Energy-efficient geographic routing algorithm in event-driven wireless sensor networks using an enhanced TOPSIS approach

Ghaihab Hassan Adday[1,2], Shamala K. Subramaniam[2,3] and Maha Salih Abdulridha[4]

[1] Department of Computer Science, College of Computer Science and Information Technology, Basrah University, Basrah City, Basrah State, Iraq
[2] Department of Communication Technology and Networks, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, Seri Kembangan, Selangor, Malaysia
[3] Universiti Putra Malaysia, Seri Kembangan, Selangor, Malaysia
[4] Department of Computer Information Systems, College of Computer Science and Information Technology, Basrah University, Basrah City, Basrah State, Iraq

ABSTRACT

Event-driven Wireless Sensor Networks (WSNs) are a fundamental component of the Internet of Things (IoT), reporting data only upon event occurrence to conserve energy. A critical aspect of these networks is geographic routing, where routing decisions are based on node locations rather than identifiers, reflecting the spatial relevance of detected events. However, conventional geographic routing algorithms suffer from workload imbalance, congestion, and high energy consumption, limiting network lifetime and reliability. To address these issues, this study proposes a novel geographic routing algorithm based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The algorithm introduces a new decision metric, Exclusive Routing Share (ERS), that identifies and prevents node overutilization, thereby mitigating bottlenecks. It selects optimal forwarding nodes based on multiple criteria: residual energy on the path, hop count, delivery ratio, distance, and ERS, enabling more balanced and energy-efficient routing than traditional shortest-path methods. The algorithm's effectiveness was evaluated through extensive simulations under varying network conditions and compared with the benchmark Fault-Tolerant Routing (FTR) algorithm. Quantitative results show a 15.4% reduction in packet error rate, a 14.9% increase in network lifetime, and a 1.46% improvement in packet delivery ratio. These findings demonstrate that the proposed TOPSIS-based approach significantly enhances energy efficiency, reliability, and workload balance in event-driven WSNs.

Subjects Computer Networks and Communications, Network Science and Online Social Networks, Optimization Theory and Computation, Theory and Formal Methods, Internet of Things
Keywords Energy preservation, Event-driven, Geographic routing, IoT, Multi-Criteria Decision Making (MCDM), TOPSIS, WSNs

Submitted 23 October 2025
Accepted 18 March 2026
Published 19 May 2026

Corresponding author
Ghaihab Hassan Adday, ghaihab.aday@uobasrah.edu.iq

Academic editor
Ankit Vishnoi

Additional Information and Declarations can be found on page 25

DOI 10.7717/peerj-cs.3837

Copyright
2026 Adday et al.

Distributed under
Creative Commons CC-BY 4.0

OPEN ACCESS

INTRODUCTION

The rapid expansion of the Fourth Industrial Revolution (IR 4.0) and the advent of the Internet of Things (IoT) have laid a key foundation for future industrial and technological advances (*Adday et al., 2023*; *Majid et al., 2022*). These paradigms highlight the importance of fluid interconnection, automation, and intelligent decision-making, all of which depend on dependable networking infrastructure. Wireless Sensor Networks (WSNs) are essential to the realization of IoT applications and are regarded as a vital component of smart cities (*Idrees & Al-Qurabat, 2021*). They enable massive-scale data collection, environmental monitoring, and real-time operations. As a result, they are essential for a wide range of intelligent services (*Bairagi, Dutta & Babulal, 2022*). Multihop networks, consisting of several distributed sensor nodes that work together to communicate and send data, are the most common way WSNs are organized. This particular arrangement enables the network to cover a broad range of geographical locations where the base station cannot communicate directly with the nodes.

Sensors are often installed in a self-organizing fashion and function under stringent energy constraints (*Moussa et al., 2023*). These limits provide difficulties in sustaining long-term network operation, as nodes must optimize energy consumption to prolong network lifespan while simultaneously meeting application demands (*Bairagi, Babulal & Dutta, 2023*). Each sensor node may detect ambient variables and produce application-specific data. Furthermore, nodes may act as relays to transmit information to adjacent nodes, ensuring reliable data transmission to the Base Station (BS). This dual function underscores the significance of local sensing precision and collaborative data transfer methods.

The autonomous and adaptive characteristics of WSNs render them exceptionally well-suited for critical, sensitive applications, including natural disaster monitoring, early earthquake detection, volcanic activity tracking, and forest fire surveillance. These applications require quick responses, strong network stability, and effective energy management to ensure continuous monitoring in uncertain conditions.

Sensor networks can be classified into three distinct groups according to their activity patterns. The three categories of systems are Time-driven, Query-driven, and Event-driven. The event-driven WSN has recently attracted increased scholarly attention from these categories (*Abdulridha, Adday & Alshawi, 2019*). It can perceive and identify environmental occurrences instantaneously, facilitating the prompt identification of diverse phenomena such as wildfires and elevated chemical concentrations. Routing in event-driven WSNs is complex due to their substantial distinctions from other network topologies, such as wired or cellular networks (*Abdalhafid et al., 2024*). Geographic routing is widely employed in event-driven networks as an efficient method in which the location of the event is more relevant than the node identifiers. Geographic algorithms provide several advantages, including minimal end-to-end latency, scalability, adaptability, and elevated delivery rates. Nonetheless, spatial routing methodologies continue to face several unresolved challenges, including significant overhead, complications in handling void regions, and uneven load distribution, which diminish the network's longevity (*Hameed et al., 2020*).

Compact batteries provide power to sensor nodes. At times, it may be infeasible to substitute or recharge such batteries. Consequently, energy efficiency is a crucial emphasis of WSN (*Kaur & Chanak, 2022*; *Moridi et al., 2020*). A significant drawback of conventional geographic routing algorithms and their variants is their reliance on a single

Table 1 Comparison of critical criteria in the state-of-the-art of geographic routing algorithms.

Algorithm	Residual energy	Distance to BS	Buffer size	Link reliability	Minimum hop count	No. of neighbors	Signal strength
EAEDR	✓	✓	✓	✗	✗	✗	✗
AGT	✓	✓	✗	✗	✗	✗	✗
FTR	✓	✓	✗	✓	✓	✗	✗
TFN	✓	✓	✓	✗	✓	✓	✗
GPSR	✗	✓	✗	✗	✗	✗	✗
LEACH-AHP	✓	✓	✗	✗	✗	✗	✗
EELDS	✓	✓	✗	✗	✗	✗	✓
GTTR	✓	✓	✗	✗	✓	✗	✗
GFR	✓	✓	✗	✓	✗	✗	✗

criterion, often distance, during the routing process. As a result, they are unable to adequately tackle several difficulties, including significant congestion and excessive energy use. Regardless of using two or more criteria in the routing process, the forwarding strategy is constrained to conform to the regulations established by these criteria.

Current geographic routing algorithms have employed several parameters, including the distance to the destination, the residual energy of nodes, and the link quality among adjacent nodes. As a result, Multi-factors Decision-Making (MCDM) algorithms have been developed to integrate additional factors for enhancing network durability (*Fang et al., 2022*; *Kareem Thajeel et al., 2023*; *Naderi & Ghanbari, 2023*; *Shelebaf & Tabatabaei, 2020*). Numerous MCDM methodologies have been suggested for improvement, including the Analytic Hierarchy Process (AHP), Elimination and Choice Expressing Reality (ELECTRE), and Weighted-Sum Model (WSM) (*Mardani et al., 2017*). The WSM is an innovative approach commonly employed in WSN routing, assessing the relative significance of each criterion (*Kumar & Parimala, 2020*). Moreover, it entails consolidating several factors to build a singular choice measure (*Singh & Pant, 2021*). This strategy has several limitations, including the need to select appropriate weights, which is inherently subjective. The WSM technique may fail to find all optimum solutions. Furthermore, they are unable to dynamically modify their forwarding strategy to accommodate varying network conditions. Table 1 presents a comparative analysis of the decision factors employed in state-of-the-art protocols. Clearly, most algorithms focus on specific metrics, such as residual energy or distance, and often ignore differences in network conditions.

The constraints of current geographic routing algorithms (including the criteria they employ) necessitate the development of a novel routing method for event-driven WSNs. Additionally, new criteria are required to ensure a more robust response to WSNs traffic. This study employs a multi-criteria decision-making approach known as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This method establishes improved criteria for selecting the optimal neighbor for data transmission to the BS. This work's contributions are as follows.

- This study presents an improved geographic routing method based on TOPSIS to enhance energy efficiency in event-driven WSNs. The algorithm is explicitly designed to reduce excessive energy consumption caused by the recurrent use of the shortest-path technique in data forwarding, thereby prolonging network longevity and promoting a more equitable energy distribution across sensor nodes.

- This study presents five enhanced criteria for the routing decision-making process inside the TOPSIS architecture. The incorporation of these criteria enables a more thorough assessment of adjacent nodes, thereby identifying the most appropriate relay node for transmitting data to the base station. The suggested method, which integrates improved criteria, achieves more efficient forwarding decisions that optimize energy conservation, dependability, and network performance.
- This study presents extensive simulation tests to evaluate the efficacy of the suggested strategy relative to existing alternatives. The assessment concentrates on essential performance indicators, including network longevity, latency, Packet Error Rate (PER), Packet Delivery Ratio (PDR), and Average Energy Consumption (AEC). These indications provide reliable and significant insights into the strength and validity of the proposed algorithm in addressing the issue under examination.

The subsequent sections of this research are structured as follows: the "Related Work" section reviews pertinent literature on elevated energy consumption in event-driven WSNs and evaluates current remedies. The "Proposed Routing Algorithm" Section provides a comprehensive elucidation of the suggested routing algorithm. "Proposed Criteria For TOPSIS" Section delineates the refined criteria for the improved TOPSIS technique. "Network Model" Section outlines the network model utilized in this study, while the "Overhead Cost Analysis" Section presents a cost analysis of the suggested method. "Simulation Setup" Section delineates the simulation configuration. "Results and Discussion" delineates the experimental findings. Ultimately, the "Conclusion" concludes the study and emphasizes the study's significant discoveries.

RELATED WORK

Geographic routing strategies for WSNs have been extensively studied, primarily because they play a crucial role in enhancing energy efficiency, reducing latency, and balancing network workload. This section reviews several prior efforts, highlighting their methodologies, strengths, and limitations to situate the motivation for the proposed work.

A hierarchical and distributed geographic routing scheme was introduced by integrating the LEACH protocol with the AHP (*Gangal, Cinemre & Hacioglu, 2024*). The presented approach allowed nodes to autonomously compute their probability of becoming cluster heads by maintaining a threshold matrix derived from energy levels and distance to the sink. While the method demonstrated improvements in clustering efficiency, its reliance on AHP introduced significant computational overhead due to the complexity of pairwise comparisons. Furthermore, the decision-making process was limited to two parameters (residual energy and distance), thereby restricting adaptability under dynamic, diverse network conditions.

The Energy-Efficient and Localization-Based Dynamic Scheduling (EELDS) strategy, developed by *Hussain et al. (2026)*, combines multi-modal localization techniques such as

Angle of Arrival (AoA) and Time of Arrival (ToA). It also employs a five-state finite-state machine to enhance energy efficiency and improve overall network performance. The protocol improves routing reliability by utilizing relay-assisted void avoidance and dynamically adjusting node activity to optimize energy consumption and prolong network lifespan. Despite EELDS exhibiting significant enhancements in energy efficiency and throughput, it entails high computational complexity owing to its multi-matrix scheduling structure and frequent state transitions.

A clustering-based routing technique presented by *Pandey & Singh (2023)*, employs the TOPSIS for cluster head selection. Five decision parameters were considered, including residual energy, node density, and distance-related factors, aiming to balance load distribution. The method achieved reasonable improvements in cluster formation and network lifetime. However, the model still emphasized distance as the dominant criterion, ignoring reliability and hop count, which are critical in packet delivery. Moreover, increasing the number of decision parameters in the TOPSIS framework significantly raised computational complexity, challenging its practicality in real-time WSN applications.

Gangwar et al. (2025) proposed Game Theory-based TOPSIS Routing (GTTR), a protocol that combines game theory with a TOPSIS-based decision framework. The protocol enhanced cluster-head selection and established energy-efficient multihop communication pathways. The method initially identified temporary cluster heads using a mixed-strategy Nash equilibrium, accounting for remaining energy, node history, intra-cluster communication distance, and node degree. A fitness function selected final cluster heads, whereas TOPSIS is employed for cluster formation and intra-cluster multihop routing. Despite its advances over conventional clustering methods, GTTR incurred a high computational cost due to repeated TOPSIS executions in both clustering and multihop path creation.

An Adaptive Geometrical Clustering Routing Protocol (AGCRP) for mobile WSNs was developed by *Abdou et al. (2026)*. The protocol segmented the network into grid cells, with each cell comprising a forwarder cluster head, a collector cluster head, and a group of cluster members. The selection of forwarder and collector clusters has been determined based on criteria like energy level, proximity to the grid center, and average distance to members. The proposed protocol failed to account for the time sensitivity and significant delays inherent in the election process for the forwarder and collector clusters.

A multi-weighted sum method was proposed for event-driven WSNs by *Biswas & Samanta (2020)*, where hop count was prioritized as the dominant factor in selecting the next-hop node. Although residual energy and delivery ratio were also included as decision metrics, the approach strongly favored the shortest-path policy. Consequently, specific nodes were frequently overloaded, while others were underutilized, leading to unbalanced energy consumption and reduced overall network stability.

The Energy Aware Event-Driven Routing (EAEDR) protocol was presented in *Hang, Trinh & Ban (2018)* and sought to improve conventional geographic routing techniques. EAEDR used event-driven communication and energy awareness to inform decisions in a sensor network. Depending on the event type, one or two suitable nodes were selected as forwarders, with residual energy, distance to the source, and distance to the sink as decision criteria. The protocol demonstrated promising results in prolonging network lifetime. However, in high-priority events, the adoption of multipath routing introduced considerable control overhead, complicated routing table maintenance, and reduced efficiency.

A hybrid method combining Triangular Fuzzy Numbers (TFNs) with TOPSIS for cluster head selection was explored in *Sen et al. (2023)*. Six parameters were considered, including reliability, residual energy, and distance metrics, to optimize the number of cluster heads. Although the method improved reliability and energy distribution, scalability was limited because the network was restricted to 14 clusters. Furthermore, the heavy reliance on distance-to-sink criteria overshadowed intra-cluster communication costs, undermining load balancing within clusters.

Tian et al. (2018) Introduced a comprehensive multi-criteria decision-making framework that integrates the AHP, Gray Correlation Analysis, and TOPSIS. The methodology used AHP to determine subjective weights for assessment indices. It combined Gray Correlation with TOPSIS to address limited information, ranking alternatives based on their proximity to the positive and negative ideal solutions. The methodology, although proficient at addressing multi-objective optimization problems with uncertain data, exhibited inherent subjectivity due to its reliance on expert input during the AHP weighting phase and incurred significant computational complexity from the elaborate multi-step integration of three separate mathematical models.

To optimize routing in WSNs, *Abou et al. (2022)* proposed an innovative framework that integrates Federated Learning (FL) with Deep Reinforcement Learning (DRL). Although Reinforcement Learning (RL) can support adaptive routing protocols, its applicability is constrained by the curse of dimensionality, which causes the state–action space to grow exponentially, limiting scalability and practical deployment. Moreover, in Multi-Agent RL (MARL) settings, the substantial data exchange required among agents introduces considerable bandwidth overhead and slows the training process.

Zheng & Zhou (2023) introduced an innovative intelligent routing system utilizing Deep Reinforcement Learning (DRL), specifically designed for highly dynamic wireless networks characterized by fast changes in network topology. The methodology uses autonomous DRL agents at network nodes that employ deep neural networks to estimate optimal routing strategies and determine the most suitable next-hop neighbor based on observed local conditions, rather than relying on pre-established rules or obsolete global topology maps. Although the algorithm improved packet delivery ratios and adapted to mobility more effectively than conventional static protocols, it incurred significant computational complexity and energy consumption by executing deep neural networks on resource-limited mobile nodes. It exhibited slow convergence rates during initial training phases in highly volatile environments.

Bairagi, Dutta & Babulal (2024) analyzed the implementation of specific protocols, including AODV, DSDV, DSR, OSLR, and M-GEAR. They evaluated network factors, including latency and packet delivery ratio, across various network sizes. The simulation results indicate that protocol performance depends on network size and that selecting the optimal protocol based on network parameters is essential.

Bairagi et al. (2024) introduced the Geographic Forwarding Energy-Efficient Routing Protocol (GF-EERP), an enhanced version of the existing GEAR protocol designed to improve energy efficiency in event-driven WSNs. The core of the GF-EERP methodology was an innovative multi-phase routing strategy that involved categorizing nodes based on their current energy levels, establishing special criteria for selecting a powerful region head node, utilizing multihop communication paths, and preemptively excluding dead nodes from the communication process. This sophisticated selection mechanism for the region head was identified as the primary contribution, enabling more intelligent, energy-aware geographic forwarding. However, the proposed approach was noted as potentially under-optimized for complex scenarios. GF-EERP was primarily suited to static WSN environments and required further adaptation to maintain its energy efficiency and accuracy in the presence of node mobility

Yan, Zhou & Ding (2016) examined primary routing protocols to analyze and comprehend energy-efficient routing. The study indicated that developing dependable routing measures, such as spatial reusability, is essential in routing design to enhance network throughput performance while maintaining manageable energy expenditure. Furthermore, certain applications require multiple QoS measures, as evaluating only a limited set of criteria can disrupt the balance between QoS assurance and energy efficiency.

Finally, *Jian et al. (2024)* presented the High-Reliability Low Latency Intelligent Geographic Routing (HRLLIGR) algorithm, an enhancement of the GPSR protocol, tailored for mobile nodes in dynamic topologies. The algorithm employed greedy forwarding with link stability metrics to increase reliability and area prediction to reduce void-related latency. While effective in highly mobile environments, the algorithm suffered from excessive complexity in managing communication between mobile nodes and the base station due to the constantly changing topology.

Despite considerable progress, substantial research deficiencies remain in geographic routing for event-driven WSNs. A significant constraint is the inability to reconcile the precision of decision-making with computational practicality. Basic processes often rely on skewed measures, leading to disproportionate energy consumption. Conversely, intricate MCDM and AI models impose significant complexity, high latency, and slow convergence, rendering them inappropriate for resource-limited nodes. Moreover, few solutions effectively adjust to fluctuating conditions, such as congestion or faults, while reconciling conflicting QoS and energy requirements. Thus, there exists an urgent need for a streamlined, all-encompassing framework to address these trade-offs. This study proposes an enhanced TOPSIS-based architecture that overcomes these deficiencies by incorporating several factors to balance energy consumption, optimize reliability, and prolong network lifespan.

PROPOSED ROUTING ALGORITHM

The TOPSIS approach is a multi-criteria technique presented to choose the best option from a group of choices (*Hajduk, 2021*). Fundamentally, TOPSIS helps decision-makers determine the best option by comparing each one to the ideal based on several criteria. TOPSIS has been widely used to design routing algorithms in WSNs, and it is a preferable choice over other methods for several reasons. Some of these reasons are that TOPSIS is straightforward to implement, scalable, can handle multiple criteria, and has flexibility in criteria weighting. Moreover, TOPSIS can be integrated with other techniques (*Murugaanandam & Ganapathy, 2019*). Lastly, TOPSIS can effectively deal with many complex and incompatible criteria.

The proposed routing algorithm employs the TOPSIS method to select the most suitable forwarding node. Each candidate node is evaluated based on two measures: its closeness to the ideal (positive) solution and its distance from the anti-ideal (negative) solution. The ideal solution represents the best values for all criteria, while the anti-ideal solution represents the worst values. Nodes that are nearer to the ideal solution and farther from the anti-ideal solution are ranked as better choices. This process ensures that multiple criteria are considered simultaneously in decision-making. The following steps outline the proposed TOPSIS method in detail.

(1) Establishing the matrix: The process begins by constructing a decision matrix for a given sensor node, where each row corresponds to a candidate neighbor node (alternative) and each column corresponds to one of the m evaluation criteria. Equation (1) illustrates the constructed X_i matrix for the proposed routing algorithm based on TOPSIS. C_{ij} represented the value of jth criterion for the ith sensor node, where n represents the available candidates (i = 1, 2, 3, …, n), and m represents the evaluation criteria (j = 1, 2, 3,…, m).

$$X_i = \begin{bmatrix} C_{11} & C_{12} & C_{13} & . & . & C_{1m} \\ C_{21} & C_{22} & C_{23} & . & . & C_{2m} \\ C_{31} & C_{32} & C_{33} & . & . & C_{3m} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ C_{n1} & C_{n2} & C_{n3} & . & . & C_{nm} \end{bmatrix}. \tag{1}$$

(2) Normalizing the matrix: Normalization is a crucial step in the proposed TOPSIS, ensuring that each criterion is on the same scale and contributes equally to the decision-making process. Equation (2) represents the transformation that is used to normalize the decision matrix for each element NR_{ij}.

$$NR_{ij} = C_{ij} / \sqrt{\sum_{i=1}^{n} C_{ij}^2}. \tag{2}$$

(3) The weight W_j is assigned to each criterion in the matrix; the weights are then multiplied by the normalized matrix using Eq. (3).

$$V_{ij} = W_j * NR_{ij} \text{ where } \sum_{j=1}^{n} W_j = 1. \tag{3}$$

(4) Finding the ideal and anti-ideal solution: The weighted decision matrix defines the ideal (positive) and anti-ideal (negative) solutions. Ideal or positive criteria represent the highest criteria values (the higher, the better), as shown in Eq. (4).

$$A^+ = (V_1^+,\ V_2^+,\ V_3^+, \ldots,\ V_n^+)$$
$$A^+ = \left\{(max\ V_{ij} | i = 1, 2, 3, \ldots .m),\ j = 1, 2, 3, \ldots .n\ \right\}. \tag{4}$$

In contrast, the anti-ideal (negative) solution has the lowest criterion value (less is more desirable), as shown in Eq. (5).

$$A^- = V_1^-,\ V_2^-,\ V_3^-, \ldots,\ V_n^-$$
$$A^- = \left\{(min\ V_{ij} | i = 1, 2, 3, \ldots .m),\ j = 1, 2, 3, \ldots .n\ \right\}. \tag{5}$$

(5) Determining the distance: The next step within the proposed algorithm involves the calculation of the Euclidean Distance (*ED*) that separates the current alternatives V_{ij} from the ideal and V_j^+ anti-ideal V_j^- solutions, as shown in Eqs. (6) and (7).

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_j^+ - v_{ij}\right)^2} \tag{6}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_j^- - v_{ij}\right)^2}. \tag{7}$$

(6) Ranking the alternatives: The final step in the proposed algorithm involves ranking the alternatives. In this step, all alternatives are ranked K_i based on their closeness to the ideal solution and distance from the anti-ideal solution using Eq. (8).

$$K_i = S_i^- / S_i^+\ +\ S_i^-\ where\ 0 \le K_i \le 1. \tag{8}$$

The following section provides a comprehensive explanation of the criteria selected for integration into the proposed routing algorithm. These criteria are essential for constructing the corresponding TOPSIS decision matrix. Moreover, they have been carefully chosen based on their relevance and impact on routing performance in event-driven WSNs.

PROPOSED CRITERIA FOR TOPSIS

The proposed algorithm ensures optimum routing by selecting the most suitable neighbor node within the transmission range as the packet is transferred from the source node to the BS along the best path. Using TOPSIS, the best node in the neighbor's information table is selected for each sensing round, with energy consumption as the primary target. The following are the five proposed criteria used to determine the most suitable node from the neighbor nodes:

- Distance: The distance between any sensor node and its neighboring nodes is a crucial criterion and fundamental in geographic routing. The main idea is to forward data packets to the farthest neighboring node, which will also be the closest node to the BS among the neighboring nodes (*Biswas & Samanta, 2020*). The proposed routing approach ensures that each hop moves the data packet significantly closer to the BS, optimizing the routing path and improving the network's efficiency. Equation (9) is used to calculate *ED* between any two neighboring nodes.

$$ED_{(N_i,N_j)} = \sqrt{(X_j - X_i)^2 + (Y_j - Y_i)^2} \tag{9}$$

where the coordinates of nodes N_i and N_j are represented by (X_i, Y_i) and (X_j, Y_j), respectively.

- Minimum Energy on the Path: Energy efficiency is critical due to sensor nodes' limited battery life. The proposed routing algorithm prioritizes extending the network lifetime. The algorithm proposes the Minimum Energy on Path (MEoP) to the BS instead of the remaining energy used in the baseline algorithm. MEoP will maximize the network lifespan. Any sensor node N_i updates its $\mathrm{MEoP_i}$ value based on the energy metrics advertised in the most recent local Beacons received from its immediate neighbors. This allows N_i to select an energy-efficient next hop using only local knowledge, avoiding the need for global route discovery or state maintenance. Simultaneously, N_i will inform all its neighbors N_j about the $\mathrm{MEoP_i}$, which could be for itself or its next hop node. This behavior ensures that the best route is selected between a node and its immediate neighbor and across the entire path to the BS. The decision-making process considers the energy levels of all nodes along the route, rather than limiting itself to the next node in the sequence. Dynamic changes in MEoP lead to frequent route modifications. In this scenario, route fluctuation is an advantageous characteristic; it serves as an implicit load-balancing mechanism that distributes energy consumption across multiple accessible paths. Moreover, because the selection of the next hop is a local process that relies on periodic Beacon exchange, these transitions occur without triggering on-demand route discovery or increasing control packet overhead. Unlike other works, which consider the remaining energy of the next-hop node along the path, the proposed algorithm uses a logarithmic transformation of energy. The logarithmic transformation of the remaining energy levels has been proposed as one of the TOPSIS criteria that helps more effectively manage a wide range of energy values. This transformation is beneficial when dealing with a wide range of energy values. It can help normalize the data, making patterns and trends more visible for energy ranking. The developed algorithm used the First Order Model to calculate the remaining energy (*Heinzelman, Chandrakasan & Balakrishnan, 2000*). Equations (10) and (11) are used to calculate the logarithmic transformation RE_i' and the selection of *MEoP* within each sensor node N_i. Where RE_i is the remaining energy of the sensor node, and RE_j is the remaining energy of the next hop node.

$$RE_i' = log(RE_i + 1) \tag{10}$$

$$MEoP_i = min\,(RE_i', RE_j'). \tag{11}$$

- Delivery Ratio: Alerting BS about an event is the main priority in event-driven WSN. Therefore, link reliability or delivery ratio is crucial. The Delivery Ratio ($\mathrm{DR_{ij}}$) between any two nodes (N_i and N_j) indicates link trustworthiness (*Biswas & Samanta, 2020*). It is calculated as the ratio of packets received by N_j to packets sent by N_i. Packet loss is more likely on links with a lower DR. A link with a higher DR is preferable to ensure link reliability. Equation (12) calculates the DR of any nearby node N_i on node N_j.

$$DR_{ij} = N_i RN_j / BN_j \tag{12}$$

where $N_i RN_j$ is the number of beacon packets that N_i received from node N_j and BN_j is the number of beacon packets broadcast by N_j. The proposed performance analysis tool periodically calculates the DR by exchanging Beacon messages and tracking the number of packets neighbors receive. The Beacon message includes a field called the Bcon_ID. Bcon_ID is a unique identifier of the Beacon message, starting with one and incremented by one at each beacon broadcasting interval. Each node also has a column, Bcon_count, in the Neighbor Information (NB-Info) table, which is initialized to 0. Upon receiving a beacon from neighbor N_j, N_i stores Bcon_ID and increments the Beacon counter by 1. Therefore, dividing Bcon_count by Bcon_ID will be the delivery ratio between N_i and N_j. As time progresses, nodes broadcast and receive more beacons, making *DR* increasingly accurate.

- Minimum Hop Count: Data transmission in WSNs incurs significant energy and time costs. The Minimum Hop Count (MHC) is essential to minimize energy consumption and end-to-end delay from the source node to the BS. The proposed algorithm prefers to select the neighboring node with the lowest MHC to the BS, thereby saving energy and preventing the data packet from being forwarded far from the final destination.
- Exclusive Routing Share: In event-driven WSNs, efficient load balancing is essential to conserve energy and extend network lifespan. The proposed Exclusive Routing Share (ERS) criterion helps achieve this by identifying nodes that are overly relied upon by their neighbors, thereby preventing network bottlenecks. ERS operates on the dependability principle. For example, if a sensor node has a high ERS, it means that many neighboring nodes rely on it as their next hop, making it a critical part of their routing paths. Continuous reliance on such specific nodes in the routing process can lead to energy depletion and eventual failure, reducing the overall network lifespan. In the worst-case scenario, the failure of this node may lead to isolated areas in the network topology. This issue can result in numerous disconnected nodes, severely impacting network connectivity and functionality. The proposed algorithm integrates this concept with the TOPSIS method, selecting neighbors with lower ERS to optimize routing. This technique balances the network load by preventing high traffic on specific nodes. As a result, it helps avoid potential bottlenecks and conserves energy throughout the network.

All these criteria were easily calculated without additional equipment or high-cost complexity by exchanging neighbor information. Neighbor information is exchanged periodically using Hello and Beacon (control) messages and stored in the NB-Info table for each sensor node. Both routing control packets are small to conserve energy and avoid network congestion. Minor modifications were made to specific fields in the control packets to better align with the requirements of the proposed algorithm, improving upon the traditional geographic routing algorithm. The modified fields are as follows.

- Node ID: A unique identifier assigned to the transmitting sensor node. It ensures that each message can be traced back to its origin.
- Position (X, Y): The geographic coordinates of the node in the deployment field. These values are used to determine distances between nodes.
- MEoP: This field is critical for energy-aware routing, as it helps avoid overusing nodes with low energy reserves.
- Hop Count: The number of hops from the node to reach the BS. This parameter is used to prevent routing loops and to estimate the overall path length.
- Next Hop: The identifier of the selected forwarding node. It specifies the immediate relay node that will handle the next transmission step toward the destination. For any sensor node N_i, any neighbor node N_j within its transmission range can potentially act as a relay node for the data report packets towards the BS in a multihop communication style. Next Hop (NH_j) is the selected neighbor node N_j that will serve as a forwarder node for node N_i in every round.
- Alternative Next Hop Count: Every node N_i knows if it has another option to be chosen as the next hop NH_j that achieves a minimum number of hops to forward data reports toward BS. Thus, the Alternative Next Hop Count (Alt-NHC$_i$) parameter indicates the availability of an alternative route for BS based on the NB-Info table.
- Exclusive Routing Share: The Exclusive Routing Share (ERS$_i$) denotes the number of neighboring nodes that rely entirely on a sensor node N_i as their next hop. These neighbors have no other choice for sending their data except *via* N_i. Equation (13) calculates this parameter for each node before sending it within the Beacon packet.

$$ERS_i = \sum_{j=1}^{m} \begin{cases} ERS_i + 1 & Alt\text{-}NHC_j = 0 \ and \ NH_j = N_i \\ 0 & Otherwise \end{cases} \tag{13}$$

Hello messages are broadcast only once at the beginning to share the hop count, next hop, geographic location, and residual energy for each node, as shown in Fig. 1, which depicts the fields or contents of the Hello packet. Figure 2 represents the contents of the Beacon packet containing Beacon ID, minimum energy on the path, hop count, alternative next hop count, exclusive routing share, and next hop. All these parameters are essential for supporting the update process of the enhanced criteria before storing them in the NB-Info table.

On the other hand, Fig. 3 illustrates an example of the updating process of the proposed criteria values within the NB-Info table for sensor nodes S_3 and S_7.

NETWORK MODEL

In the proposed network model, K is the number of sensor nodes, K_i ($i = 0, 1, 2, 3, \ldots, K-1$), that are randomly scattered in a Two-Dimensional *2D* geographical area with dimensions of (X, Y). Any two nodes, such as K_i and K_j, can communicate directly if the ED_{ij} between

Node ID	Position(X,Y)	Remaining Emergency	HC	NH

Figure 1 The content of the hello message. Full-size DOI: 10.7717/peerj-cs.3837/fig-1

Node ID	Beacon ID	MEoP	Alt-NHC	HC	NH	ERS

Figure 2 The content of the Beacon message. Full-size DOI: 10.7717/peerj-cs.3837/fig-2

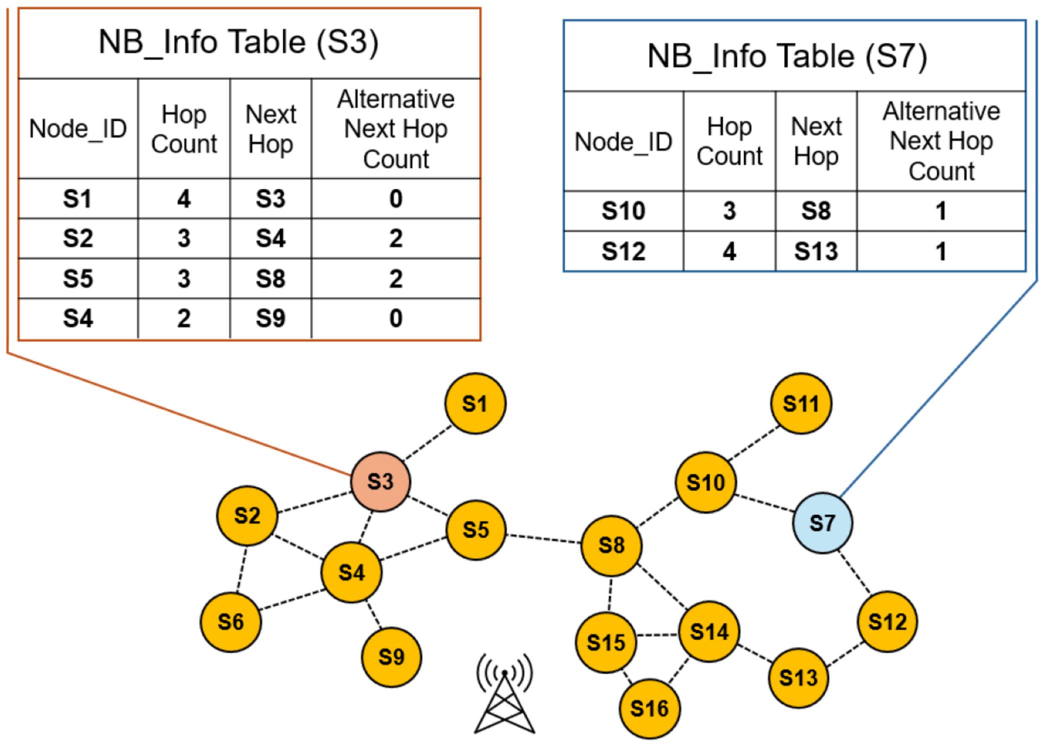

Figure 3 Updating the NB-Info table. Full-size DOI: 10.7717/peerj-cs.3837/fig-3

them is less than or equal to their transmission range D. The proposed network model assumes a static deployment in which all sensor nodes remain stationary throughout the operation. Each node is location-aware and maintains knowledge of its own residual energy levels. The communication model is homogeneous, so all sensor nodes and the BS share the same transmission range. The proposed routing algorithm uses a multihop communication style to forward data packets toward the BS, as shown in Fig. 3. Any node that is not a neighbor of the BS will choose one of its neighbors as the forwarding node to transmit its sensed data to the BS, according to the NB-Info table. The NB-Info table is periodically updated by exchanging routing control packets, which provide all the necessary information for the sensor node to construct its TOPSIS matrix. Early on, every sensor node sets its hop count and next hop to $HC_i = \infty$ and next hop = 0, while the BS broadcasts a Hello with a hop count and next hop of 0. Whenever any node receives a hello

Algorithm 1 Control packets for NB-Info table generation.

Input: Hello message, Beacon message
Output: NB-Info table
Function Initialization ()
  If K_i is BS Then
    Broadcast (Hello Message);
  End If
End Function
Function Received Hello ()
  If K_i receives Hello from a neighbor K_j
     Compute $ED_{(k_i,k_j)}$using Eq. (9)
     Store N_ID, Pos(x, y), HC, and $ED_{(k_i,k_j)}$ in NB-Info;
  End If
 End Function
 Function Send Hello ()
  After receiving a Hello message from any node K_j
  For each K_j in the NB-Info table Do
    Broadcast (Hello);
 End For
End Function
Function Send Beacon ()
 For each K_j in the NB-Info table Do
    Send $ED_{(k_i,k_j)}$, HC_i, $MEoP_i$, and ERS_i to all Neighbors
 End For
End Function
Function Received Beacon ()
 If K_i receives Hello from a neighbor K_j
   Store All the needed Information in the NB-Info table
   Compute the criteria To Build the TOPSIS matrix
   Update all criteria inside the NB-Info table;
 End IF
End Function

message from a neighbor K_i will compute the distance and store the energy level inside the NB-Info table. If HC_i which was initially set as ∞ is greater than $HC_j + 1$. K_i assign its hop count as $HC_j + 1$ and resend a Hello message to inform others. On the other hand, Beacon messages are broadcast periodically to update the neighbors' information inside K_i in a similar manner. Algorithm 1 outlines the pseudocode steps for the Hello and Beacon message exchanges and the generation of the NB-Ino table.

Figure 4 presents an example from the network simulation tool, which conducts experiments related to the TOPSIS steps. The example focuses on sensor node K_{44}, located at the left of the network topology. The example demonstrates how the proposed TOPSIS algorithm selects the most suitable node as the next hop.

The mentioned sensor node generates the TOPSIS matrix for four neighboring nodes based on five criteria, as illustrated in Eq. (14). In this matrix, each row represents an alternative, and each column represents a criterion.

$$K_{44} = \begin{bmatrix} Node\_ID & ED & MEoP & DR & MHC & ERS \\ 62 & 70.76 & 2.10 & 1.00 & 2 & 0 \\ 47 & 49.18 & 2.11 & 1.00 & 2 & 0 \\ 49 & 43.41 & 2.16 & 1.00 & 2 & 0 \\ 89 & 49.04 & 2.10 & 0.92 & 3 & 0 \end{bmatrix}. \tag{14}$$

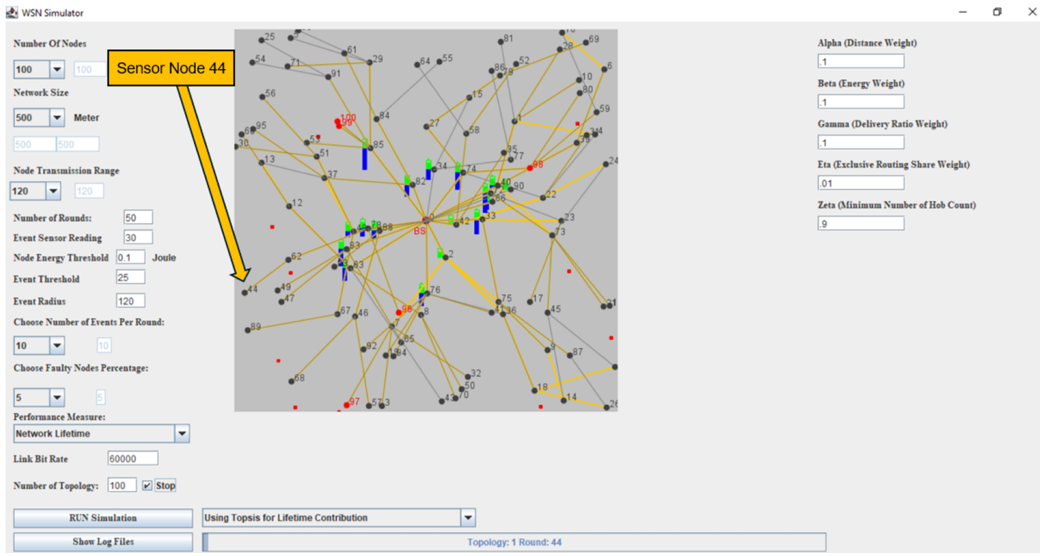

Figure 4 Simulation scenario for the proposed routing algorithm.
Full-size DOI: 10.7717/peerj-cs.3837/fig-4

The normalization matrix for the second stage of the proposed TOPSIS is given in Eq. (15) for the sensor node K_{44}. The subsequent third stage, involving the ideal (positive) and anti-ideal (negative) solutions, is presented in Eqs. (16) and (17), respectively.

$$K_{44} = \begin{bmatrix} Node\_ID & ED & MEoP & DR & MHC & ERS \\ 62 & 0.19 & 0.14 & 0.15 & 0.39 & 0.00 \\ 47 & 0.13 & 0.14 & 0.15 & 0.39 & 0.00 \\ 49 & 0.12 & 0.15 & 0.15 & 0.39 & 0.00 \\ 89 & 0.13 & 0.14 & 0.14 & 0.58 & 0.00 \end{bmatrix} \tag{15}$$

$$\mathrm{A}^{+} = (0.19, 0.15, 0.15, 0.39, 0.00) \tag{16}$$

$$A^{-} = (0.12, 0.14, 0.14, 0.58, 0.00). \tag{17}$$

Equations (18) and (19) illustrate the fourth and fifth stages of TOPSIS. Based on the proposed routing algorithm, the alternative options indicate that sensor node K_{62} will act as a forwarder node for sensor node K_{44} in this sensing round.

$$S^{+} = (0.0043, 0.2204, 0.2252, 0.2057) \tag{18}$$

$$S^{-} = (0.299, 0.1973, 0.1967, 0.2057) \tag{19}$$

$$K_{62} = 0.98, K_{86} = 0.50, K_{47} = 0.47, K_{49} = 0.46.$$

OVERHEAD COST ANALYSIS

This section examines the computational and communication costs associated with the proposed algorithm.

Computational cost analysis

In event-driven WSNs, energy is critical because sensing, communication, and data processing consume power in sensor nodes. Among these activities, communication requires significantly more energy than sensing and data processing. For instance, the energy cost of transmitting 1 kilobit of data over 100 m is approximately equivalent to executing 3 million instructions on a general-purpose processor. However, explaining the computational cost for any new proposed routing algorithm is essential. The routing algorithm's computational cost centers on the frequent exchange of neighbor status information. The number of neighbor nodes, N, affects the computational complexity of the TOPSIS method because it executes a fixed number of independent stages regardless of input size or problem complexity. In this context, its time complexity is O(N × M), where N is the number of neighbors, and M is the number of criteria. Therefore, the proposed method has a time complexity of O(N × M). For simplicity, the proposed TOPSIS will not consider the nearest nodes to the BS, since these critical nodes already include the BS in their NB_Info Table and thus know its location. This simplification reduces computational overhead, making the total computational cost suitable for WSN requirements.

Communication cost analysis

The communication cost for the developed algorithm is determined by the control packet overhead and the data packet transmission cost. Control packet overhead (M_{route}) involves initial neighbor discovery (Hello message broadcasting) and periodic beacon broadcasting. All N sensor nodes broadcast a Hello message once. Thus, the cost is N. In contrast, all N sensor nodes broadcast a single beacon message in each beacon interval. If the network lifetime consists of S beacon intervals, the total beacon overhead is ($S \times N$). Therefore, the total routing control overhead M_{route} is derived as shown in Eq. (20)

$$M_{route} = N + \sum_{S=1}^{S} N = N(1 + S). \tag{20}$$

On the other hand, for an event-driven WSN, the cost of transmitting data depends on the number of events N_{event} and the average hop count H_{avg} from the source to the BS. Using the First Order Model (*Heinzelman, Chandrakasan & Balakrishnan, 2000*), the energy cost for transferring data packets is calculated using the Eq. (21).

$$E_{data} = \ N_{event} \times H_{avg} \times (E_{Tx}(1, d) + E_{RX}(l)) \tag{21}$$

where E_{TX} and E_{RX} are the transmission and reception for an l-bit packet over distance d.

SIMULATION SETUP

This section presents a detailed analysis of the simulation configurations for the proposed geographic routing algorithm based on TOPSIS. The developed WSN simulation tool is used specifically for routing process testing. The developed DES simulator based on the JAVA programming language was used to evaluate the proposed algorithm and compare it with benchmark work results reimplemented in the proposed simulator. This work has chosen the Fault-Tolerant Routing (FTR) algorithm as a baseline algorithm (*Biswas & Samanta, 2020*). The proposed geographic routing algorithm will forward the data reports to the BS *via* a multihop communication.

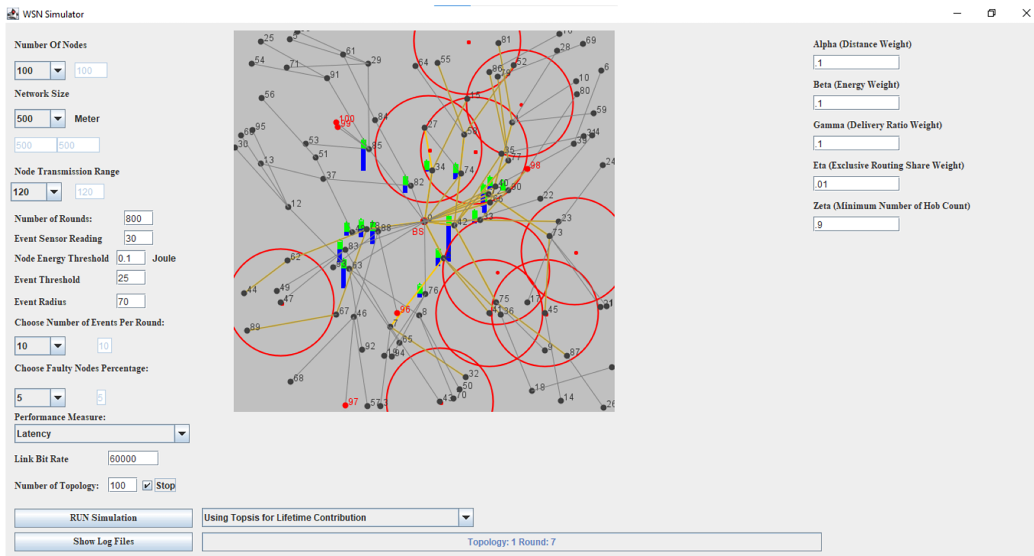

Figure 5 **Simulator interface for latency metric simulation setup.**
Full-size DOI: 10.7717/peerj-cs.3837/fig-5

For the simulation of the network lifetime metric, the proposed routing algorithm has been compared with the benchmark algorithm for 2, 4, 8, and 10 events per round. One hundred sensor nodes were randomly scattered over an area (500 × 500). The BS is located at each topology's center (250, 250), as shown in Fig. 5. The transmission range of all nodes is 120 m, and all sensor nodes have the same initial energy. To accurately compare the proposed method with the baseline algorithm, the proposed performance analysis tool averages the results from 100 random network topologies.

In addition, the proposed routing algorithm assigned five weighting factors to the TOPSIS criteria, where $W_j \in [0, 1]$ and $\sum_{j=1}^{n} W_j = 1$. The proposed algorithm in this work adopts equal weights for the five enhanced criteria. This emphasizes the importance of the proposed criteria in event-driven WSNs. Because no universally accepted analytical method exists for determining weights, a trial-and-error approach was employed, with multiple configurations systematically tested through extensive simulations. The final values were selected to achieve a balanced improvement across key performance metrics, including network lifetime, energy efficiency, delivery ratio, and latency, thereby significantly enhancing the proposed algorithm's performance.

On the other hand, in the simulation setup for the latency performance metric, 100 nodes were randomly scattered within an area (500, 500), and 10 events per round were simulated, with rounds ranging from 200 to 800 in steps of 200. The BS is also located at the center (250, 250) of each topology, as shown in Fig. 5, which illustrates the network simulator's Graphic User Interface (GUI) representing the simulation setup used to calculate latency. This work proposes five weight values for each TOPSIS criterion within the proposed routing algorithm. Detailed simulation parameters are comprehensively listed in Table 2.

Table 2 Simulation terminology and values.

Terminology	Value
Field size (Height and the width)	(500 × 500)
Number of sensor nodes	100
BS location	(250, 250)
Transmission range	120
Number of events	2, 4, 8, 10
Number of rounds	200, 400, 600, 800
Initial energy	$(15-\text{rand}\ (0, 1)) \times 10^{-2}$
Hello message frequency	Once during the initialization phase
Beacon interval	5 s
Hello message size	24 bytes
Beacon message size	24 bytes
Radio dissipation (E_{elec})	50 nJ/bit
Transmission amplifier (E_{amp})	100 pJ/bit/m^2
Residual energy for each sensor node	
Energy threshold	0.1 Joule
Weighting factors α, β, δ, γ, and Ω	0.25

RESULTS AND DISCUSSION

Network lifetime, latency, PER, and PDR are the main metrics that indicate network efficiency and reliability, with energy consumption being a critical factor in overall performance. The following are the experimental results for the proposed algorithm compared with the baseline algorithm regarding these metrics.

Network lifetime

Network lifetime is a critical performance metric in event-driven WSNs and is defined as the time from network initialization to the first node's energy depletion. It reflects the network's sustainability and efficiency, making it a primary focus in WSN research. Figure 6 shows a comparison of the network lifetime (in seconds) achieved by the proposed TOPSIS routing algorithm and the FTR algorithm. This comparison is evaluated across varying network load conditions. Figure 6 highlights the superior performance of the proposed routing algorithm in extending network lifetime compared to the benchmark algorithm. This improvement, averaging 14.9%, is primarily due to the algorithm's TOPSIS-based approach, which avoids low-energy paths. By balancing energy consumption and delaying the depletion of individual nodes, the algorithm postpones the first-node death, significantly extending the network's operational period. The integration of the ERS criterion plays a key role in achieving this enhancement.

Latency

Latency refers to the average time required for an event report to travel from a source node to the base station. In WSNs, low latency is essential for applications that require

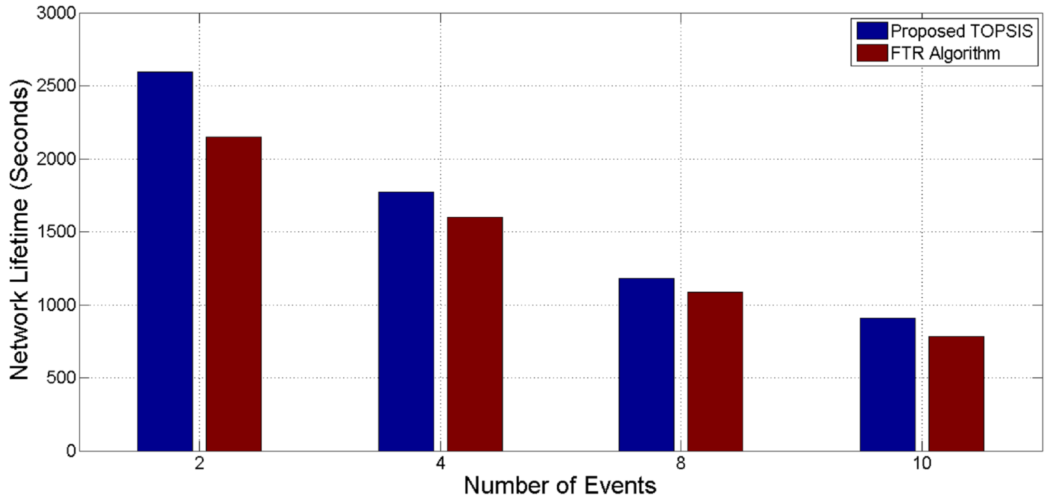

Figure 6 Network lifetime for the FTR algorithm and the proposed algorithm with 2, 4, 8, and 10 events per round. Full-size DOI: 10.7717/peerj-cs.3837/fig-6

timely data delivery, such as real-time monitoring and emergency response systems. Equation (22) calculates the latency for the proposed algorithm and the baseline work.

$$Latency = \sum_{i=1}^{N} (RT_i - ST_i)/N \tag{22}$$

where N is the total number of reports delivered by the BS. While RT_i and ST_i are the received and sent times for the *ith* event reports, respectively. Figure 7 compares the latency of the proposed routing algorithm and the baseline algorithm, showing that both initially experienced relatively high latency (approximately 750 ms). This is primarily due to the frequent exchange of control packets, such as Hello and Beacon messages.

In the first 200 rounds, the proposed algorithm achieves slightly lower latency (4% improvement) than the baseline. This is attributed to the TOPSIS-based routing method, which avoids congested nodes by considering the load on neighboring nodes, thereby reducing congestion and enhancing latency. However, as rounds progress and some nodes deplete their energy, latency in the proposed algorithm gradually increases. This is because the algorithm avoids critical, energy-depleted nodes, often requiring data packets to take longer paths. While this approach balances energy consumption and prevents overloading key nodes, it increases latency over time. In contrast, the baseline algorithm, which does not optimize workload distribution, exhibits lower latency in later rounds. However, this comes at the cost of uneven energy consumption and reduced network lifespan, highlighting the trade-offs between latency and energy efficiency in the proposed approach.

PER

PER is a key metric in WSNs that measures the ratio of lost packets to the total packets sent, reflecting data transmission reliability. Figure 8 compares the proposed algorithm

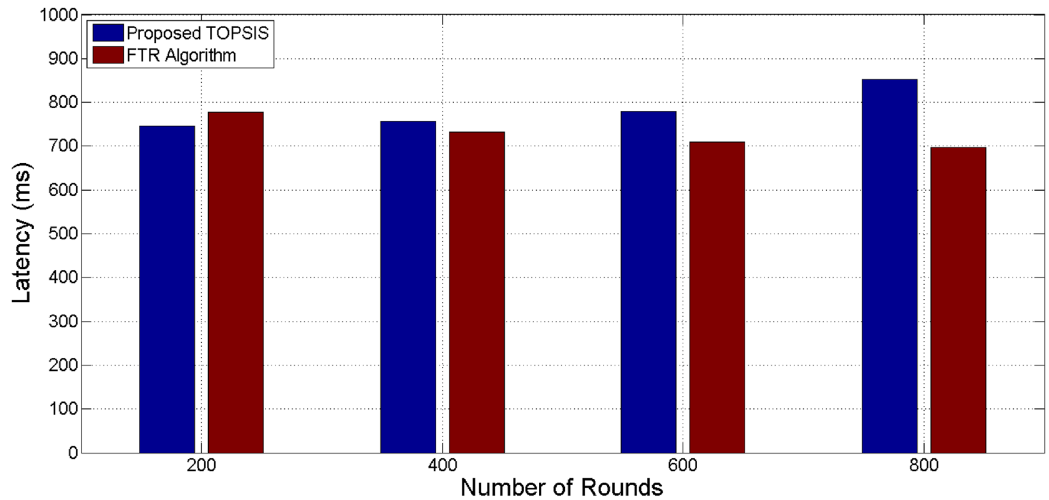

Figure 7 **Latency for the FTR algorithm and the proposed algorithm with a varying number of rounds from 200 to 800, with a step length of 200.** Full-size DOI: 10.7717/peerj-cs.3837/fig-7

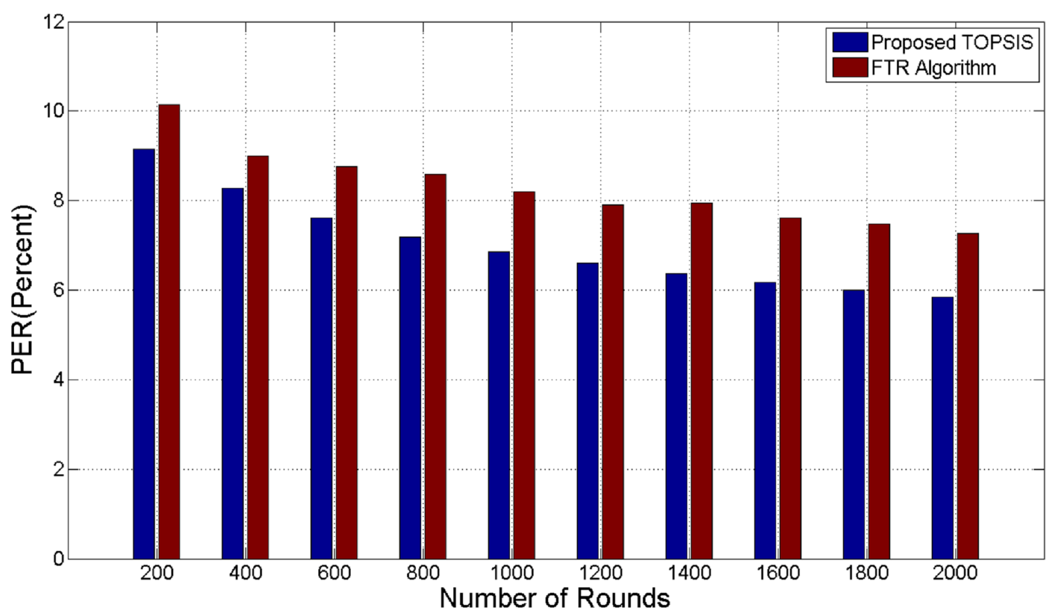

Figure 8 **PER for the FTR algorithm and the proposed algorithm with a varying number of rounds from 200 to 2,000, with a step length of 200.** Full-size DOI: 10.7717/peerj-cs.3837/fig-8

with the FTR algorithm, demonstrating consistently lower PER values for the proposed algorithm across all rounds.

This improvement highlights its enhanced reliability in data transmission. The proposed algorithm demonstrates stability and resilience over time, with PER decreasing as rounds progress due to the DR criterion, which becomes increasingly accurate. Additionally, the ERS criterion balances network usage by avoiding overloading specific nodes, reducing retransmissions, and ensuring smooth data delivery to the base station BS.

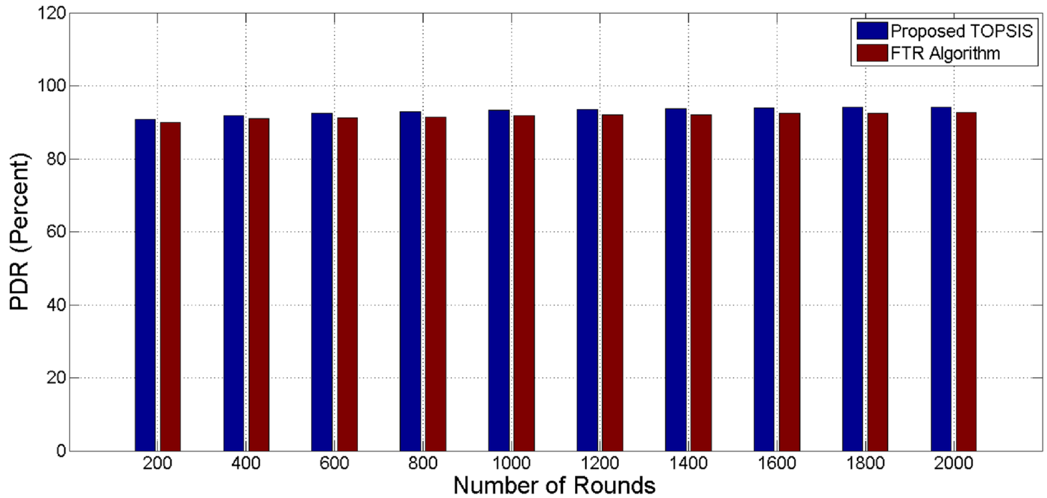

Figure 9 **PDR for the FTR algorithm and the proposed algorithm with a varying number of rounds from 200 to 2,000, with a step length of 200.** Full-size DOI: 10.7717/peerj-cs.3837/fig-9

The MEoP criterion further enhances performance by selecting energy-efficient routes, thereby reducing PER and improving energy efficiency. The proposed algorithm extends the network's operational lifetime by reducing packet errors and minimizing retransmissions. It achieves an average 15.4% reduction in PER compared to the baseline FTR algorithm, demonstrating its superior performance.

PDR

It is an important metric in networking that measures the success rate of data packets delivered from the sender to the receiver. The PDR can be calculated using Eq. (23).

$$PDR = Number\ of\ Received\ Event\ Reports/Number\ of\ Sent\ Event\ Reports * 100\%. \quad (23)$$

Figure 9 compares the PDR, expressed as a percentage, between the proposed TOPSIS algorithm and the FTR algorithm as the number of network rounds increases. The proposed routing algorithm based on TOPSIS provides higher PDR than the benchmark algorithm, with an improvement percentage reaching 1.46%. The proposed routing algorithm achieved an average PDR of 93%, demonstrating an event-driven WSN with high performance and quality.

AEC

The developed DES simulation tool can measure additional performance metrics, such as the AEC, that were not previously reported in the benchmark work. Equation (24) calculates the AEC for the proposed routing algorithm.

$$AEC = \sum_{i=1}^{nodes} initial\ energy_i - RE_i/no.\ of\ nodes. \quad (24)$$

Figure 10 shows the AEC, comparing the energy consumed per round across different events counts for the proposed geographic routing algorithm.

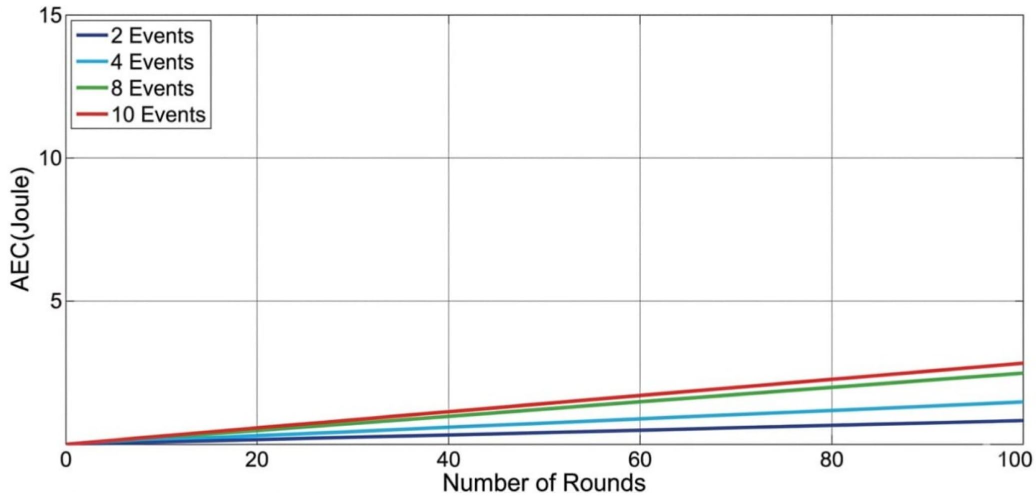

Figure 10 **ACE for the proposed algorithm with 2, 4, 8, and 10 events per round.**
Full-size DOI: 10.7717/peerj-cs.3837/fig-10

AEC remains relatively low for two events per round and increases gradually over time. This indicates that the proposed algorithm effectively has low energy consumption under low-load conditions by selecting energy-efficient paths and balancing routing load distribution. With four and eight events per round, the AEC rises more quickly as the number of rounds progresses, reflecting the additional energy burden of handling more events. In contrast, when the number of events is 10 per round, the AEC grows steeply, indicating that high load conditions significantly strain the network's energy resources. This high consumption rate is expected because many events necessitate more transmissions, increasing the routing demands on critical nodes with high ERS. The simulation results prove that the proposed algorithm is particularly effective in low to moderate-load environments. It can sustain energy-efficient routing in these scenarios by avoiding unnecessary energy depletion. This characteristic makes the algorithm well-suited for event-driven WSN applications, such as fire detection or border monitoring, where events are intermittent rather than constant.

A series of One-Way Analysis of Variance (ANOVA) tests was performed to assess the statistical significance of performance differences between the benchmark and proposed approaches. This analysis aims to determine whether the observed performance differences between the benchmark algorithm and the developed TOPSIS-based routing algorithm are statistically significant or merely due to random variation inherent in stochastic simulations. The simulation results from the two routing approaches were regarded as separate groups for every performance metric. The ANOVA was performed at the $\alpha = 0.05$. The null hypothesis (H_0) assumed that there was no significant difference in performance metrics between the algorithms, while the alternative hypothesis (H_1) implied a statistically significant variance. The one-way ANOVA assesses the ratio of between-group variation to within-group variance through F-statistics. A higher F-value indicates greater differentiation between groups means relative to internal variability. The

Table 3 One-way ANOVA statistical significance test results.

Performance metric	Simulation scenario	F-statistic	p-value	Result (α = 0.05)
Network lifetime	2 Events	14.01	0.0002	Significant
	4 Events	12.34	0.0005	Significant
	8 Events	8.58	0.0038	Significant
	10 Events	20.35	<0.001	Significant
PDR	Round 200	16.79	<0.001	Significant
	Round 1,000	21.23	<0.001	Significant
	Round 1,600	22.72	<0.001	Significant
PER	Round 200	79.81	<0.001	Significant
	Round 1,000	60.77	<0.001	Significant
	Round 1,600	46.02	<0.001	Significant
Latency	Round 200	4.74	0.0307	Significant
	Round 600	21.74	<0.001	Significant
	Round 800	84.90	<0.001	Significant

associated *p*-value measures the probability that the observed differences arise under the null hypothesis. The analysis, presented in Table 3, evaluates four principal metrics: Network lifetime, PDR, PER, and latency.

- Network Lifetime: Significant improvements were observed across all event scenarios (2, 4, 8, and 10 events), with F-statistics ranging from 8.58 to 20.35 and all *p*-values remaining below 0.005.
- Data packets Reliability (PDR and PER):
- The test results demonstrated high statistical significance ($p < 0.001$) over rounds 200, 1,000, and 1,600. Significantly, PER exhibited the most variance, evidenced by an F-statistic of 79.81 at the round 200.
- Latency: Statistical significance was established for all evaluated rounds. Although the F-statistics were lower at round 200 ($F = 4.74$, $p = 0.0307$), it significantly increased by the round 800 ($F = 84.90$, $p < 0.001$), signifying an expanding performance difference as the simulation advanced.

While the metrics above showed significant divergence, the ANOVA results for AEC indicated no statistically significant difference between the two techniques ($p > 0.05$). This finding is critical, as it validates that the proposed method achieves superior network longevity and data reliability without increasing energy costs relative to the benchmark. Consequently, the TOPSIS-based strategy demonstrates enhanced energy efficiency by optimizing routing paths rather than increasing energy dissipation.

The observed gains in network lifetime, PER, and PDR significantly outweigh the marginal increase in latency, as shown in Figs. 6, 7, 8, 9, and 10. These results confirm that the selected TOPSIS weight vector achieves a well-balanced, application-aware compromise among competing performance metrics. The performance improvements stem from integrating the ERS, DR, and MEoP criteria, which prioritize energy sustainability and link reliability over strictly minimizing hop count or latency. Specifically, the algorithm intentionally avoids overused and topologically critical nodes, which are often located on shortest paths, to prevent premature energy depletion and congestion. This design choice may force data packets to traverse slightly longer routes, resulting in a limited increase in latency, particularly as network rounds progress and energy levels of specific nodes decline. However, this behavior enables balanced energy consumption, reduces packet error rate, maintains a high packet delivery ratio through reliable multihop paths, and substantially extends network lifetime. Unlike baseline methods that favor shortest-path routing without considering workload distribution, the proposed approach ensures long-term network stability at the cost of a modest and controlled latency increase. Moreover, in typical event-driven WSN scenarios, such as fire or intrusion detection, events are infrequent and generate low traffic loads. Therefore, the network is not subjected to sustained congestion, and latency remains acceptable, especially in early rounds. Overall, the proposed algorithm deliberately trades a negligible increase in latency for guaranteed and significant improvements in energy efficiency, reliability, and network longevity, making it well-suited for event-driven applications where stability and lifetime are of primary importance.

CONCLUSION

This research proposes an enhanced geographic routing algorithm based on the TOPSIS method to extend network lifetime in event-driven WSNs. The proposed algorithm is designed to overcome open issues within current geographic routing protocols. By incorporating five improved criteria, including ERS, the algorithm effectively selects the most suitable relay nodes while considering network topology. Integrating these criteria enables the algorithm to evenly distribute the workload, reduce energy holes, and prevent critical nodes from becoming overburdened, thereby enhancing overall network performance. Additionally, the algorithm ensures energy efficiency by using a logarithmic energy scale and accounting for energy levels along the entire path. The approach prioritizes network lifetime and energy efficiency. However, it comes at the cost of higher latency, as the approach does not explicitly optimize the time required for data packet delivery. The proposed algorithm has demonstrated significant improvements over the baseline FTR algorithm, achieving an average enhancement of 15.4% in PER, 14.9% in network lifetime, and 1.46% in PDR. Future work will expand the experimental evaluation to include diverse network topologies and various transmission ranges, specifically targeting asymmetric BS placements, such as corner and edge locations. This will provide a more rigorous assessment of the algorithm's robustness. Furthermore, future work will involve a comprehensive comparative analysis of the proposed method against a broader spectrum of emerging routing protocols and hybrid optimization techniques. This comparison aims to further establish the algorithm's scalability and adaptability in dynamic WSN environments. Lastly, we will investigate mechanisms such as hierarchical clustering, specifically, integrating TOPSIS into the cluster head selection process to extend the algorithm's applicability to large-scale WSNs.

ACKNOWLEDGEMENTS
The authors express their gratitude to the Editor and the reviewers for their valuable remarks and ideas.

ADDITIONAL INFORMATION AND DECLARATIONS

Funding
This research was funded by Universiti Putra Malaysia, University Driven Research Grant, Digital and ICT (UDRP-Digital and ICT) and the FSKTM, UPM-Publication Grant. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Grant Disclosures
The following grant information was disclosed by the authors:
Universiti Putra Malaysia, University Driven Research Grant, Digital and ICT (UDRP-Digital and ICT).
FSKTM, UPM-Publication.

Competing Interests
The authors declare that they have no competing interests.

Author Contributions
- Ghaihab Hassan Adday conceived and designed the experiments, performed the experiments, performed the computation work, authored or reviewed drafts of the article, and approved the final draft.
- Shamala K. Subramaniam conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Maha Salih Abdulridha conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, and approved the final draft.

Data Availability
The following information was supplied regarding data availability:

The raw data and code are available in the Supplemental Files.

Supplemental Information
Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj-cs.3837#supplemental-information.

REFERENCES
Abdalhafid AA, Subramaniam SK, Zukarnain ZA, Ayob FH. 2024. Multi-link operation in IEEE802.11be extremely high throughput: a survey. *IEEE Access* **12**:46891–46906 DOI 10.1109/ACCESS.2024.3378997.

Abdou M, Amer HM, Khalil TA, Abdelsalam MM. 2026. Computer standards & interfaces an adaptive geometrical clustering routing protocol (AGCRP) for energy-efficient mobile wireless sensor networks in smart cities. *Computer Standards & Interfaces* **95**:104056 DOI 10.1016/j.csi.2025.104056.

Abdulridha MS, Adday GH, Alshawi IS. 2019. Fast simple flooding strategy in wireless sensor networks. *Journal of Southwest Jiaotong University* **54(6)** DOI 10.35741/issn.0258-2724.54.6.12.

Abou Z, Houda E, Nabousli D, Kaddoum G. 2022. Cost-efficient federated reinforcement learning-based network routing for wireless networks. In: *2022 IEEE Future Networks World Forum (FNWF)*. Piscataway: IEEE, 243–248.

Adday GH, Subramaniam SK, Zukarnain ZA, Samian N. 2023. Friendship degree and tenth man strategy: a new method for differentiating between erroneous readings and true events in wireless sensor networks. *IEEE Access* **11**:1 DOI 10.1109/access.2023.3332476.

Bairagi PP, Babulal KS, Dutta M. 2023. Power management in wireless sensor networks. In: Bagwari A, Tomar GS, Bagwari J, Barbosa JLV, Sastry MKS, eds. *Advanced Wireless Communication and Sensor Networks*. First Edition. Oxfordshire, UK: Taylor & Francis Group, 151–172 DOI 10.1201/9781003326205.

Bairagi PP, Dutta M, Babulal KS. 2022. Location based routing protocols and its performances in wireless sensor networks: an investigation. In: *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), ICESC*, 583–590 DOI 10.1109/ICESC54411.2022.9885717.

Bairagi PP, Dutta M, Babulal KS. 2024. An energy-efficient protocol based on recursive geographic forwarding mechanisms for improving routing performance in WSN An energy-efficient protocol based on recursive geographic forwarding mechanisms for improving routing performance in WSN. *IETE Journal of Research* **70(3)**:2212–2224 DOI 10.1080/03772063.2023.2186501.

Bairagi PP, Kataria G, Dutta M, Babulal KS, Sharma B, Rathi V. 2024. Impact of network size on routing protocols performance in wireless sensor network: a simulation. *Journal of Electrical Systems* **20**:1169–1178 DOI 10.52783/jes.1473.

Biswas P, Samanta T. 2020. True event-driven and fault-tolerant routing in wireless sensor network. *Wireless Personal Communications* **112(1)**:439–461 DOI 10.1007/s11277-020-07037-3.

Fang K, Wang T, Zhou X, Ren Y, Guo H, Li J. 2022. A TOPSIS-based relocalization algorithm in wireless sensor networks. *IEEE Transactions on Industrial Informatics* **18(2)**:1322–1332 DOI 10.1109/TII.2021.3076770.

Gangal V, Cinemre I, Hacioglu G. 2024. A distributed leach-AHP routing for wireless sensor networks. *IEEE Access* **12**:19307–19319 DOI 10.1109/ACCESS.2024.3359750.

Gangwar S, Prasad IB, Yogita, Yadav SS, Pal V, Kumar N. 2025. GTTR: a game theory-based TOPSIS optimized routing protocol for WSNs. *IEEE Sensors Journal* **25(2)**:3608–3617 DOI 10.1109/JSEN.2024.3391185.

Hajduk S. 2021. Multi-criteria analysis in the decision-making approach for the linear ordering of urban transport based on TOPSIS technique. *Energies* **15(1)**:274 DOI 10.3390/en15010274.

Hameed AR, Islam S, Raza M, Khattak HA. 2020. Towards energy and performance-aware geographic routing for IoT-enabled sensor networks. *Computers & Electrical Engineering* **85**:106643 DOI 10.1016/j.compeleceng.2020.106643.

Hang NTT, Trinh NC, Ban NT. 2018. Energy aware event driven routing protocol and dynamic delivering scheme for multievent wireless sensor network. In: *2018 2nd International Conference on Recent Advances in Signal Processing, Telecommunications & Computing (SigTelCom)*, 224–229 DOI 10.1109/SIGTELCOM.2018.8325795.

Heinzelman WR, Chandrakasan A, Balakrishnan H. 2000. Energy-efficient communication protocol for wireless microsensor networks. In: *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences.* Vol. 110 DOI 10.1109/HICSS.2000.926982.

Hussain A, Li S, Hussain T, Waheeb R. 2026. Energy-efficient and localization-based dynamic scheduling scheme for underwater acoustic sensor networks. *Kuwait Journal of Science* **53(1)**:100506 DOI 10.1016/j.kjs.2025.100506.

Idrees AK, Al-Qurabat AKM. 2021. Energy-efficient data transmission and aggregation protocol in periodic sensor networks based fog computing. *Journal of Network and Systems Management* **29(1)**:4 DOI 10.1007/s10922-020-09567-4.

Jian X, Xie L, Zhu X, Liu S, Li Y, Jolfaei A, Alfarraj O, Yu K. 2024. High-reliability low-latency intelligent geographic routing protocol for vehicle road cooperation system. *IEEE Internet of Things Journal* **12(2)**:1774–1788 DOI 10.1109/JIOT.2024.3465519.

Kareem Thajeel I, Samsudin K, Jahari Hashim S, Hashim F. 2023. Dynamic feature selection model for adaptive cross site scripting attack detection using developed multi-agent deep Q learning model. *Journal of King Saud University—Computer and Information Sciences* **35(6)**:101490 DOI 10.1016/j.jksuci.2023.01.012.

Kaur G, Chanak P. 2022. An energy aware intelligent fault detection scheme for IoT-enabled WSNs. *IEEE Sensors Journal* **22(5)**:4722–4731 DOI 10.1109/JSEN.2022.3146853.

Kumar G, Parimala N. 2020. A weighted sum method MCDM approach for recommending product using sentiment analysis. *International Journal of Business Information Systems* **35(2)**:185–203 DOI 10.1504/IJBIS.2020.110172.

Majid M, Habib S, Javed AR, Rizwan M, Srivastava G, Gadekallu TR, Lin JC-W. 2022. Applications of wireless sensor networks and internet of things frameworks in the industry revolution 4.0: a systematic literature review. *Sensors* **22(6)**:2087 DOI 10.3390/s22062087.

Mardani A, Zavadskas EK, Khalifah Z, Zakuan N, Jusoh A, Nor KM, Khoshnoudi M. 2017. A review of multi-criteria decision-making applications to solve energy management problems: two decades from 1995 to 2015. *Renewable and Sustainable Energy Reviews* **71**:216–256 DOI 10.1016/j.rser.2016.12.053.

Moridi E, Haghparast M, Hosseinzadeh M, Jafarali Jassbi S. 2020. Novel fault-tolerant clustering-based multipath algorithm (FTCM) for wireless sensor networks. *Telecommunication Systems* **74(4)**:411–424 DOI 10.1007/s11235-020-00663-z.

Moussa N, Nurellari E, Azbeg K, Boulouz A, Afdel K, Koutti L, Salah MB, El Belrhiti El Alaoui A. 2023. A reinforcement learning based routing protocol for software-defined networking enabled wireless sensor network forest fire detection. *Future Generation Computer Systems* **149**:478–493 DOI 10.1016/j.future.2023.08.006.

Murugaanandam S, Ganapathy V. 2019. Reliability-based cluster head selection methodology using fuzzy logic for performance improvement in WSNs. *IEEE Access* **7**:87357–87368 DOI 10.1109/ACCESS.2019.2923924.

Naderi M, Ghanbari M. 2023. Adaptively prioritizing candidate forwarding set in opportunistic routing in VANETs. *Ad Hoc Networks* **140**:103048 DOI 10.1016/j.adhoc.2022.103048.

Pandey SK, Singh B. 2023. TOPSIS-based optimal cluster head selection for wireless sensor network. *Research Reports on Computer Science* **2(3)**:77–86 DOI 10.37256/rrcs.2320232638.

Sen S, Sahoo L, Tiwary K, Senapati T. 2023. Entropy weighted TOPSIS based cluster head selection in wireless sensor networks under uncertainty. *Telecom* **4(4)**:678–692 DOI 10.3390/telecom4040030.

Shelebaf A, Tabatabaei S. 2020. A novel method for clustering in WSNs via TOPSIS multi-criteria decision-making algorithm. *Wireless Personal Communications* **112(2)**:985–1001 DOI 10.1007/s11277-020-07087-7.

Singh M, Pant M. 2021. A review of selected weighing methods in MCDM with a case study. *International Journal of System Assurance Engineering and Management* **12(1)**:126–144 DOI 10.1007/s13198-020-01033-3.

Tian G, Zhang H, Zhou M, Li Z. 2018. AHP, gray correlation, and TOPSIS combined approach to green performance evaluation of design alternatives. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* **48(7)**:1093–1105 DOI 10.1109/TSMC.2016.2640179.

Yan J, Zhou M, Ding Z. 2016. Recent advances in energy-efficient routing protocols for wireless sensor networks: a review. *IEEE Access* **4**:5673–5686 DOI 10.1109/ACCESS.2016.2598719.

Zheng Z, Zhou Y. 2023. Packet routing in dynamic network: deep reinforcement learning-based approach. In: *2023 9th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS)*, 29–34 DOI 10.1109/ICCSS58421.2023.10270531.