sensing in Cognitive Radios", *Proceedings of IEEE Annual International Symposium Personal, Indoor and Mobile Radio Communications*, pp. 1975-1979, 2014.

[13] K.M. Thilina, K.W. Choi, N. Saquib and E. Hossain, "Pattern Classification Techniques for Cooperative Spectrum Sensing in Cognitive Radio Networks: SVM and W-KNN Approaches", *Proceedings of IEEE International Conference on Global Communications*, pp. 1260-1265, 2012.

[14] Soumitra Das and Sanjeev Wagh, "Prolonging the Lifetime of the Wireless Sensor Network Based on Blending of Genetic Algorithm and Ant Colony Optimization", *Journal of Green Engineering*, Vol. 4, No. 3, pp. 245-260, 2015.

[15] Mehr Moslem Afrashteh, "Design and Implementation a New Energy Efficient Clustering Algorithm using Genetic Algorithm for Wireless Sensor Networks", *World Academy of Science, Engineering and Technology*, Vol. 5, No. 4, pp. 373-376, 2011.