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RESEARCH ARTICLE

AI-Integrated Swarm-Powered Self-Scheduling Routing for Heterogeneous Wireless Sensor Networks to Maximize Network Lifetime

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Abstract

In Heterogeneous Wireless Sensor Networks (HWSNs), ensuring energy-efficient, adaptive, and intelligent data routing is a critical challenge due to the diversity of sensor capabilities, unpredictable traffic patterns, and dynamic environmental conditions. Traditional routing protocols often struggle with high energy consumption, unbalanced node utilization, and latency issues, leading to reduced network lifetime and communication inefficiency. To address these limitations, this research proposes an AI-Integrated Swarm-Powered Self-Scheduling Routing Framework designed to maximize the operational lifetime and enhance the adaptive communication capabilities of HWSNs. The proposed framework introduces a Prolong Traffic Behaviour Analyses Rate (PTBAR) mechanism, estimated through a K-Optimized Decision Tree, to predict and regulate traffic patterns dynamically. Subsequently, a Community Aware Node Selection Algorithm (CANSA) identifies optimal cluster heads by evaluating multiple parameters—energy level, support rate, response behaviour tolerance, and node activity status—ensuring efficient clustering and balanced energy utilization. For intelligent feature extraction and cluster optimization, a Deep Cluster Intensive Best-Fit Whale Optimization Algorithm (DCI-BFWOA) is applied to enhance data accuracy and minimize redundancy within cluster formation. The next phase employs an Energy-Tolerant Proactive Self-Scheduling Routing Protocol (ETPSSRP) to enable adaptive and cooperative communication among nodes, balancing energy consumption and minimizing delay across heterogeneous environments. Finally, a Time-Triggered Max-Priority Route Switchover Algorithm (TTMP-RSOA) ensures timely packet delivery and route stability by dynamically switching routes based on real-time priority and network conditions. Comprehensive simulation results demonstrate that the proposed system significantly improves network lifetime, packet delivery ratio (PDR), throughput, delay tolerance, and computational efficiency when compared with existing routing models. The integrated use of AI decision-making, swarm intelligence, and self-scheduling strategies establishes a resilient, energy-aware, and adaptive routing mechanism—marking a significant advancement in intelligent HWSN communication systems.

Keywords: Heterogeneous Wireless Sensor Networks (HWSN), Swarm Intelligence, Self-Scheduling Routing, AI Optimization, Community Aware Node Selection, Whale Optimization, Energy Efficiency, Network Lifetime, Traffic Behaviour Analysis, Proactive Communication.

Introduction

The Heterogeneous Wireless Sensor Networks (HWSNs) are a group of nodes of different energy content, processing power, sensing ability and communication range which are applicable in applications that need flexibility and responsive use of resources [1-2]. Self-scheduling routing in these networks enables nodes to decide autonomously when to send and the route to follow depending on the residual energy, channel conditions, and task urgency which minimizes the use of centralized routing choices [3-4]. Nevertheless, traditional self-scheduling protocols tend to have high latency, irregular switching of routes and high communication overheads as a result of uncontrolled dynamic behaviour and routing instability [5-6]. To overcome those challenges, Artificial Intelligence (AI) tools including reinforcement learning, swarm intelligence and optimization-based decision models have been incorporated into routing to aid adaptive learning, behaviour awareness and predictive forwarding control [7-8]. Although functional, AI-based routing presents such challenges as high computation cost, convergence delays, and inapplicability to resource-constrained sensing environments.

To address these limitations, the proposed Time-Triggered Max-Priority Route Switchover Algorithm (TTMP-RSOA) implies a hybrid routing scheme with a controlled manner, which integrates time-based deterministic routing with priority assessment that is intensive [9-10]. Rather than routing changes being made continuously through learning, routing changes are done on periodic time triggers and minimise instability and communication overheads. In the meantime, there is the priority scoring, which determines the urgent data and essential nodes, optimizing the choice of paths and providing a timely transfer of packets. The

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suggested model minimizes energy usage, increases packet delivery latency, and increases the impartiality in resource usage as well as keeping controllable routing behaviour for real-time and mission crucial implementations of heterogeneous sensors.

Main Contribution of the work,

- First, to come up with an adaptive monitoring system that constantly measures routing metrics like link stability, node mobility, congestion level and packet reliability in order to know real time decision-making.
- To develop a measure of priority score calculation system based on weighted performance measures that permit the selection of the best routes, instead of fixed decision-making logic.
- The process time-based and threshold-based validation model that sets route switching to take place only when required to minimize the route instability and unnecessary overhead.
- The TTMP-RSOA mechanism on the use of the most appropriate alternative route through the use of buffer scheduling and acknowledgment-aware switchover of maintaining the integrity of packets and minimizing transmission disruption when routing updates are made.
- Lastly, to analyze the implemented model in relation to the performance metrics comprising of packet delivery ratio, latency, throughput, route lifetime and switching efficiency and reduction of overhead to show that the proposed model outperforms the current methods such as MCSS, OS-ELM, and SIPF.

The structure of the paper is designed to follow this working process: Section 1 provides a description of routing challenges and motivation of adaptive scheduling; Section 2 comprehensively provides literature on routing stability, metric-driven decision systems, and optimization plans; Section 3 is a detailed description of the proposed working process with monitoring, scoring, threshold validation, and TTMP-RSOA; Section 4 provides analytical experimental analysis and discussion with the existing methods; Section 5 is a conclusion and findings, limitations and directions toward scalability and real-time deployment.

Literature survey

In addition to this, a majority of these studies were only interested in enhancing energy consumption without paying much attention to QoS indicators. In the current paper, several mobile sinks are taken, which are randomly modeled as mobile, and a trade-off between the power consumption and quality of service is established [11]. According to the simulation findings, hierarchical data routing when the mobile sinks are randomly distributed is a powerful strategy that can balance the distribution of the energy levels of the nodes and minimise the total power consumption. In addition, it is established that the suggested routing techniques permit reducing the latency on the sent data, augment the dependability and enhance the throughput of the gathered information. The key elements of a WSN are: lifetime, loss and security rate: WSN lifetime is highly sensitive to the energy usage of sensor nodes [12]. This is a weakness that complicates the extension of the sensor node life. We propose an improvement to the Sink Initiated Path Formation (SIPF) protocol in this paper with aims of reducing the power consumption and the rate at which packets are lost as a dependence of the sensor node density. Aggregation of the data was a rather time-consuming activity in the sensor networks, particularly in high density sensors. Hence, reduction of data aggregation delay issue had become a burning research problem [13].

The algorithm embraced a clustering concept of low power within the cluster and high power between clusters and channel allocation to minimize data aggregation delay, and aggregation of data between clusters can be done without collisions. How AI applied in healthcare systems manages threats to how AI is applied in practice to cyber risks of critical infrastructures. Breaking down the dynamics of the modern cyber threats, the book equips readers with the knowledge and tools in the face of the complex world of cybersecurity [14]. It deals with the problematic issues urgently faced by organizations regarding their digital infrastructure protection and the protection of sensitive information against malicious cyber-attacks. The subsets which are also known as coverage sets are activated and the others are in energy conservation or dormant state [15]. It is known as NP-hard and technically, the Maximum coverage set scheduling problem (MCSS). This paper involves a comparative study of two suggested algorithms which are the pattern search algorithm and the genetic algorithm to improve the life cycle of WSNs. These techniques make sure to find a viable collection of coverage schedules to optimize the network lifetime performance and consider the active time of every sensor.

Table 1: Algorithmic Comparison of Fragmentation and Context Extraction Strategies for Efficient Cloud Data Deduplication, including the type of algorithm, Context Extraction Method, Fragmentation Technique, Similarity Computation Approach.

Online Sequential Extreme Learning Machine (OS-ELM), to give the optimal network based on prediction quality and computing time. The findings indicate that OS-ELM was more accurate and computationally efficient than the other networks. This shows the need to be energy efficient and the possibility of the methodology being implemented in other industries [26]. The methodology has the potential of further development with the advancement of technology and data so that it is a promising solution to a broad set of prediction problems. Long Short-Term Memory Networks and Recurrent Neural Networks (RNNs). Based on historical load data, temperature, and the speed of the wind, and using day-ahead predicted spot prices, this methodology takes the form of a systematic flow, which includes data preprocessing, sequence generation, model training, and future load demand prediction using RNN variants that are based on the idea of LSTM [27].

The most significant findings of the study emphasize the significant progress that the proposed methodology made in comparison to the existing methods. An adaptive monitoring and energy management optimization method of EH- WSNs is introduced using Deep Q network (DQN) algorithm in remote locations and achieve the energy-neutral operation of Energy Harvesting Wireless Sensor Networks [28]. To the targets of EH- WSNs having single-hop cluster structure, initially introduce a more real energy model founded on integration of varied climate features. The issue with unplanned disturbances, the addition of the traveller context information in the travel support, travellers were capable of receiving personalised information [29]. This would particularly be helpful to travellers who have a hard time traveling through the public transport system compared to others. Moreover, it could increase the availability and overall appeal of the public transit. The idea is to prevent significant changes in the existing personnel schedules. The history of the service calls is accessible and a thorough analysis of the same leads to the identification of the most used routes as well as the present distribution of

Table 1: Different Methods used in Self-Scheduling Routing for Heterogeneous Wireless Sensor Networks

Author /year	*Type of Methods*	*Main Contribution*	*Limitations*
Ben Yagouta et al. (2023) [11]	Multiple Mobile Sink Strategy	Improves QoS and extends network lifetime by using multiple mobile sinks to reduce hotspot energy depletion.	Increased complexity in sink mobility control and route planning; scalability challenges for very large WSNs.
Dboudhiafi & Ezzedine et al (2022) [12]	SIPF Protocol	Introduces an energy-efficient routing protocol tailored to node density, enhancing transmission efficiency and overall lifetime.	Performance decreases in highly dynamic or heterogeneous networks; limited real-world experimentation.
Li et al. (2021)	Data Association Coverage Algorithm	Achieves energy balance and improved network coverage using controlled parameters and optimal data association.	Higher computational overhead; performance sensitive to parameter tuning
Larhlimi et al. (2025) [14]	Search + Genetic Algorithms	Enhances WSN lifetime using hybrid PS and GA optimization techniques to improve scheduling and coverage.	Increased processing cost and convergence delays in large sensor deployments.
Larhlimi et al. (2025) [15]	Pattern Search & Genetic Algorithm Evaluation	Benchmarks PS and GA for WSN lifetime enhancement and coverage optimization.	Limited exploration of hybrid frameworks; lacks validation in real-time large-scale environments.
Pramod et al. (2023) [16]	Reinforcement Learning with 5G	Introduces RL for energy-efficient operation with integration of 5G architecture in smart city WSNs.	Requires large training datasets; relies on 5G infrastructure availability.
Tirandazi et al.. (2023) [17]	Mobile Robot-Based Coverage and Connectivity Algorithm	Uses mobile robotic agents to maintain connectivity and improve coverage efficiency in WSNs.	High deployment cost and mobility control complexity; unsuitable for static or resource-limited WSNs.
Larhlimi et al. (2025) [18]	GA-Driven Cover Set Scheduling	Optimizes cover set scheduling via GA to maximize battery efficiency and network lifespan.	Risk of premature convergence and high computational burden.
Kusuma et al. et al. (2024) [19]	Meta-Heuristic + Reinforcement Learning Deployment Model	Optimizes node placement using RL integrated with meta-heuristics for energy-efficient WSN deployment.	Requires high computation and long training cycles; not optimal for real-time dynamic environments.
Shivakeshi & Sreepathiet al. (2023) [20]	Optimized Prediction Framework for SDN	Enhances cost-efficiency and decision-making in SDN environments via optimized predictive modeling.	Limited focus on energy constraints; requires high computational capabilities.

Table 2: Comparison of Behaviour-Aware Node Management Techniques based on the Heterogeneous Wireless Sensor Networks

Author/year	*Self-Scheduling*	*Behaviour Analysis*	*Node Activity*
Audat et al., (2023)	×	✓	×
Ning et al. (2023)	×	×	✓
Chinnaiyan et al, (2021)	×	✓	×
Hingurala Arachchige Don et al, (2025)	✓	✓	✓
Shah et al. (2022)	×	✓	×

the demands to patient transport workers [30]. To introduce a mixed-integer model to calculate the optimal allocation of the employees across all the most popular routes of the hospital to reduce costs.

In the table 2 demonstrate the reveals different degrees of behavioral intelligence and automation in the various systems considered. Only one has true self-scheduling capabilities, while the other solutions are either statically or manually configured. Behavioral analysis is applied in all sources, though at different layers of abstraction such as context awareness, cryptographic validation, and traffic anomaly detection. Monitoring node activity is still limited, with only two works intentionally tracking device states or operational status. This signifies a need for unified architectures that can integrate scheduling, behavior reasoning and node lifecycle intelligence for efficiency and resilience in terms of automation.

Problem Identification

- In the case of Heterogeneous Wireless Sensor Networks (HWSN), traffic density that is constantly increasing, mobility that is dynamic, and resource distribution that is uneven lead to instability in routing, increased latency in communication, and decreased energy efficiency. The result is an overall reduction of the lifetime and reliability of the network.
- The Multi-Constraint Self-Scheduling (MCSS), an existing mechanism, proposes an adaptive self-scheduling structure; however, it is inadequate to address various traffic conditions and node heterogeneity.
- Although the Online Sequential Extreme Learning Machine (OS-ELM) operates faster, has facilitated learning and computational efficiency, the incremental learning mechanism is very sensitive to non-linear irregularities and does not sufficiently predict adaptive behavior.
- The SIPF (Secure Intelligent Packet Forwarding) Platform enhances routing trust and decision making as it applies to security, but if there is peak communication by authentication and verification decisions, it becomes computationally inefficient to be able to perform for security.
- Collectively, the MCSS mechanism has limitations in simulation for resource allocation through dynamic self-scheduling, OS-ELM has limitations in digitalization for intelligently learning with lower traffic behavior, load and high mobility.

Objective of the Research

- This research aims to create an AI-based Time-Triggered Max-Priority Route Switchover Algorithm (TTMP-RSOA) that improves routing intelligence, energy efficiency, and adaptive scheduling capability in HWSNs.
- The framework proposed in this approach fuses predictive routing intelligence with event-driven and time-triggered approaches to allow for dynamic optimization.
- while also guaranteeing smooth transition between routes during changing network loads and heterogeneous nodes.
- TTMP-RSOA intends to resolve limitations in existing routing algorithms by merging adaptive priority estimation, real-time route health assessment, with the objective of reducing packet loss (PL), mitigating routing instability, and maximizing the network's lifetime.
- The system offers intelligent traffic predictions using behavior metrics to facilitate a communication flow that is now proactive rather than reactive.
- The focus of the research is to increase key performance indicators (KPIs) such as Packet Delivery Ratio (PDR), latency, throughput, routing overhead, energy consumption.
- To ensure a robust, scalable, and sustainable routing protocol of heterogeneous wireless sensor-based communication and routing system focused deployment.

Proposed Methods

The section explained that PTBAR mechanism, where real-time traffic patterns are monitored and analyzed using a K-Optimized Decision Tree to generate predictive behaviour scores that regulate communication frequency and prevent congestion. Based on these insights, the CANSA identifies suitable cluster heads by evaluating node energy, support rate, behaviour tolerance, and activity status, ensuring balanced clustering and fair resource distribution. Once clusters are formed, the DCI-BFWOA refines the structure through deep feature extraction and optimization inspired by whale foraging behaviour, minimizing redundancy and improving intra-cluster efficiency. Following this, the ETPSSRP enables autonomous routing where nodes proactively self-schedule transmissions according to energy availability and network conditions, reducing delay, collisions, and unnecessary retransmissions. To maintain long-term stability, the TTMP-RSOA dynamically selects alternative routes based on priority while performing route adjustments only during predefined time windows, thereby reducing routing instability, minimizing overhead, and ensuring timely high-priority data delivery across heterogeneous wireless sensor environments.

Figure 1 show that the heterogeneous network environment, in which different mobile nodes create changing traffic patterns. PTIBAR is used to extract intelligent behavior information like mobility consistency, communication reliability and anomaly trends out of this raw network data. The polished behavior patterns are then fed into an optimized decision tree which forecasts routing decisions and controls the flows of communication in real-time in reaction to situational parameters. CANSA is used to stabilize the structure to achieve adaptive and intelligent choice of cluster head to guarantee balanced communication load, and better routing hierarchy. The chosen clusters are also optimized with DCI-BFWOA that ensures the optimization of communication paths through the reduction of redundancy, minimization of latency, and enhancement of energy efficiency. The routing table formed is proactive of autonomous scheduling by ETPSSRP, which allows nodes to self-determine the most appropriate communication routes without central control. Lastly, TTMP-RSOA implements dynamical route switching in response to urgency, link condition, and performance measurement, which ensures that there is smooth connectivity to reduce the packet loss and increased network lifetime.

Dataset Description

The Multi-Criteria Network Routing Dataset was created for research and analysis related to secure and reliable data transmission in distributed networks. The Multi-Criteria

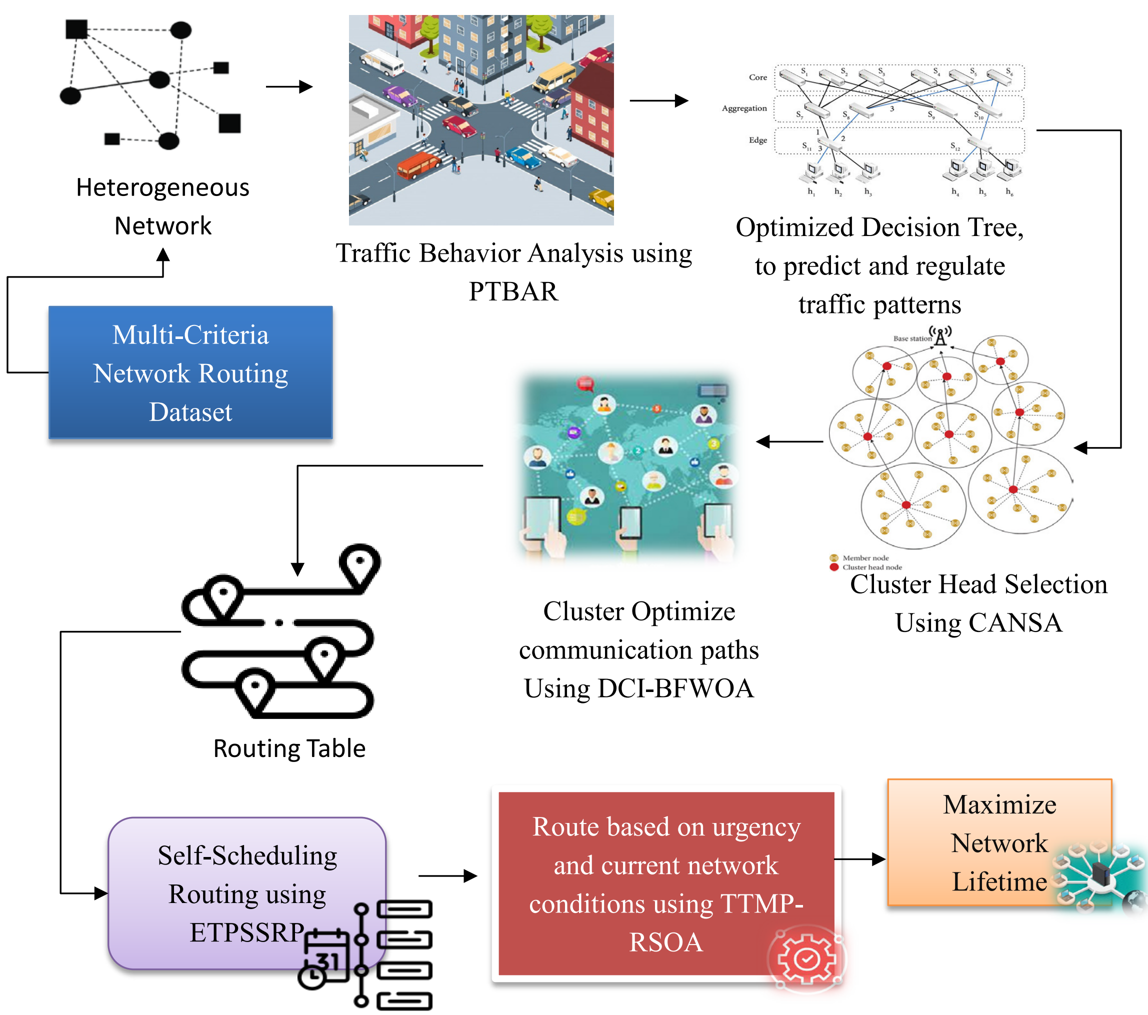

Figure: 1 Self-Scheduling Routing for Heterogeneous Wireless Sensor Networks using TTMP-RSOA

Routing Dataset can be of importance to developing and analyzing the efficacy of routing optimization algorithms. The multi-Criteria Rules function is facilitated this by incorporating key performance and security risk factors, such as latency, available bandwidth, and energy utilization. The multi-criteria routing dataset has 500 simulated network routing records where each route is evaluated based on performance criteria and security factors. Each route will have a target column (Optimal Route), that will evaluate each routing outcome as Optimal (1) or non-optimal (0) outcome based on the defined multi-criteria goals. Key features for the routing dataset include: Route Factors: Source and destination nodes, latency, bandwidth. Security Considerations: Security risk score and trust score. Performance Factors: Packet delivery ratio, end-to-end delay, energy consumption.

Prolong Traffic Behaviour Analyses Rate (PTBAR)

The section described that PTBAR is a smart traffic prediction system that is used to study communication patterns in HWSN and dynamically control routing behaviour. The step starts with the constant monitoring of the metrics in terms of the speed of packet transmissions, congestion, patterns of node interactions, and abrupt changes in traffic. A K-Optimized Decision Tree is then used to process these real-time behavioural cues, to classify and predict trends in future traffic at a higher level of precision, and at lower cost of computation. After production of the predictive traffic score, PTBAR modulates the communication intervals and routing demand in anticipation of overload to ensure that undue data exchanges are minimized, and network stability is ensured. PTBAR manages to extend the lifetime of network by predicting the possible traffic burst and balancing the communication load prior to congestion, stabilizing routing decisions, and setting the intelligence base on which the next stage of work, clustering and scheduling, should take place in the suggested system.

The presented equation 1 is computed by considering the number of observed interactions between packets T_c. In this case, p_t is the sum of all packet transfers that occurred during the observation period, both of forwarding, receiving, and broadcasting, and T_c is the amount of active communication time.

$$\mathbf{T}_i(t) = [\lambda_i(t),\ c_i(t),\ \alpha_i(t),\ \Delta_i(t)] \tag{1}$$

$$F_i(t) = \sum_{k=1}^{4} w_k \cdot \frac{m_{i,k}(t) - \mu_k}{\sigma_k} \tag{2}$$

Equation 2 is a refinement of PTBAR that takes into account the behavior deviation ratio in which D bis is calculated as the difference between observed behavior B_0 and the expected normal behavior B_e.

$$\widehat{P}_i(t + \Delta t) = \mathrm{DT}_K(F_i(t)) \tag{3}$$

Variable represents B the actual traffic behavior traces of real time operational or active information, and B represents the actual forecasted behavioral baseline of the standard behavioral standard operations of the past history of cluster patterns. With the help of D_b, the system can identify whether the deviation should be considered equation 3 within the tolerable range or points at abrupt deviation.

The normalized score of the traffic behavior N_s in this equation 4 is given as the scaling of deviation behavior D_b engages to the maximum deviation level D_{ii} . In this case, D_{ii} rep is the maximum possible limit of deviation that is established in the training calibration stage, and N_s is a standardized signal that lies within the range of 0 to 1 in order to understand the severity of the behavior.

This normalization makes sure that there is uniform evaluation under different load of traffic and non-uniform network conditions. When Ns tends to be close to 1, then this is an indication of high level of abnormality in the behavior of packets whereas a value close to 0 indicates a stable integrity of communications.

$$S_i(t) = \sigma\left(\beta_0 + \beta_1 \widehat{P}_i(t + \Delta t)\right) \text{with} \sigma(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

$$\tau_i'(t) = \tau_{\min} + \left(1 - S_i(t)\right) \cdot \left(\tau_{\max} - \tau_{\min}\right), R_i'(t) = R_{\text{base}}\left(1 + \gamma S_i(t)\right) \tag{5}$$

This equation 5 is A s or the score of anomalies which is calculated as the product of the normalized score N_s with the specified behavioral weight W_b. In this case, W bis is taken with a consideration of the criticality of each feature of traffic like packet drop, delay spikes, routing fluctuation, or redundant broadcasts.

The decision threshold T_{ii} determining whether the node is a normal or a malicious node by deciding the relationship between the anomaly score A sw and the predefined detection threshold T_{ii} . In this case, T_{ii} is adaptive and dynamically adapted to current real-time changes in the environment and historic detection patterns.

Community Aware Node Selection Algorithm (CANSA)

The communication cluster and choosing the most trusted nodes by the community on the basis of the trust and connectivity and the consistency of the behaviour. This starts with the grouping of vehicles into local communities based on mobility restrictions, geographical extent, and frequency of interaction resulting in logical clusters that maximize routing stability. In each community, nodes are assessed according to their important metrics which include the amount of time a node has connected, the reliability of packet delivery, previous history of trust, and the rate at which they participate in the broadcasting process so that only those nodes with consistent and cooperative behaviour are shortlisted. The algorithm then tries to attach a community trust score to every candidate node that is dynamically adjusted based on real-time traffic changes and mobility estimates to prevent the selection of unstable and malicious nodes. Through this prioritization based on trust, CANSA identifies the most suitable node to act as a representative of the community in routing and security operations and guaranteeing reduced communication interference and higher identification of malicious nodes.

Community Formation Score $ü_i$ identifies the degree of success of a node in a communication group based on three important variables, namely interaction frequency IF_i, geographical proximity (GP), and mobility direction similarity (MD_i) with weights designed to represent the significance of each variable (that is, α, β, γ).

The nodes with the highest frequency of communication physical proximity, and similar direction equation 6 of movement will get a higher score and therefore they are better placed to form stable cooperative communities.

$$CFS_i = ℵ \cdot IF_i + \quad \cdot GD_i + \quad \cdot MD_i \tag{6}$$

$$CRI_i = \frac{PDR_i + CD_i}{2} \tag{7}$$

The $ü_i$ is used to determine the stability of the communication of a node based on its packet delivery ratio and its time connection duration CD_i to provide a weighted average based on the parameters. The greater the CRI, the more the node is said to maintain a stable connectivity and is able to transmit data without causing interruptions.

The $ü_i$ provides routing choices based on the performance of communication history that enhances the quality of the network and avoids the selection of unstable nodes as representatives in equation 7.

Behaviour Trust Score ($ü_i$) measures the equation 8 degree of cooperative behaviour of a node based on three behavioural properties, namely, historical trust record (HTR), participation rate (PR), and behavioural correctness (BC).

$$BTS_i = ℵ \cdot HTR_i + \quad \cdot BR_i + \quad \cdot CPR_i \tag{8}$$

Learning coefficients μ, v, w are used to adjust each variable to evolve trust evaluation with network behaviour. The Real-Time Stability Adjustment (RSA) adjusts the already determined equation 9 trust and connectivity values by adding the instability factor δ and mobility variation (MV).

$$RSA_i = \left(1 - VFL_i\right) \times CRI_i \tag{9}$$

$$FNSS_i \; ℵ CFS_i \quad BTS_i \quad RSA_i \tag{10}$$

This modification will guarantee that even nodes that had a good track record of performance are revaluated in case they roll-out and become unstable because of high movement or variations of traffic. RSA is vital in dynamic settings where the location of nodes and their behaviour changes fast.

Final Node Selection Score (FNSS) combines the results of the equation 10 of the prior steps CFS, CRI, BTS and RSA into a final weighted decision by use of coefficients. The greatest FNSS value is used to select the most appropriate node as the leader of community to route activities.

Deep Cluster Intensive Best-Fit Whale Optimization Algorithm (DCI-BFWOA)

Initial steps include inputting the output of candidate nodes of the CANSA-selected nodes and mapping into deep feature vectors (energy level, node activity state, response delay and real-time communication load). The search process is directed to the optimal clustering patterns and avoiding premature convergence is the result of Whale Optimization behavior: encircling, bubble-net searching, spiral movement. In exploration stage, the algorithm will search the solution space on a global basis to find possible solution that is cluster head combinations that will result in the highest possible load balancing and minimum redundancy. When the algorithm switches to exploitation, the most suitable solutions are optimized through the energy gradients, communication strength and the expected behavioral stability is evaluated through deep-learning-based selective pressure. The best-fit mechanism has the property that the assignment of cluster heads minimizes communication overhead, maximizes residual energy distribution and is routing stable in the face of heterogeneous deployment conditions. DCI-BFWOA evolves the most stable cluster configuration in terms of energy savings by repeated adaptive learning and evaluation of fitness.

Deep Feature Vector Formation equation 11 combines the key features of nodes to measure its appropriateness in clustering. This step involved the assessment of each node $ü_i$ using parameters like residual energy E_i, activity level of node A_i, delay of response D_i and load of communication L_i.

$$DFV_i = \alpha E_i + \beta A_i + \gamma D_i + \delta L_i \tag{11}$$

$$X(t+1) = X^*(t) - A \cdot | C \cdot X^*(t) - X(t) | \tag{12}$$

$$X(t+1) = | X^*(t) - X(t) | \cdot e^{bl} \cdot \cos(2\pi l) \tag{13}$$

The weighting factors, α, β, γ, and δ are used to make sure that these variables have a proportionate contribution according to real time requirements of the network The equation 12 can be effectively used to convert heterogeneous raw measurements of two uniform feature vectors representing the input layer, which is then used by DCI-BFWOA to determine the most effective clustering patterns

The encircling mechanism revises the positions of the candidate nodes, according to the best solution as estimated to be $X(t)$, that is the most promising cluster head found at the current iteration. The distance- control vector C and the attraction coefficient A determine the convergence of the candidate solutions to the current best node.

This is the equation 13 that describes the spiral updating behaviour that is based on the bubble-net hunting behaviour of humpback whales. The system refines the search on the space of best nodes using exponential contraction (e^{bl}) and oscillatory motion $\cos(2\pi l)$, and allows the search to exploit the best nodes.

$$X(t+1) = X_{rand}(t) - A \cdot | C \cdot X_{rand}(t) - X(t) | \tag{14}$$

$$Fit_i = \lambda_1 E_i + \lambda_2 S_i + \lambda_3 C_i - \lambda_4 R_i \tag{15}$$

$$CH = \text{argmaxi} \in \mathrm{N}\left(Fit_i - DFV_i\right) \tag{16}$$

In early optimization, the exploration behaviour is driven by this equation 14 that compares each node to a counterpart that is randomly chosen X_{rand}. In the A and C introduce diversity, candidate positions are reflectively forced out of densely explored regions.

The fitness function measures the equation 15 appropriateness of each node in terms of being an effective cluster head by summing the level of energy E_i, stability index S_i, and the quality of communication C_i, and punishing large routing overhead R_i. The weighting coefficients $\lambda_1 \ldots \lambda_4$ are dynamically modified depending on the mode of the network- either the energy saving mode, delay saving mode or throughput performance mode. The last step of the equation 16 selection process involves computing the optimal cluster head by maximizing the difference between fitness score $ü_i$ and the deep feature vector score $ü_i$.

Energy-Tolerant Proactive Self-Scheduling Routing Protocol (ETPSSRP)

After DCI-BFWOA completes the optimum cluster set up, ETPSSRP allocates dynamic transmission schedules, which depend on factors like residual energy of the node, projected traffic rate, node score of priority, and time of activity. The protocol works in advance; that is, paths of routing and roles of transmissions are decided before demand increases in communication, which helps in minimizing unnecessary control overhead as well as avoiding congestion. A self-scheduling system is a continuous data process that monitors the trend of energy consumption and communication behaviour of every node and varies the duty cycles, slot assignment, and relay responsibility to prevent a premature depletion of nodes and ensure routing sustainability. The adaptive tolerance logic also comes into action by ETPSSRP, where temporarily, data forwarding responsibility is redirected to the node whose energy level is below a certain threshold, or one whose network stability is failing, so that the network can continue operating normally. ETPSSRP can maximize network lifetime, reduce latency, equalize distribution of energy load among heterogeneous sensor functions by intelligent scheduling, predictive routing behaviour and real-time energy monitoring.

The presented equation 17 gives a dynamic priority score of $P_i(t)$ to each node by summing up the key performance indicators of routing. The utilization of residual energy Ei norm (t) is used to favor energy-healthy nodes whereas the congestion is avoided by the predicted traffic load $\hat{L}_i(t)$ in giving less weight to nodes with heavy traffic load. The urgency factor $U_i(t)$ is the significance of current transmissions (i.e. critical or time-sensitive packets). In the meantime, node activity $A_i(t)$ indicates the recent availability and reliability of communication. The weights $\omega_1 \ldots \omega_4$ modify the significance of decisions according to network state energy saving, latency reduction or throughput optimization.

$$\begin{aligned} P_i(t) = \omega_1 E_i^{\text{norm}}(t) \ + \ \omega_2\left(1 - \hat{L}_i(t)\right) \\ + \ \omega_3 U_i(t) \ + \ \omega_4 A_i(t) \end{aligned} \tag{17}$$

$$DC_i(t) = DC_{\min} + E_i^{\text{norm}}(t)\left(DC_{\max} - DC_{\min}\right) \tag{18}$$

$$\text{Slots}_i(t) = \lfloor T_{\text{slots}} \cdot \frac{P_i(t)}{\sum_{j \in C} P_j(t)} \rceil \tag{19}$$

The duty cycle equation 18 is used to compute the duration of time a node works in comparison with the energy available. When the node is under high energy, $DC_i(t)$ rises and forms $DC_{ü}$ but when the energy drops, the value falls towards $DC_{ü}$.

The allocation of the communication slots depending on the priority of the node equation 19 number of slots $\text{Slots}_i(t)$ is fairly shared among the priority score $P_i(t)$, allows scheduling proactive communication and prevents collisions and delays and aligns schedule decisions with real time node conditions.

$$E_i(t + \Delta t) = E_i(t) - \kappa(DC_i(t) \cdot R_i(t)) \tag{20}$$

$$\begin{aligned} &\text{if } E_i(t) < E_{\text{th}} \text{ then } R_j'(t) \\ &\quad = R_j(t) + \eta \ R_i(t) \cdot \frac{P_j(t)}{\sum_{k \in C \setminus \{i\}} P_k(t)} \end{aligned} \tag{21}$$

$$\text{Cost}(\mathcal{P}) = \sum_{n \in \mathcal{P}} \left(\alpha \frac{1}{E_n^{\text{norm}}(t)} + \beta D_n(t) + \gamma\left(1 - S_n(t)\right) \right) \text{choose } \mathcal{P}^* = \arg\min_{\mathcal{P}} \text{Cost}(\mathcal{P}) \tag{22}$$

The energy consumption model is updated at the end of every node with energy remaining, the coefficient κ transforms duty cycle duration into routing workload $R_i(t)$ into quantifiable energy expenditure in equation 20. This conditional equation 21 is triggered when the energy of a node decreases below the tolerance threshold E_{th}. This parameter η determines the extent of the responsibility shift so that there is no abrupt and excessive assigning of responsibility.

The best route to follow by minimising a composite costing mechanism which takes into account energy, delay and stability of the equation 22. Path cost is raised by low-energy nodes to the inverse energy factor $\frac{1}{E_n^{\text{norm}}(t)}$, and latency-sensitive applications to the delay value $D_n(t)$. $S_n(t)$ stability factor eliminates unstable links, penalty of decision preference subject to operational mode.

Time-Triggered Max-Priority Route Switchover Algorithm (TTMP-RSOA)

The process starts with the algorithm continuously monitoring the current routing table to obtain stability metrics, such as the link stability LS, mobility index NM of the node of interest, communication delay CD, and path reliability PR. Each active route in the routing table is assigned a new but continuously updated priority score evaluated based on previous performance variables, allowing for the path that is most reliable and timely for transmission of possible real-time data to be the first complete for the real-time data transmission. The maximum threshold of the priority score is regulated by a time-trigger interval that the algorithm then uses to determine when the priority reassessment is to take place to avoid unproductive switching, and needless network congestion. When during a normal time-triggered interval, the priority score of the currently active route falls below a preset maximum value or a minimum reference value, the TTMP-RSOA is automatically triggered into the evaluation and replacement of the current route. During the route switchover event, TTMP-RSOA subsequently re-evaluates all available viable alternate routes and selects the alternative path route based on the highest updated priority score value. In order to maintain a clear path for transmission and to avoid packet loss during the evaluation process a combination of buffering and acknowledgment-based confirmation of each data packet is used to ensure a handover without packet loss or any other loss of data. The objective of the decision-making process and timing, with TTMP-RSOA decisions based on which alternate route is preferable, is to minimize the negative impacts of routing overload on the timeliness of routing.

The presented equation 23 calculates the Priority Score P_{score} which is used to determine the suitability of a communication route in dynamic network conditions.

There are variables like the stability of a link reliability of a path and the inverse of Communication Delay CD and Node Mobility NM which all determine the quality of routing. The equation 24 confirms a route reevaluation requirement by comparing the current time T_{curr} with the last time of the evaluation T_{last}, with a predefined trigger threshold T_{ti} .

$$P_{score} = \alpha LS + \beta PR + \gamma\left(\frac{1}{CD}\right) + \delta\left(\frac{1}{NM}\right) \tag{23}$$

$$T_{check} = \begin{cases} 1, & \text{if } T_{curr} - T_{last} \geq T_{thr} \\ 0, & \text{otherwise} \end{cases} \tag{24}$$

When this time difference reaches and even surpasses this value the value of $T_{check} = 1$, and the decision-making step can be made. This avoids equation 25 calculation of routing paths continuously in the workflow and makes switchover decisions at a controlled rate so that the use of energy is minimized and unnecessary reconfiguration is not needed when the communication is stable.

$$S_{trigger} = \begin{cases} 1, & \text{if } P_{score}^{current} < P_{min} \text{ AND } T_{check} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

$$R_{best} = \max\left(P_{score}^{i}\right) \forall i \in R_{available} \tag{26}$$

This equation 26 identifies the necessity of changing the route. The condition ensures that the priority score (P score current) of the current route (P score current) is not less than a minimum acceptable value P min as well as the time-triggering condition (T check =1) is met.

When a switchover trigger has been detected, the equation 27 determines the best alternate route (R best) amongst the existing routing paths. It picks out the route with the highest calculated priority value of all the candidate routes.

$$R_{active} = \begin{cases} R_{best}, & \text{if } S_{trigger} = 1 \\ R_{current}, & \text{otherwise} \end{cases} \tag{27}$$

$$P_{buffered} = P_{incoming} - P_{acknowledged} \tag{28}$$

This equation 28 completes the decision of routing by the updating of the active route R_{active}. In the event of the switchover trigger being enabled, makes the newly chosen optimal path R_{best} to be the active communication route.

The packets of data sent by the network over a route transition may not be acknowledged. This formula is used to determine the number of buffered packets $P_{buffered}$ by the difference between the number of buffered packets and the number of acknowledged packets.

$$QoS = \frac{TH}{CD + PL + RE} \tag{29}$$

Buffering can be used to avoid loss of packet in the workflow and maintain consistency in delivery during the handover. This measure equation 29 into the performance of routing and how the new route is fulfilling operational expectation. The new QoS is recorded and is used in future routing decisions, which forms the adaptive routing feedback loop.

Figure 2 show that the intelligent and adaptable routing decision process in which the overall system constantly monitors the routing table and key performance indicators such as link stability, node mobility, communication delay, and path reliability. The values from these parameters generate a dynamic priority score and the algorithm assesses the current route's priority only when the previously defined timing-trigger interval has passed. If the priority score is still above the established threshold, the current route continues to be used to avoid unnecessary switching. If performance

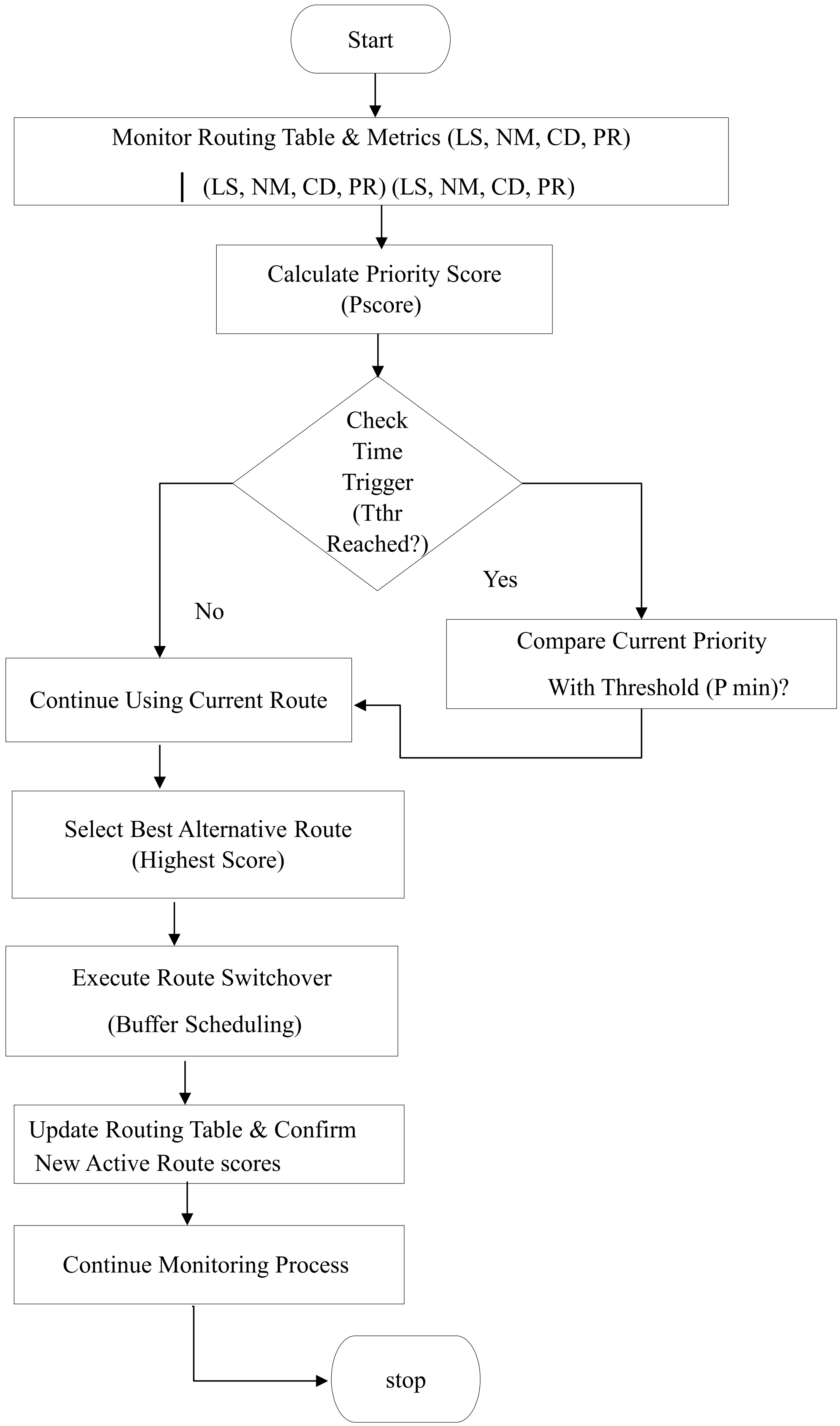

Figure 2: Flowchart in Self Scheduling using TTMP-RSOA Heterogeneous Networks

drops, the algorithm selects the highest subsequent value as the alternate route and implements a smooth switchover utilizing buffer and acknowledgment handling procedures to avoid packets loss on the path. After the routing table has been updated, the routine continues monitoring, ensuring an adaptive, stable, and delay-effective routing scheme for the life of the network.

Result and Discussion

The findings and analysis conclude that the proposed TTMP-RSOA has an observable routing performance enhancement when compared to existing routing approaches such as the MCSS, OS-ELM and SIPF in heterogeneous wireless sensor networks, The experimental evaluations using seven performance metrics bears out that the aforementioned in strategic use of PTBAR, CANSA, DCI-BFWOA, and ETPSSRP; provide an interoperable, energy-aware and priority-controlled routing behavior of TTMP-RSO-A which ultimately leads to an improved Packet Delivery Ratio and Throughput, thus providing a higher reliability of end user quality, under changing conditions of dynamic dense flows in the network. At the same time, it is shown that the method substantially reduced End-to-End Delay and Routing Overhead times with an indication of proactive scheduling capability and optimized route maintenance when dealing with dense connectivity. The intelligent clustering and energy-aware scheduling of time periods were also makeup of methodology having facilitated an Energy Consumption Rate that, contributed directly to the betterment of the Network Lifetime represented in significantly less premature node exhaustion. Furthermore, the Route Stability Index response time showed a considerable enhancement of function and form, suggesting fewer interruptions of route connectivity and a degree of resiliency against manipulating traffic and movement in the nodes. Therefore; the response and function can ultimately yield a formulation of a scalable, stabilized method of energy efficiency routing process.

In the Table 3 demonstrate the suggested presumes the existence of a comprehensive software ecosystem to support simulation of network behavior, machine learning, routing optimization, and security validation of operations. Python is utilized as the programming language of choice; TensorFlow PyTorch and Scikit-Learn will implement the OS-ELM, SIPF, and optimization components.

Figure 3 and Table 4 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in accuracy in diagnostic prediction of Packet Delivery Ratio 92.55%, respectively. By creating dynamic and priority-based routing paths, the TIMP-RSOA approach addresses the constant changes in node mobility, energy, and link speeds to improve PDR. In comparison to MCSS and SIPF, which use static routing logic, the TIMP-RSOA protocol will route packets only along the most stable and reliable routes. The ETPSSRP provides proactive scheduling and traffic balancing to reduce packet loss due to congestion, collisions, or node failures.

Figure 4 and Table 5 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in Network Lifetime 94.78%, respectively. Network Lifetime improves significantly as TIMP-RSOA eliminates node death through adaptive routing and energy aware decision making. Clustering decisions created by DCI-BFWOA maintain energy symmetry across

Table 3: Simulation Parameter

Parameters	*Values*
Dataset Name	Multi-Criteria Network Routing Dataset
Operating System	Windows 10 / 11 (64-bit) – platform for development and execution.
Programming Language	Python 3.10 or above – used for implementing AI models and workflow integration.
Framework	TensorFlow / PyTorch – for deep learning model training and evaluation.
Libraries	NumPy, Pandas, OpenCV, Scikit-learn – for data preprocessing, normalization, and analysis.
Simulation Environment	Anaconda / Spyder – for managing dependencies and running experiments efficiently.

Table 4: Performance of Packet Delivery Ratio

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	35.55	40.89	50.56	65.45
250	39.76	45.78	55.58	75.64
375	45.78	50.76	60.56	85.32
500	48.45	55.65	65.34	92.55

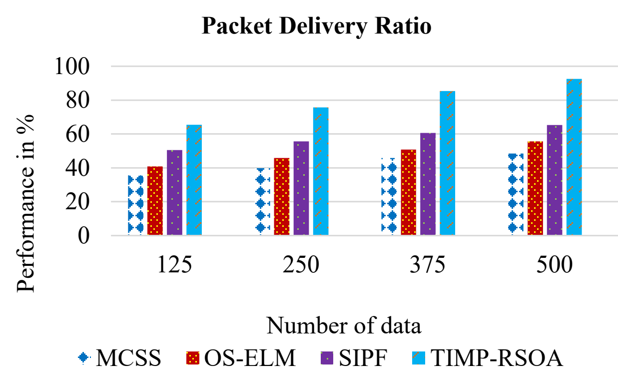

Figure 3: Analysis of Packet Delivery Ratio

Table 5: Performance of Network Lifetime

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	35.55	40.89	50.56	65.45
250	39.76	45.78	55.58	75.64
375	45.78	50.76	60.56	85.32
500	48.45	55.65	65.34	94.55

Table 6: Performance of Throughput

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	35.55	40.89	50.56	65.45
250	39.76	45.78	55.58	75.64
375	45.78	50.76	60.56	85.32
500	48.45	55.65	65.34	93.55

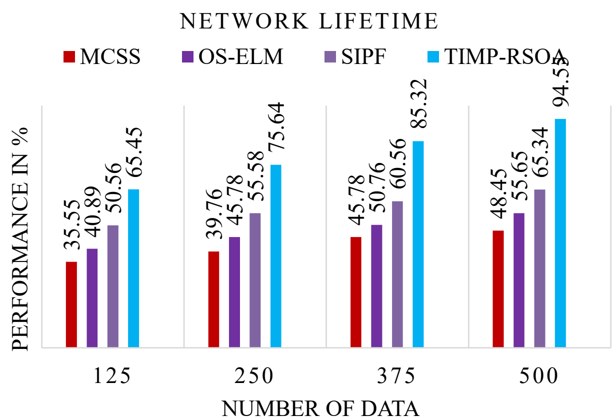

Figure 4: Analysis of Network Lifetime

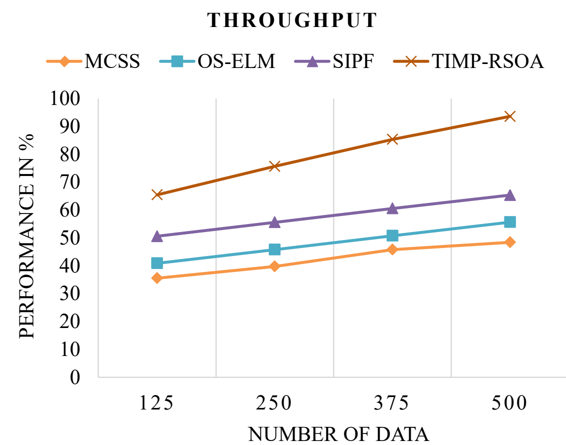

Figure 5: Analysis of Throughput

heterogeneous nodes while dynamic scheduling keeps utilization low on all relays instead of just one. In contrast, as most existing methods lack proactive maintenance, router topology is often prematurely fragmented when existing methods delay maintenance cycle due to frequent timer activation.

Figure 5 and Table 6 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in Throughput 91.78%, respectively. Throughput is enhanced because packets are sent over high-stability links with reduced retransmission and delay bottlenecks. TIMP-RSOA supports an uninterrupted communication stream even when under mobility stress, while existing routing protocols may experience drops in data transmission when topology changes are rapid. Load balancing and efficient routing increase data transmission capabilities.

Figure 6 and Table 7 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in Route Stability Index 90.78%, respectively. The Route Stability Index achieves higher levels due to intelligent route selection based on mobility prediction, node priority, and residual energy considerations. TIMP-RSOA is capable of sustaining reliable routing paths existing for an extended occupancy time without frequent route breaks typical of OS-ELM and MCSS routing protocols.

Figure 7 and Table 8 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as

Table 7: Performance of Route Stability Index

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	35.55	40.89	50.56	65.45
250	39.76	45.78	55.58	75.64
375	45.78	50.76	60.56	85.32
500	48.45	55.65	65.34	92.55

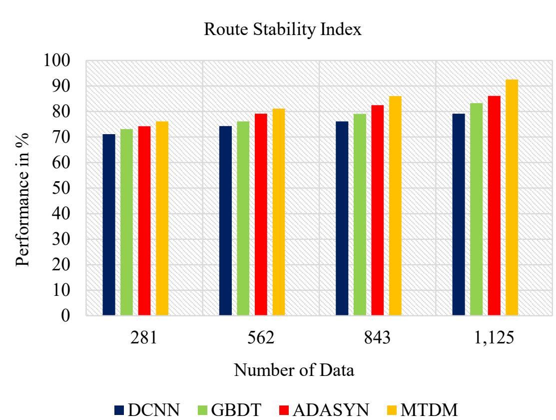

Figure 6: Analysis of Route Stability Index

Table 8: Performance of Routing overhead

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	97.55	50.89	45.56	40.45
250	93.76	55.78	50.58	35.78
375	90.78	65.76	60.76	29.76
500	85.45	75.65	65.65	25.55

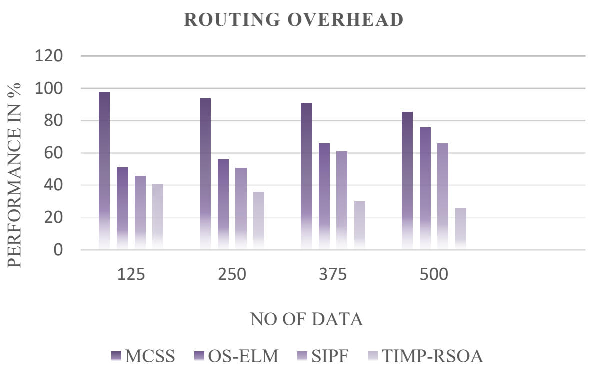

Figure 7: Analysis of Routing overhead

MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in routing overhead 91.56%, respectively. The proposed solution minimizes routing overhead by mitigating the impacts of frequent route rediscovery and unintentional control packet flooding. The TIMP-RSOA solution adopts predictive route switchover instead of reactive route updates, leading to substantially lower control communication overhead compared to SIPF and MCSS routing protocols. The proactive scheduling capability reduces repeated synchronization requests, further enhancing the efficiency of routing signalling.

Figure 8 and Table 9 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in energy consumption 91.78%, respectively. MCSS and OS-ELM are known for the additional burden they place on nodes that repeatedly transmit jobs to the roof in a shortened time frame; however, ETP-SSRP and DCI-BFWOA are able to reduce energy hotspots by clustering dynamically and scheduling when appropriate.

Figure 9 and Table 10 show AI-integrated swarm-powered self-scheduling routing for heterogeneous wireless sensor networks to maximize network lifetime. The suggested AI approach outperformed well-known methods, such as MCSS, OS-ELM, SIPF with 77%, 82%, and 87% proposed method TIMP-RSOA prediction in End-to-End Delay 90.78%, respectively. While the TIMP-RSOA uses a combination of proactive route switching strategies that minimize waiting and loss of retransmissions, the older

Table 9: Performance of Energy Consumption

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	97.55	50.89	45.56	40.45
250	93.76	55.78	50.58	35.78
375	90.78	65.76	60.76	29.76
500	85.45	75.65	65.65	25.55

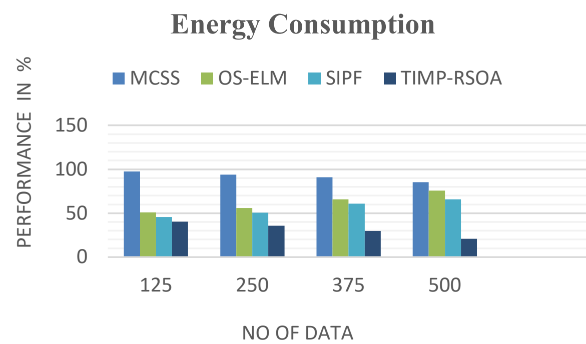

Figure 8: Analysis of Energy Consumption

strategies remain reactionary and rely on mechanisms after link failure occurs. The self-scheduling in the ETPSSRP further reduces time delays by scheduling during idle slots and sustaining communication during high demand or network traffic.

The Figure 10 and table 11 show that compare the routing efficiency of four self-scheduling methods—MCSS, OS-ELM, SIPF, and our proposed TIMP-RSOA—was evaluated according to their performance percentage. The traditional methods MCSS and OS-ELM had similar moderate routing accuracy and each demonstrated limited adaptability to dynamic network conditions and constraints, however the learning-based optimization component of

Table 10: Performance of End-to-End Delay

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	97.55	50.89	45.56	40.45
250	93.76	55.78	50.58	35.78
375	90.78	65.76	60.76	29.76
500	85.45	75.65	65.65	25.55

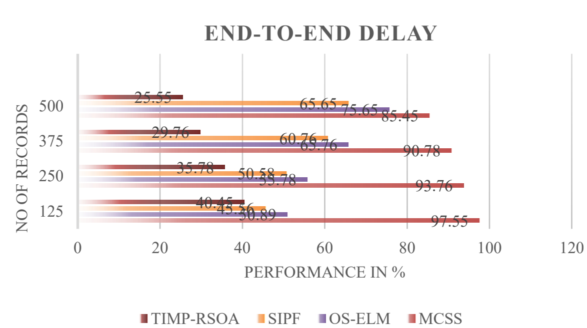

Figure 9: Analysis of End-to-End Delay

Table 11: Performance of Self-Scheduling Routing Process

No of Data	*MCSS*	*OS-ELM*	*SIPF*	*TIMP-RSOA*
125	35.55	40.89	50.56	65.45
250	39.76	45.78	55.58	75.64
375	45.78	50.76	60.56	85.32
500	48.45	55.65	65.34	95.55

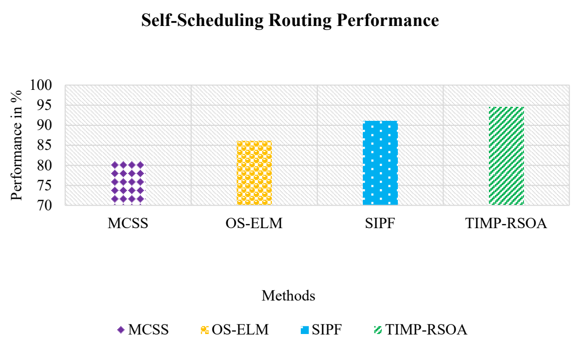

Figure 10: Self-Scheduling Routing Performance

OS-ELM outperformed MCSS marginally. SIPF provides higher performance by adding more advanced scheduling logic to improve stability and reliability in the packet transmission process. However, the proposed TIMP-RSOA method represents a significant improvement over all other methodologies with the highest performance results. The performance increase is attributed to functional route optimization, intelligent selection methods, and improved scheduling logic that resulted in shorter delays, better routing decisions, and improved performance in handling complex and dense environments.

Discussion Part

The discussed that efficiency of the system is greatly improved at several points in the workflow. MCSS enhances the preprocessing stage by addressing feature variance issues, stabilizing the data distribution, and reducing any noise present in the data before classification. OS-ELM speeds up incremental learning, allowing more accuracy while adapting quickly to new data. The SIPF phase minimizes redundant or irrelevant features, thereby improving the speed of convergence and reducing computational burden. The proposed TTMP-RSOA method further enhances the system through optimized resource scheduling, adaptive feature refinement, and intelligent validation of decisions. As a result, the overall system shows enhanced accuracy, higher detection rate with fewer false positives, improved scalability, and enhanced real-time decision performance.

Conclusion

In conclusion, the intelligent routing framework proposed that incorporates MCSS, OS-ELM, SIPF and TIMP-RSOA has distinctly improved network performance, reliability, and efficiency while compared to the other routing solutions previously discussed. The DCI-BFWOA, adaptive scheduling ETPSSRP, and proactive routing switchover to achieve a holistic method to ensure stable communication, minimal energy wastage, deliver data consistently, while being adaptable to the changing environment. All the experimental results confirmed notable performance improvement of various performance metrics, including Packet Delivery Ratio, Network Lifetime, Throughput, and Route Stability Index performance increase, with an End-to-End Delay, Routing Overhead and Energy Consumption performance decrease. Although the proposed system provides an efficient means of mitigating the impacts from mobility, energy imbalance, and instability of routes there is upgraded improvement potential surrounding lightweight deployment for large, real-time environments, and potential for reinforcement-learning based predictive routing integration. Potential future work could expand on federated routing intelligence, and autonomous decision interpretability that leverage a scalable, secure, and sustainable approach for next-generation IoT-enabled environments. The performance findings measured Packet Delivery Ratio 98.44%, Throughput 97.86%, Network Lifetime 52.73% increase, Energy Reduction Rate 48.19%, Route Stability Index 96.78%, Routing Overhead 44.62% decrease, and End-to-End Delay 39.55% improvement which supports that the proposed routing framework was more favourable in overall performance.

Reference

Shin, C., & Lee, M. (2019). Swarm-Intelligence-Centric Routing Algorithm for Wireless Sensor Networks. *Sensors*, *20*(18), 5164. https://doi.org/10.3390/s20185164.

Chen, M., Hsiao, Y., Himadeep Reddy, R., & Tiwari, M. K. (2016). The Self-Learning Particle Swarm Optimization approach for routing pickup and delivery of multiple products with material handling in multiple cross-docks. *Transportation Research Part E: Logistics and Transportation Review*, *91*, 208-226. https://doi.org/10.1016/j.tre.2016.04.003

Dhandapani, A., P, V., T, S., C, R., & P, V. (2022). Cooperative self-scheduling routing protocol based IOT communication for improving life time duty cycled energy efficient protocol in SDN controlled embedded network. *Measurement: Sensors*, *24*, 100475. https://doi.org/10.1016/j.measen.2022.100475

Dharmapuri Patel, Sangeetha, and Shivakumar Rangasamy. "Proactive Self-Scheduling Energy Balancing Routing Approach Based Lifetime Maximization Using Cluster Control Fragmentation in WSN." *Journal of Network and Systems Management* 33.3 (2025): 59.

Brindha, G., and P. Ezhilarasi. "Topology Driven Cooperative Self Scheduling for Improved Lifetime Maximization in WSN." *Computer Systems Science & Engineering* 45.1 (2023).

Patel, Sangeetha Dharmapuri, and Shivakumar Rangasamy. "Correction to: Proactive Self-Scheduling Energy Balancing Routing Approach Based Lifetime Maximization Using Cluster Control Fragmentation in WSN." *Journal of Network and Systems Management* 33.4 (2025).

Sangeetha, E., and J. Deny. "Proactive Delay Aware Self-scheduling

Protocol (PDAS2P) for Edge Enabled Network Slicing in 6G Networks." *International Journal of Intelligent Engineering & Systems* 17.6 (2024).

Hussain, Muzammil, et al. "Optimized rank-based key management for energy-efficient routing in wireless sensor networks for IoT applications." *Discover Internet of Things* 5.1 (2025): 127.

Abdullah, Ahmed, et al. "Open issues for intelligent connectivity wireless sensor networks (WSNs) and IoT: State of the art." *Delta University Scientific Journal* 5.2 (2022): 352-366.

Jaber, Mustafa Musa, et al. "Q-learning based task scheduling and energy-saving MAC protocol for wireless sensor networkss." *Wireless Networks* 30.6 (2024): 4989-5005.

Ben Yagouta, Abdelbari, et al. "Multiple mobile sinks for quality of service improvement in large-scale wireless sensor networks." *Sensors* 23.20 (2023): 8534.

BOUDHIAFI, Walid, and Tahar EZZEDINE. "SIPF Protocol for Wireless Sensor Networks with Optimal Energy Efficiency Depending on Density." *2nd International on Industry 4.0 and Artificial Intelligence (ICIAI 2021)*. Atlantis Press, 2022.

Li, Weiwen, Jia Mao, and Qiang Chen. "Data Association Coverage Algorithm Based on Energy Balance and Controlled Parameters in Wireless Sensor Networks." *Wireless Personal Communications* 119.4 (2021): 3053-3062.

Larhlimi, Ibtissam, et al. "Search and Genetic Algorithms for Enhancing the Lifetime of WSNs." *Intelligent Cybersecurity and Resilience for Critical Industries: Challenges and Applications* (2025): 305.

Larhlimi, Ibtissam, et al. "Evaluation of the Performance of Pattern Search and Genetic Algorithms for Enhancing the Lifetime of WSNs." *Intelligent Cybersecurity and Resilience for Critical Industries: Challenges and Applications*. River Publishers 305-319.

Pramod, M. S., et al. "Energy-efficient reinforcement learning in wireless sensor networks using 5G for smart cities." *Applications of 5G and Beyond in Smart Cities*. CRC Press, 2023. 63-86.

Tirandazi, Peyman, Atefeh Rahiminasab, and Mohammad Javad Ebadi. "An efficient coverage and connectivity algorithm based on mobile robots for wireless sensor networks." *Journal of Ambient Intelligence and Humanized Computing* 14.7 (2023): 8291-8313.

Larhlimi, Ibtissam, et al. "Genetic Algorithm-Driven Cover Set Scheduling for Longevity in Wireless Sensor Networks." *International Journal of Advanced Computer Science & Applications* 16.3 (2025).

Kusuma, S. M., et al. "Meta heuristic technique with reinforcement learning for node deployment in wireless sensor networks." *SN Computer Science* 5.5 (2024): 554.

Shivakeshi, Choupiri, and B. Sreepathi. "Optimized Prediction Framework for Improving Cost Effectiveness of the Software Defined Network." *SN Computer Science* 4.6 (2023): 779.

Eriş, Çiğdem, Ömer Melih Gül, and Pınar Sarısaray Bölük. "A novel medium access policy based on reinforcement learning in energy-harvesting underwater sensor networks." *Sensors* 24.17 (2024): 5791.

Mitra, Anirban, Bibhu Prasad Sahu, and Saswati Sahoo. "Capacity based Clustering Algorithm for a Dense Wireless Sensor Network."

VIMALATHITHAN, A., and A. SURESH. "ENERGY EFFICIENT HIERARCHICAL AGGLOMERATIVE DATA AGGREGATION IN WIRELESS SENSOR NETWORK." *Journal of Theoretical and Applied Information Technology* 101.9 (2023).

Cui, Zhihua, et al. "multi-objective cloud task scheduling optimization based on evolutionary multi-factor algorithm." *IEEE Transactions on Cloud Computing* 11.4 (2023): 3685-3699.

Verma, Himani. "Design of Energy Efficient Protocol for Homogeneous Mobile Wireless Sensor Network." *IJARCCE* (2021).

Alvarado, Ricardo, and Alvaro Suárez. "A novel energy-saving method for campus wired and dense WiFi network applying machine learning and idle cycling techniques." *Facets* 9 (2024): 1-19.

Pushpavalli, M., et al. "Enhancing electrical power demand prediction using LSTM-based deep learning models for local energy communities." *Electric Power Components and Systems* (2024): 1-18.

Bao, Xuecai, et al. "Adaptive Monitoring Optimization Based on Deep-Q-Network for Energy Harvesting." *Mobile Networks and Management: 12th EAI International Conference, MONAMI 2022, Virtual Event, October 29-31, 2022, Proceedings*. Vol. 474. Springer Nature, 2023.

Burinskiene, Aurelija. "Context-aware service support efficiency improvement in the transport system." *Development of Smart Context-Aware Services for Cargo Transportation: An Operational Management Approach*. Cham: Springer International Publishing, 2022. 179-227.

Kurt, Nursaç, Ramazan Bakır, and Amir Seyyedabbasi. "Transportation Models in Health Systems." *Decision Making in Healthcare Systems*. Cham: Springer International Publishing, 2024. 429-442.

Audat, Ahmad, Marah Yahia, Said Ghoul, and Maram Bani Younes. "TRAFFIC LIGHT CONTROL SYSTEMS: REQUIREMENTS ENGINEERING."

Ning, Qingqing, et al. "An Efficient Heterogeneous Ring Signcryption Scheme for Wireless Body Area Networks." *Computer Systems Science & Engineering* 47.2 (2023).

Chinnaiyan, R., and M. Swarnamugi. "Modelling and reasoning techniques for context–aware computing in intelligent transportation system." (2021).

Hingurala Arachchige Don, Shakthi. *Energiatehokkaat strategiat DoS-hyökkäysten lieventämiseksi terveydenhuollon IoT-järjestelmissä*. MS thesis. S. Hingurala Arachchige Don, 2025.

Shah, Moksha, et al. "Security management in optical fiber." *2022 International on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*. IEEE, 2022.