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Research Article

An Energy Efficient Mathematically Modified Monarch Butterfly Optimization for Routing in WSN

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ABSTRACT

Wireless Sensor Networks (WSNs) are significant for monitoring physical and environmental variables, requiring efficient routing algorithms. This paper presents a novel approach called Energy Efficient Mathematically Modified Monarch Butterfly Optimization (EEMMBO) for routing in Wireless Sensor Networks (WSNs). The hybrid technique combines the accuracy of Mathematical Model Integer Linear Programming (ILP) in decision-making with the exploratory nature of Monarch Butterfly Optimization (MBO). ILP effectively handles specific choices and complex limitations, while MBO introduces variety into solutions, avoiding being stuck in suboptimal outcomes. The inspiration for this research is the fundamental importance of Wireless Sensor Networks (WSNs) in many applications, where efficient routing is vital for successful data gathering and monitoring. The sensor nodes come with limited energy and processing capacities, whereas conventional routing algorithms frequently face challenges in balancing decision-making accuracy and adaptability to changing settings. This research seeks to tackle these obstacles by introducing a prominent technique, the Energy Efficient Mathematically Modified Monarch Butterfly Optimization (EEMMBO), for routing in Wireless Sensor Networks (WSNs). The primary research goal is two-fold: firstly, to create a strong Mathematical Model using Integer Linear Programming (ILP) that guarantees accurate decision-making, and secondly, to incorporate the exploratory characteristics of Monarch Butterfly Optimization (MBO) to improve solution diversity and adaptability. This research aims to improve the efficiency, resilience, and adaptability of WSN routing by using a hybrid approach. The proposed EEMMBO combines different methods effectively and demonstrates its ability to enhance energy efficiency, resilience, and adaptability in WSN routing scenarios.

Keywords: Energy consumption, sensor node, network, optimization, sleep scheduling, and mathematical model.

Introduction

Recent years have seen an expanded interest in Wireless Sensor Networks (WSNs) in different applications, for example, natural monitoring, manufacturing plant robotizing, environment following, security observation, smart transportation, and savvy urban areas. This innovation has brought some advantages to clients from various areas. It is imagined that tens to thousands of sensor nodes working on little batteries will be conveyed to function autonomously to develop WSNs in numerous situations. Wireless sensor networks may comprise divergent sorts of sensors such as seismic, warm, optic, infrared, acoustic, and radar, which can screen a wide run of surrounding conditions, including temperature, humidity, light condition, the nearness or nonattendance of objects, mechanical stretch levels on connected objects, and the portability characteristics such as speed and course [1]. The detected information is assembled and sent to a base station straightforwardly or utilizing multiple hops depending on the network topology and routing conventions. In expansion to the capacity to test its environment, each sensor node has one or more inbuilt radios to communicate with other nodes through wireless communication protocols, for example, ZigBee out of many. Subsequently, micro-sensing and remote communication combinations offer many conceivable outcomes of WSN applications [2].
A Wireless Sensor Network (WSN) is a wireless network that consists of spatially distributed autonomous devices called sensors [3]. These sensors are specifically designed to monitor physical or environmental factors. This system incorporates a wireless communication gateway to the wired world and many distributed nodes. A wireless sensor network consists of specialized transducers and a communication infrastructure [4]. Its

purpose is to observe and record conditions at several places. Parameters frequently monitored include temperature, humidity, density, wind direction and speed, light intensity, vibration levels, sound concentration, power-line voltage, chemical concentrations, pollutant levels, and vital body functions. A sensor network consists of multiple detecting stations known as sensor nodes, each of which is small, lightweight, and easy to carry. Every sensor node has a transducer, a compact computer for processing and storing sensor output, a transmitter for communication, and a power source like a battery [5].

The network's topology designs the actual arrangement of the sensors inside the observed region. We can recognize a wide range of possible architectures. The nodes can be laid out in star topology, where the sink or the base station is connected to each node [6]. The sensor nodes may be physically laid as a single hop network, where any node can communicate directly with any other node. In a multi-hop network, sensor nodes can be arranged in a tree or graph topology. The topology is determined by the application which will be executed. Which also has an impact on network parameters, including delay, connectivity, information handling, network lifespan, and durability. In multi-hop WSNs, routing is essential for transmitting data from one node to another or the base station. Nevertheless, the sleep scheduling of sensor nodes may meddle with routing because an intermediate node chosen by the routing protocol may go to sleep mode during the communication of a packet via it. Thus, a routing protocol for a WSN has to be adequately integrated with the sleep scheduling method of the WSN [7].

Sensor nodes frequently have inadequate battery power. Power utilization is always an important issue to be determined for sensor nodes because the node may be installed in a nonhuman environment, and replacing the battery regularly may be costly, and, for some implementations, incomprehensible Speedy usage of the sensors' remaining energy diminishes the lifetime of the network and, after that, influences the sensing accessibility [8]. Numerous studies have been conducted to address the issue of prolonging the network's lifespan following the scheduling and management of the sensor's battery sparing. Battery energy can be spared by changing the power levels for sensing events. That is, depending on the type of workload, the sensing can be maximized or minimized so that energy consumption can be reduced and, as a result, the network's lifetime can be extended. In another way, battery power can be saved by shutting down sensor nodes that are not currently participating in any activity. Nodes are either inactive or in sleep mode to reduce power consumption. A scheduling algorithm changes the node status from active to sleep or vice versa for balanced power consumption [9].

In the Wireless Sensor Networks (WSN) field, the first crucial step is defining the routing problem. This involves carefully considering important factors and limitations. The routing problem is framed by describing the Wireless Sensor Network (WSN) environment, including information about the quantity and arrangement of sensor nodes and the characteristics of the data being monitored. Prominent goals, such as improving energy efficiency, reducing latency, and enhancing reliability, have been defined to guide the routing formulation process [10]. Decision variables are subsequently established to reflect crucial elements like node routing and path selection. At the same time, the objective function encapsulates the core of optimization by balancing energy consumption, reducing latency, and maximizing reliability. Constraints in wireless sensor networks (WSNs) are influenced by specific characteristics such as limited energy resources, communication range, and reliability thresholds [11].

Further refining entails conducting a particular analysis to balance competing factors, adapting to changing environmental conditions and verifying the accuracy of the mathematical model through practical simulations. Furthermore, sensitivity analysis examines the model's ability to react to variations in parameters and constraints [12]. The thorough description of assumptions, the ultimate mathematical model, and additional considerations provide a solid basis for creating routing algorithms specifically designed for the complex requirements of Wireless Sensor Networks (WSNs), guaranteeing practical and efficient solutions.

Related Works

Wireless Sensor Networks (WSNs) are vital for gathering and analyzing large quantities of data, making them indispensable for various applications. Nevertheless, obstacles such as network congestion, energy efficiency, and data transfer optimization continue to exist. This literature review examines recent progress in tackling these difficulties using novel methods. A prevalent problem in Wireless Sensor Networks (WSNs) is the congestion near the root nodes. This congestion results in inefficiencies, particularly in scenarios involving traffic convergence. Despite its widespread usage, the OSCAR approach continues to encounter performance challenges due to network intricacy. The proximity of nodes amplifies issues such as collisions during transmission and energy consumption resulting from duplicate data. In order to address these issues, a new and innovative method is suggested: a Fuzzy-Based Sleep Scheduling Mechanism (FBESSM). FBESSM dynamically activates or deactivates sensors to minimize power consumption. The evaluation parameters, including throughput, packet loss, lifespan, energy consumption, and latency, demonstrate the higher performance of FBESSM compared to OSCAR. This highlights the usefulness of FBESSM across many network measures [13].

Compressive Data Gathering (CDG) is recognized as a very efficient technique for minimizing data transmission and, consequently, lowering energy consumption in Wireless Sensor Networks (WSNs).

Integrating sleep scheduling with CDG improves energy efficiency even more. Nevertheless, current sleep scheduling techniques frequently entail centralized optimization issues or stochastic decision-making, resulting in energy imbalances and early energy exhaustion. In this regard, we provide an RLSSA-CDG algorithm, which utilizes reinforcement learning to schedule sleep in CDG. RLSSA-CDG achieves load balancing and accurate data reconstruction using finite Markov decision processes and mode-free Q learning. It is a distributed system that avoids superfluous control message exchanges. The simulation findings confirm its superiority in energy usage, network longevity, and data recovery accuracy [14].

For WSN applications, the duration of network operation and the ability to determine the location of nodes are crucial factors, particularly in situations where nodes are installed randomly and remain unattended for long periods. The Energy-Aware Connected k-Neighborhood (ECKN) suggested in this study combines position estimation, packet routing, and sleep scheduling to tackle these issues effectively. ECKN utilizes trilateration for localization, a routing protocol that relies on Greedy Geographic Forwarding (GGF), and a sleep scheduler based on connected k-neighborhood (CKN). Evaluation experiments have shown that ECKN prolongs the network's lifespan, localizes nodes, and maintains satisfactory packet delivery rates, all while lowering network overhead [15].

Ensuring continuous coverage of the target region is of utmost importance in Energy Harvesting-Based Wireless Sensor Networks (EH-WSNs). A proposed routing protocol called HCEH-UC (An Adaptive Hierarchical-Clustering-Based Routing Protocol for EH-WSNs) is utilized to achieve this objective. The HCEH-UC algorithm utilizes hierarchical clustering to regulate energy usage and dynamically manages the number of nodes operating in energy-harvesting mode. The simulation findings validate that HCEH-UC extends the maximum duration of coverage for Wireless Sensor Networks (WSNs), guaranteeing continuous target coverage through energy harvesting technology [16].

Another area of concentration is enhancing the efficiency of gathering and transmitting data in Wireless Sensor Networks (WSNs) to extend the duration of network operation. The Particle Swarm Optimisation (PSO) technique is utilized for cluster formation, and a Fuzzy-Based Energy-Efficient Routing Protocol (E-FEERP) is introduced. E-FEERP optimizes data transmission by considering aspects such as battery energy, average Distance to the base station, node density, and communication quality. The simulation findings indicate enhancements in throughput, residual energy, load balancing ratio, packet delivery ratio, energy consumption, and network longevity compared to existing methods [17].

The Butterfly Optimisation Algorithm (BOA) is employed to optimize the selection of cluster heads to improve the network lifetime of Wireless Sensor Networks (WSNs). The suggested methodology integrates Ant Colony Optimisation (ACO) to identify routes based on Distance, residual energy, and node degree. The suggested methodology's usefulness is demonstrated through a comparative comparison with traditional and existing methodologies, focusing on metrics such as living nodes, dead nodes, energy usage, and data packets the base station receives [18].

These studies provide several methods for tackling important issues in Wireless Sensor Networks (WSNs), such as congestion, energy efficiency, network lifespan, and data transfer optimization. Various methods, such as fuzzy-based sleep scheduling, reinforcement learning for CDG, and adaptive hierarchical clustering, enhance the capabilities and dependability of Wireless Sensor Networks in different application domains. The suggested solutions offer enhanced performance metrics and show promising outcomes for the future advancement of WSN technologies.

Conventional methods used in Wireless Sensor Networks (WSNs) sometimes encounter difficulties concerning energy efficiency, specifically concerning sleep scheduling. Several current sleep scheduling algorithms may inadequately handle wireless sensor networks' dynamic and intricate characteristics (WSNs), resulting in unsatisfactory energy usage, network lifespan, and overall effectiveness. The research gap exists in the necessity for a sleep scheduling method that is both adaptable and efficient, taking into account the varied and changing conditions within wireless sensor networks (WSNs).

The Energy Efficient Mathematically Modified Monarch Butterfly Optimisation (EEMMBO) for Routing-Based Sleep Scheduling fills a research gap by integrating the accuracy of Integer Linear Programming (ILP) with the investigative characteristics of Monarch Butterfly Optimisation (MBO). EEMMBO guarantees precise sleep scheduling beyond the constraints of energy usage and adaptability seen in conventional approaches. By combining the decision-making accuracy of ILP with the exploratory capabilities of MBO, it effectively manages discrete decisions and intricate restrictions. EEMMBO is particularly noteworthy for its ability to optimize energy efficiency, latency, and dependability, offering a full solution. The system's adaptability to changing conditions in the Wireless Sensor Network enables real-time modifications according to fluctuations in network traffic, environmental factors, and energy availability.

The EEMMBO technique effectively addresses the research gap in sleep scheduling mechanisms within WSNs. EEMMBO enhances sleep scheduling strategy by integrating the accuracy of ILP with the investigative approach of MBO, resulting in improved adaptability and efficiency. This hybrid technique addresses the shortcomings of conventional methods by offering a holistic solution that enhances energy efficiency, reduces latency, and improves reliability in dynamic wireless sensor network (WSN) situations.

Energy Efficient Mathematically Modified Monarch Butterfly Optimization for Routing

The Energy Efficient Mathematically Modified Monarch Butterfly Optimisation (EEMMBO) is a novel method that integrates mathematical modelling and the exploratory characteristics of the Monarch Butterfly Optimisation (MBO) algorithm. It is specifically designed to tackle routing issues in Wireless Sensor Networks (WSN). In the context of Wireless Sensor Networks (WSNs), where conserving energy is crucial for maximizing the lifespan of the network, reducing latency is important for timely data transmission, and ensuring reliability is essential for strong communication, the goal of EEMMBO is to discover optimized routes that achieve a balance between these competing objectives.

The methodology incorporates Integer Linear Programming (ILP) as the mathematical modelling element, utilizing its capacity to manage discrete decisions and intricate restrictions inherent in WSN routing. ILP offers a predictable and accurate framework for making decisions. The inclusion of MBO brings in a speculative aspect, drawing inspiration from the foraging actions of monarch butterflies. The stochastic character of MBO enables the algorithm to systematically examine a wide range of solutions systematically, hence avoiding becoming stuck in local optimal solutions and improving the overall resilience of the route optimization process. The procedure of EEMMBO is outlined in this section.

In the context of Wireless Sensor Networks (WSN), Integer Linear Programming (ILP) can be applied to address various optimization problems, including routing. The ILP formulation for a generic WSN routing problem typically involves decision variables, an objective function, and a set of constraints. Here is a basic ILP formulation for a WSN routing problem:

Let x_{ij} be a binary decision variable representing whether node i is selected as a relay node on the path to node (x_{ij}=1 if selected, x_{ij}=0 otherwise). Minimization is given in Equation 1.

$Minimize\ Z = \sum_i \sum_j C_{ij} \cdot x_{ij}$---------(1)

Cij represents the cost of selecting node i as a relay on the path to node j. This cost can be a combination of energy consumption, latency, or other relevant metrics.

The flow conservation constraint ensures that the data flow within the network is balanced at each node, except for the source and destination nodes. It is given in Equation 2.

$\sum_j x_{ij} - \sum_j x_{ji} = \begin{cases} 1\ if\ i = s(source\ node) \\ -1 if\ i = d(destination\ node) \\ 1 otherwise \end{cases}$---------(2)

This equation states that for each node i, the difference between the sum of outgoing flows (x_{ij}) and incoming flows (x_{ji}) should be 1 if i is the source node, -1 if i is the destination node, and 0 for all other nodes. This ensures that the flow is conserved within the network, guaranteeing that every unit of data sent from the source node reaches the destination node. The energy constraint regulates the network's total energy consumption, ensuring that it does not exceed a predefined maximum threshold. It is expressed in Equation 3.

$\sum_i \sum_j E_{ij} \cdot x_{ij} \leq E_{max}$---------(3)

In this equation, E_{ij} represents the energy consumption on the link between nodes i and j, and Emax is the maximum allowable energy consumption for the entire network. This constraint guides the ILP model to find a routing configuration that minimizes energy usage, contributing to the overall energy efficiency of the WSN. The reliability constraint ensures that the cumulative reliability of the selected links in the network meets or exceeds a minimum required threshold. It is formulated in Equation 4.

$\sum_i \sum_j R_{ij} \cdot x_{ij} \leq R_{min}$---------(4)

Here, R_{ij} represents the reliability of the link between nodes i and j, and R_{min} is the minimum required reliability. This constraint emphasizes the importance of establishing reliable communication links within the network, which is crucial for maintaining robust and dependable data transmission. The communication range constraint ensures the selected links are within the permissible communication range. It is represented in Equation 5.

$Distance(i, j) \leq R_{comm} \cdot x_{ij}$---------(5)

In this equation, Distance(i,j) is the physical Distance between nodes i and j, and R_{comm} is the maximum communication range. This constraint enforces the spatial limitations on selecting relay nodes, considering the practical range of communication for the sensor nodes. The binary constraint specifies that the decision variables x_{ij} are binary, taking values of either 0 or 1 in Equation 6.

$x_{ij} \in \{0,1\}$---------(6)

This constraint reflects the discrete nature of relay node selection. A value of 1 indicates that node i is selected as a relay on the path to node j, while 0 signifies that it is not selected. The binary nature of these variables is fundamental for formulating an ILP problem, allowing for clear and distinct choices in the routing configuration. These constraints collectively shape the ILP model for WSN routing, guiding the optimization process to find relay node configurations that balance flow, conserve energy, ensure reliability, adhere to communication range constraints, and maintain the binary nature of decision variables.

The sleep scheduling technique of Monarch Butterfly Optimisation (MBO) entails replicating the feeding patterns of monarch butterflies to ascertain the most advantageous sleep schedule for the nodes inside a Wireless Sensor Network (WSN). The MBO algorithm draws inspiration from the migratory behaviour of monarch butterflies, which involves a blend of deterministic and random motions. Within the domain of sleep

schedule, the MBO algorithm is employed repetitively to ascertain the optimal timing for individual sensor nodes to switch between active and sleep states.
The MBO algorithm efficiently manages the sleep scheduling of WSNs by appropriately balancing deterministic and exploratory movements. It adjusts to changing circumstances, guaranteeing that the sleep cycle remains flexible to network demands and ambient factor variations. The algorithm's capacity to investigate a wide range of options renders it appropriate for optimizing sleep schedules in WSNs, enhancing energy economy and overall network performance.
Initialization: In the initiation phase, a binary decision matrix X represents individual sensor nodes' sleep or active states over discrete time intervals. Each row corresponds to a sensor node, and each column denotes a time interval. Population P encompasses diverse X configurations, encapsulating various potential sleep schedules. The binary decision matrix X is formulated with dimensions N×T, where N represents the number of sensor nodes and T denotes the discrete time intervals. Each element X_{ij} of the matrix signifies the sleep (0) or active (1) state of node i at time j.
$X_{ij} \in \{0,1\} \forall i \in \{1,2, \dots \dots, N\}, j \in \{1,2, \dots ., T\}$---------(7)
Fitness Evaluation: The fitness function f(X) plays a pivotal role in assessing the performance metrics of the network, such as energy consumption or network coverage. The objective is to identify a sleep schedule that optimally aligns with the chosen performance criteria.
$f(X) = Optimization\ Criteria$---------(8)
Movement and Exploration: Within sleep scheduling, random perturbations are applied to a subset of potential sleep schedules to emulate exploratory behaviour observed in natural phenomena. This randomness mitigates the risk of entrapment in local optima, fostering adaptability to dynamic network conditions.
$X' = RandomExploration(X)$ ---------(9)
Deterministic Movement: Deterministic movement entails adjusting a subset of potential sleep schedules based on the prevailing best-performing solutions. This process introduces a stabilizing influence, steering the algorithm towards more optimal solutions. In sleep scheduling, deterministic adjustments may involve aligning sleep patterns with historically successful configurations.
$X'' = Deterministic\ Adjustment(X')$ ---------(10)
Update Solution Set: The refreshed population P amalgamates outcomes from random perturbations and deterministic adjustments. Solutions exhibiting improvements in the fitness function are retained, contributing to an iterative enhancement of sleep schedules. This systematic progression ensures the algorithm converges towards effective sleep scheduling configurations.
$P = P \cup \{X''\}$---------(11)
Termination Criteria: Termination criteria dictate the cessation of the sleep scheduling optimization process. This could be contingent on a predetermined number of iterations or the fulfilment of a convergence criterion. The convergence criterion gauges whether the algorithm has achieved a stable and productive sleep schedule for the sensor nodes.
$Termination\ Condition = CheckConvergence(P)$ ---------(12)
In the specialized domain of sleep scheduling for Wireless Sensor Networks (WSNs), this mathematical model provides a structured methodology for iteratively optimizing the sleep schedules of individual nodes, encompassing both stochastic exploration and deterministic adjustments. The resultant solution encapsulates an optimized sleep schedule that harmonizes energy efficiency and specified performance objectives within the WSN environment.

Result and Discussion

The process of establishing a network simulation using NS-2 (Network Simulator version 2) entails numerous crucial steps. Prior to anything else, it is important to install the NS-2 program by according to the official instructions or utilizing a package manager for a more efficient installation process. Afterwards, it is necessary to establish the network topology, which involves determining the nodes and their interconnections.
An illustrative script, named `simple.tcl`, showcases the establishment of two nodes and a connection between them. Subsequently, traffic is organized by implementing a CBR (Constant Bit Rate) traffic source and linking it to a UDP (User Datagram Protocol) agent. The simulation incorporates routing and transport protocols, such as AODV (Ad hoc On-Demand Distance Vector), by connecting routing agents to the nodes. The simulation parameters, such as the duration and trace file details, are established prior to executing the simulation with the `ns` command in the terminal. Ultimately, the outcomes can be examined, and tools such as Nam (Network Animator) can be utilized to visually represent the dynamics of the network. Adapting the scripts to particular protocols, network intricacies, and situations is essential for accurately simulating and examining the intended network performance. To obtain comprehensive information and tailor the settings to your needs, consult the NS-2 documentation and pertinent resources.
Wireless Sensor Networks (WSNs) are essential in a wide range of applications, including environmental monitoring and industrial operations, where efficient routing is of utmost importance. This study conducts a comparative analysis of three routing algorithms: Energy Efficient Mathematically Modified Monarch Butterfly Optimization (MMMBO), Monarch Butterfly Optimization combined with Ant Colony Optimization (MBO-

ACO), and Fuzzy-based Energy Efficient Routing Protocol (E-FEERP). The purpose is to evaluate their effectiveness in various scenarios of Wireless Sensor Networks (WSN) by measuring multiple performance metrics.

Efficiently managing routing overhead is crucial for optimizing network resources. MMMBO regularly exhibits reduced levels of Routing Overhead in comparison to its peers. With 100 nodes, MMMBO demonstrates a Routing Overhead of 4.66, surpassing the performance of MBO-ACO (7.56) and E-FEERP (9.68). MMMBO's total network optimization is enhanced by the efficiency in routing decision-making.

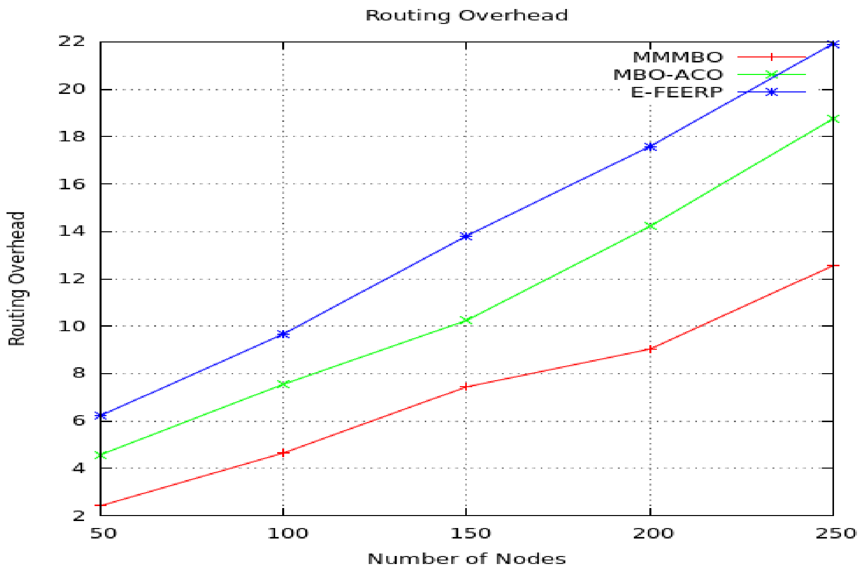

Figure 1. Comparison of Routing Overhead

The analysis of Routing Overhead in Figure 5 showcases MMMBO's efficiency in managing routing tasks with lower overhead compared to MBO-ACO and E-FEERP. As the network scales, MMMBO maintains a favorable position, demonstrating scalability and effective routing resource utilization.

Ensuring a high Packet Delivery Ratio is crucial for dependable data transfer. MMMBO regularly attains superior Packet Delivery Ratios across many node configurations. With 150 nodes, MMMBO achieves a Packet Delivery Ratio of 88, beating both MBO-ACO (83) and E-FEERP (80). This tendency enhances the dependability of MMMBO in effectively transmitting data packets.

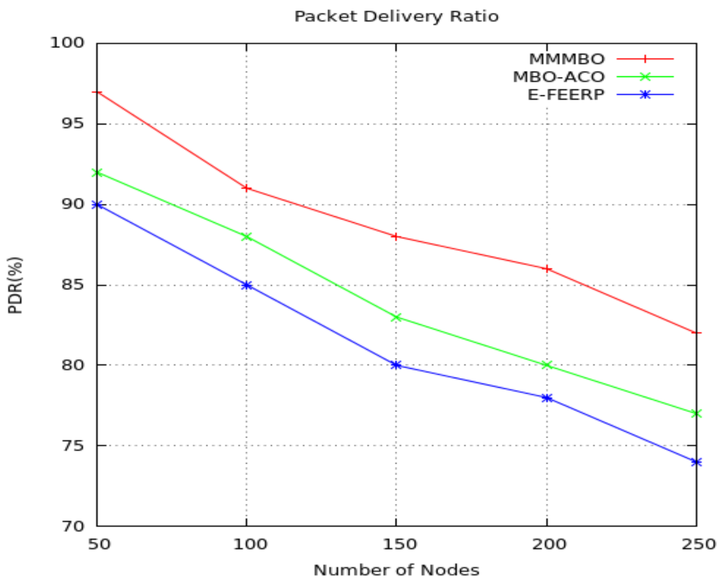

Figure 2. Comparison of PDR

Figure 2 reveals that MMMBO consistently achieves higher Packet Delivery Ratios compared to MBO-ACO and E-FEERP. This emphasizes MMMBO's reliability in ensuring a successful and consistent delivery of packets within the network, critical for maintaining data integrity.

Minimizing packet loss is essential for maintaining data integrity and ensuring reliability. MMMBO routinely demonstrates superior performance in terms of Packet Loss rates, which indicates a higher level of success in transmitting data packets. With 50 nodes, MMMBO achieves a Packet Loss rate of 3, outperforming both MBO-

ACO (7) and E-FEERP (10). As the number of nodes increases, MMMBO continues to demonstrate its supremacy by consistently delivering packets, thereby highlighting its reliability.

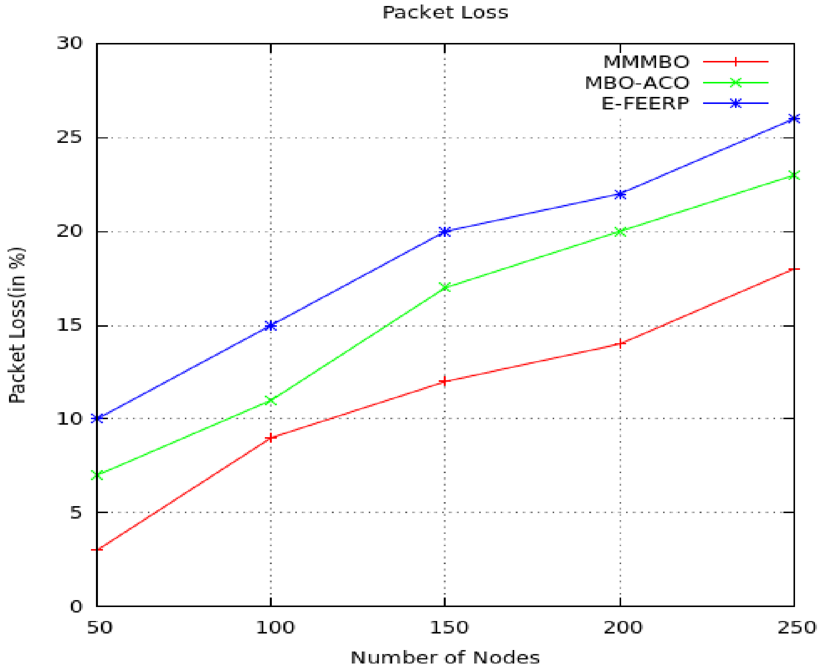

Figure 3. Comparison of Packet Loss

Figure 3 illustrates the Packet Loss metrics, highlighting MMMBO's ability to maintain lower packet loss rates compared to MBO-ACO and E-FEERP. This emphasizes MMMBO's reliability in ensuring successful data packet delivery, particularly in scenarios with varying node densities.

Ensuring a prolonged lifespan of the network is crucial for the long-term viability of Wireless Sensor Networks (WSNs). MMMBO demonstrates exceptional durability, maintaining extended network lifespans across diverse node setups. With 50 nodes, MMMBO guarantees a complete network lifetime of 100, although MBO-ACO and E-FEERP encounter minor reductions. The durability of MMMBO remains evident even with bigger networks, demonstrating its capacity to maintain network lifetime.

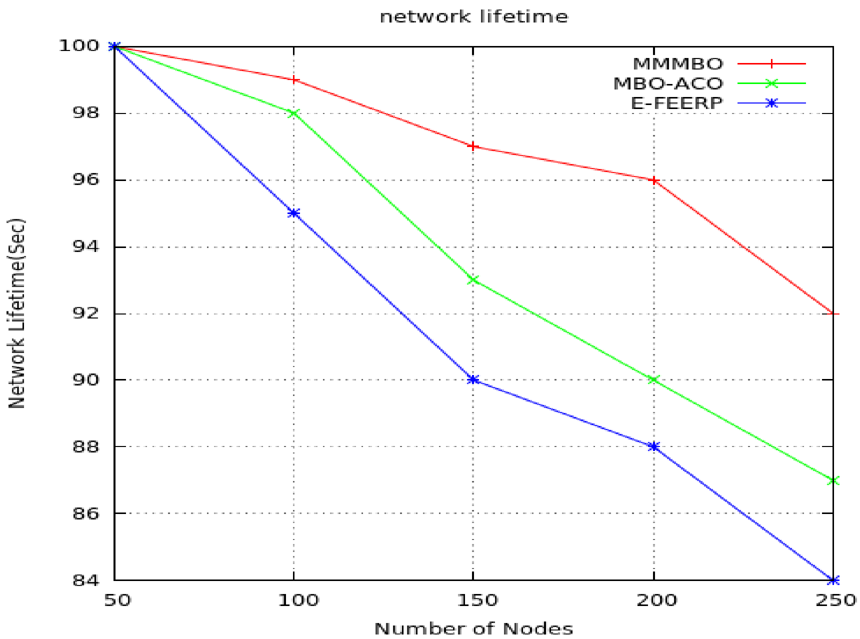

Figure 4. Comparison of Network Lifetime

Examining Network Lifetime (Figure 4), MMMBO demonstrates superior longevity compared to MBO-ACO and E-FEERP. MMMBO's network lifespan remains consistently high even as the number of nodes increases, indicating its robustness and efficiency in sustaining network operations over an extended period.

The importance of energy efficiency in Wireless Sensor Networks (WSNs) cannot be overstated, as it has a direct influence on the longevity of the network. MMMBO demonstrates superior energy optimization by achieving lower Average Energy Consumed values compared to MBO-ACO and E-FEERP. MMMBO has superior energy efficiency compared to MBO-ACO and E-FEERP, consuming only 0.35 units of energy at 100 nodes, while MBO-ACO consumes 0.5 units and E-FEERP consumes 0.64 units. The tendency persists as the node density increases, highlighting MMMBO's expertise in energy-efficient routing.

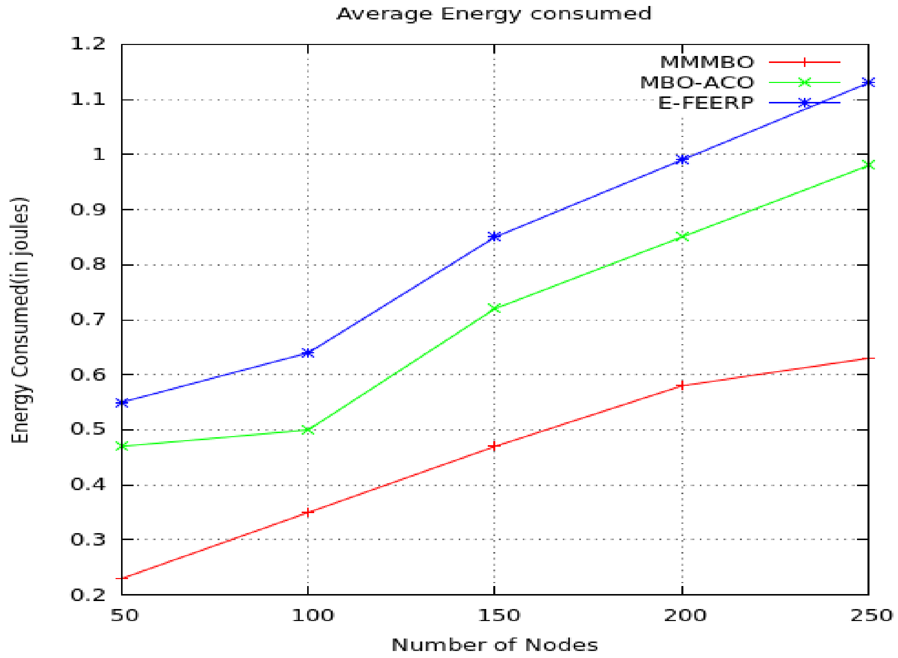

Figure 5. Comparison of Energy Consumption

In Figure 5, the Average Energy Consumed analysis depicts MMMBO as a more energy-efficient option compared to MBO-ACO and E-FEERP. MMMBO consistently consumes less energy across various network sizes, emphasizing its ability to optimize resource consumption while maintaining network performance.
The Average Delay statistic offers insights into the effectiveness of transmitting data packets, with lower values suggesting decreased communication latency. MMMBO consistently achieves superior performance compared to its rivals in all node configurations. MMMBO, with 50 nodes, achieves an Average Delay of 2.012, which is considerably better than the Average Delays of MBO-ACO (4.23) and E-FEERP (6.34). As the number of nodes increases, MMMBO continues to demonstrate its excellent performance in eliminating communication delays, thus maintaining this trend.

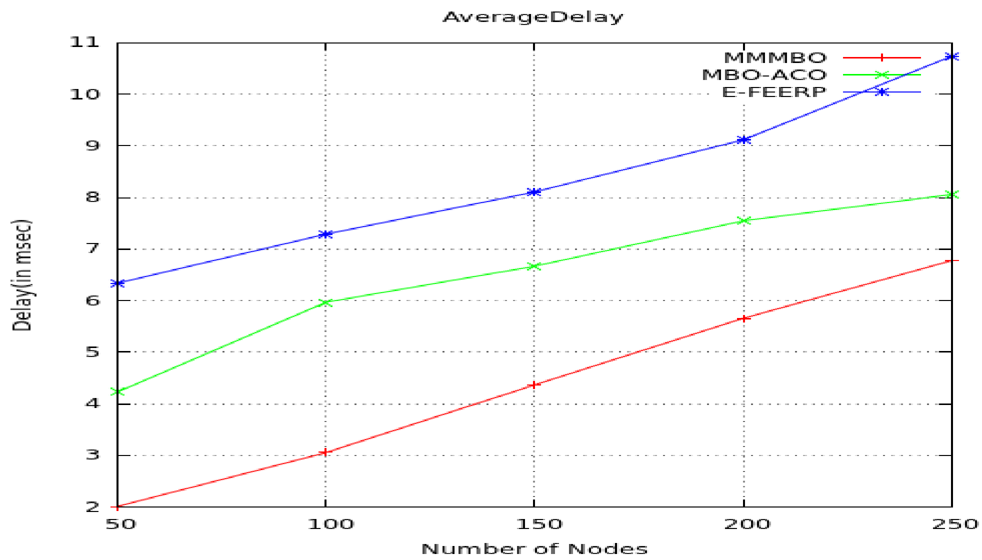

Figure 6. Comparison of Delay

The comparison of Average Delay (Figure 6) among MMMBO, MBO-ACO, and E-FEERP reveals noteworthy insights. MMMBO consistently outperforms MBO-ACO and E-FEERP across different node configurations. As

the number of nodes increases, MMMBO exhibits significantly lower delay times, showcasing its effectiveness in minimizing data transmission time.
Average Throughput measures the network's effectiveness in transmitting data packets. MMMBO regularly exhibits superior Average Throughput values in comparison to MBO-ACO and E-FEERP. MMMBO reaches a throughput of 0.64 at 200 nodes, surpassing the throughput of MBO-ACO (0.52) and E-FEERP (0.5). This highlights MMMBO's capacity to enhance data transmission speeds in dynamic wireless sensor network (WSN) situations.

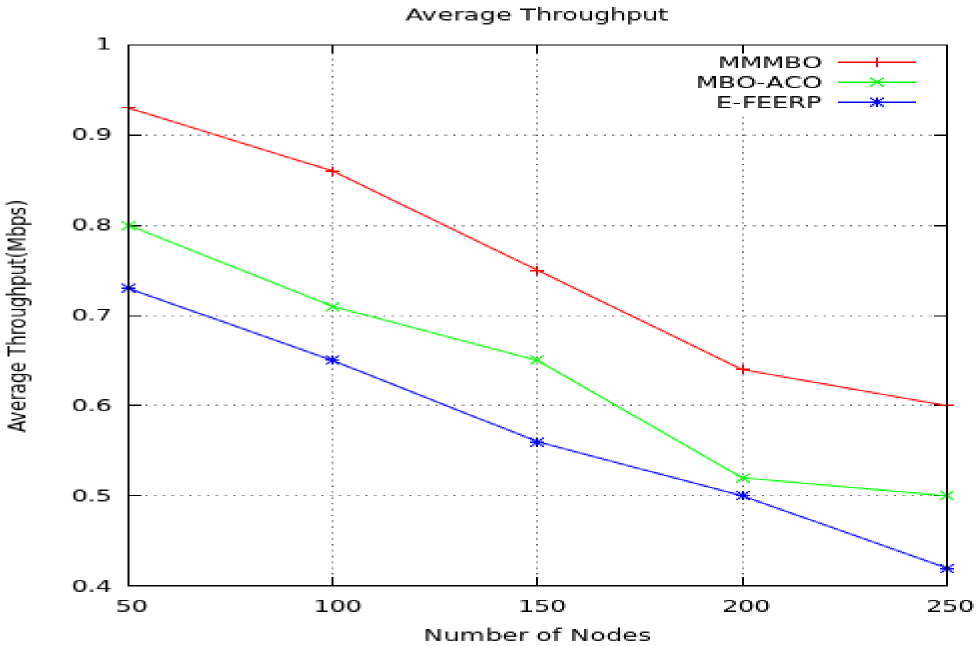

Figure 7. Comparison of Average Throughput

In Figure 7, the analysis of Average Throughput indicates that MMMBO consistently outperforms MBO-ACO and E-FEERP in terms of higher data transfer rates. MMMBO's superior throughput showcases its efficiency in maximizing data transmission capabilities, making it a preferred choice for scenarios demanding efficient and rapid data transfer.
The thorough analysis demonstrates that MMMBO consistently outperforms competitors across a wide range of performance criteria. The proficiency of MMMBO lies in its ability to minimize communication delays, optimize energy consumption, preserve network lifetime, reduce packet loss, manage routing overhead, ensure high packet delivery ratios, and maintain efficient throughput. This makes MMMBO a robust and versatile routing algorithm for Wireless Sensor Networks, regardless of the density of nodes.

Conclusion

The Energy Efficient Mathematically Modified Monarch Butterfly Optimization (EEMMBO) has great potential in addressing the routing issues of Wireless Sensor Networks (WSNs). EEMMBO combines the accuracy of Integer Linear Programming (ILP) with the investigative characteristics of Monarch Butterfly Optimization (MBO) to provide a well-rounded approach for decision-making and adaptation. This study not only focuses on the fundamental significance of effective routing in Wireless Sensor Networks (WSNs) for data collection, but also introduces a hybrid sleep scheduling mechanism within the Energy Efficient Multi-hop Multi-path Broadcast (EEMMBO) framework. The sleep scheduling algorithm utilizes the accuracy of ILP to maximize energy usage, while the exploratory behavior of MBO guarantees adaptation to changing network conditions. EEMMBO demonstrates its effectiveness in strengthening WSN routing efficiency, robustness, and flexibility through the creation of a strong Mathematical Model, increased solution variety, and the inclusion of sleep scheduling. This research enhances the progress of routing approaches in Wireless Sensor Networks (WSNs), by tackling significant obstacles and promoting the creation of stronger and more flexible solutions in the ever-changing environment of sensor network applications.
Potential future improvements for MMMBO in WSNs may prioritize dynamic adaptability to evolving situations, integration of sophisticated security measures, enhancement of scalability for bigger networks, execution of real-world deployment tests, and investigation of hybridization with other optimization techniques. The purpose of these advancements is to improve MMMBO's ability to adjust, protect, expand, and be practically useful in WSN settings.

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