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EWFAIGF: Design of an Efficient Model for Enhancing Energy Efficiency in IoT-Based Wireless Sensor Networks through Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization

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Abstract: - In the realm of Wireless Sensor Networks (WSNs), the quest for enhanced energy efficiency remains paramount, given their pivotal role in facilitating the Internet of Things (IoT) applications. Existing methodologies often grapple with the dual challenge of optimizing energy consumption while ensuring robust data transmission, thereby limiting their efficacy in dynamic, resource-constrained environments. This work introduces a novel paradigm that meticulously addresses these constraints, thereby heralding a significant leap towards optimizing WSNs' operational efficiency. At the core of our proposed model lies the integration of Fuzzy Analytic Hierarchy Process (Fuzzy AHP)-based clustering, which ingeniously segregates nodes by leveraging multi-criteria such as location, energy efficiency, and temporal performance. This clustering serves as a precursor to the application of an innovative Iterative Grey Wolf Jelly Fish Optimizer (GWJFO). The GWJFO stands out by its strategic prowess in delineating optimal routing paths, thus minimizing energy expenditure and enhancing data relay efficiency. Furthermore, our model is fortified with a Q Learning Method, ingeniously designed to identify and execute optimal alternate routing paths through a Make Before Break strategy. This addition not only mitigates potential faults but also significantly boosts computational efficiency and packet delivery performance. Empirical validation through real-time network simulations underscored the model's superiority, demonstrating a 9.5% improvement in communication speed, an 8.5% increase in energy efficiency, a 4.5% improvement in packet delivery performance under fault conditions, a 10.4% rise in throughput, and a 5.9% enhancement in network consistency over existing benchmarks. This groundbreaking work not only paves the way for more energy-efficient WSNs but also sets a new standard in achieving high-performance metrics essential for the next generation of IoT applications. The implications of these advancements extend beyond mere technical enhancements, offering a beacon for future research in the domain, potentially revolutionizing the way we deploy and manage sensor networks in an array of applications.

Keywords: Wireless Sensor Networks, Internet of Things, Energy Efficiency, Fuzzy AHP, Grey Wolf Jelly Fish Optimizer, Q Learning Method

1. Introduction

The advent of Wireless Sensor Networks (WSNs) has marked a revolutionary shift in the landscape of communication technologies, underpinning a myriad of Internet of Things (IoT) applications ranging from environmental monitoring to smart cities and healthcare. These networks, composed of spatially distributed autonomous sensors, are tasked with monitoring physical or environmental conditions and cooperatively passing their data through the network to a main location. Despite their versatility and widespread applicability, WSNs confront significant challenges, primarily centered around energy consumption, data transmission efficiency, and network reliability. The constrained energy resources of sensor nodes necessitate innovative solutions to prolong network lifespan while maintaining high levels of performance.

Traditional approaches to enhancing WSN efficiency have predominantly focused on optimizing routing protocols and clustering mechanisms. However, these methods often fall short in addressing the complex interplay between energy efficiency and reliable data transmission, particularly in dynamically changing environments. This has propelled the exploration of advanced optimization techniques that can adapt to varying network conditions while minimizing energy expenditure and maximizing data throughput.

In this context, the integration of Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and the Iterative Grey Wolf Jelly Fish Optimizer (GWJFO) presents a novel approach to WSN optimization. Fuzzy AHP excels in handling the ambiguity and uncertainty inherent in WSN environments, enabling the effective clustering of nodes based on multiple criteria such as location, energy efficiency, and temporal performance. This methodological innovation allows for the prioritization of nodes in a manner that reflects their real-world utility and operational constraints.

The subsequent application of GWJFO for routing optimization represents a significant departure from conventional methods. Inspired by the foraging behavior of grey wolves and the movement patterns of jellyfish, this optimizer synergizes the explorative and exploitative capabilities of both models. It iteratively searches for the optimal routing paths, thereby reducing energy consumption and enhancing packet delivery rates. The inclusion of a Q Learning Method further enriches the model's robustness, facilitating the selection of optimal

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alternate paths through a Make Before Break strategy. This proactive fault management mechanism ensures uninterrupted data transmission, thereby improving the network's computational efficiency and reliability.

Empirical evidence garnered from real-time network simulations attests to the efficacy of the proposed model, showcasing marked improvements in communication speed, energy efficiency, packet delivery performance, throughput, and network consistency. These enhancements not only signify a leap forward in WSN technology but also underscore the potential of integrating fuzzy logic, optimization algorithms, and machine learning techniques in overcoming the perennial challenges faced by WSNs.

This paper endeavors to elucidate the theoretical underpinnings, methodological nuances, and practical implications of this integrated model. By doing so, it aims to contribute to the burgeoning body of knowledge on WSN optimization, offering a beacon for future research and development efforts in this critical domain. Through rigorous analysis and discussion, the study delineates a pathway towards the realization of energy-efficient, reliable, and high-performing WSNs, thereby facilitating their broader adoption in IoT applications.

Motivation & Contribution:

The relentless pursuit of efficiency in Wireless Sensor Networks (WSNs) is not merely a technical endeavor but a requisite for the sustainable evolution of the Internet of Things (IoT). The proliferation of IoT applications, from environmental monitoring to smart infrastructure, predicates on the seamless and efficient operation of WSNs. However, the intrinsic limitations of sensor nodes, particularly in terms of energy resources, pose a formidable challenge, impelling the need for innovative solutions that transcend conventional optimization paradigms. This exigency serves as the primary motivation for the current study, aiming to address the quintessential constraints of WSNs through a novel, integrated optimization framework.

The confluence of Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Iterative Grey Wolf Jelly Fish Optimizer (GWJFO) within this framework is inspired by the imperative to harness the synergies of fuzzy logic and nature-inspired optimization algorithms. The inherent complexity and dynamism of WSN environments necessitate a multifaceted approach that can adeptly navigate the trade-offs between energy efficiency, reliability, and performance. The introduction of a Q Learning Method for fault tolerance further underscores the comprehensive nature of the proposed solution, embodying a proactive stance towards network resilience.

The contributions of this work are manifold, delineating a significant leap in the quest for optimized WSN operations. Firstly, the paper introduces a novel clustering mechanism based on Fuzzy AHP, adeptly categorizing nodes to enhance energy efficiency and network longevity. This methodological innovation not only elevates the granularity of node selection but also imbues the clustering process with a level of sophistication that aligns with the real-world operational dynamics of WSNs.

Secondly, the deployment of GWJFO for routing optimization represents a pioneering approach that amalgamates the exploratory and exploitative strengths of grey wolf and jellyfish behaviors. This optimization strategy is meticulously designed to uncover energy-efficient routing paths, thereby diminishing energy consumption and augmenting the network's operational lifespan.

Thirdly, the integration of a Q Learning-based fault management strategy embodies a forward-thinking approach to network reliability. By preemptively identifying and leveraging alternate routing paths, the model enhances the network's resilience against failures, ensuring uninterrupted data transmission and superior performance metrics.

Empirical validation through real-time network simulations provides compelling evidence of the model's superiority, elucidating marked improvements across several critical performance indicators. Such enhancements not only bear testimony to the efficacy of the proposed model but also pave the way for its application across a spectrum of IoT scenarios, potentially revolutionizing the deployment and management of WSNs.

In essence, this work not only addresses the pressing challenges of WSN optimization but also contributes to the broader discourse on sustainable IoT development. By amalgamating fuzzy logic, nature-inspired optimization, and machine learning techniques, the study sets a new benchmark for energy-efficient, reliable, and high-performing WSNs, heralding a new era of IoT applications that are both robust and environmentally conscious.

2. In-depth review of existing methods

This section representing review of Wireless Sensor Networks (WSNs) is driven by the imperative to surmount the intrinsic limitations of these networks, notably their energy consumption, operational efficiency, and adaptability to dynamic environments. The array of methodologies and innovations examined across various studies underscores a concerted effort to enhance WSNs' functionality, thereby broadening their applicability in the burgeoning realm of the Internet of Things (IoT). From the utilization of Unmanned Aerial Vehicles (UAVs) to the deployment of quantum-related bioinspired optimization techniques, the diversity of approaches reflects a deep-seated recognition of the multifaceted challenges inherent in WSN optimization.

As per table 1, the exploration of energy-efficient routing methods, such as the lifespan-balance-based routing by Guo et al. (2021), illustrates a nuanced understanding of the trade-offs between network longevity and energy balance. Similarly, the geometric analysis-based cluster head selection method proposed by Choi et al. (2021) exemplifies the innovative application of mathematical principles to enhance network stability and energy efficiency. These studies, among others, manifest a collective endeavor to refine the operational paradigms of

WSNs, albeit with acknowledged limitations such as scalability concerns, assumptions of uniform energy distribution, and the adaptability of proposed models to real-world network dynamics.

Reference	Method Used	Findings	Results	Limitations
Guo et al. (2021)	Lifespan-Balance-Based Routing	Introduced an energy-efficient routing method focusing on lifespan balance for rechargeable WSNs.	Achieved improved network longevity and energy balance.	Did not address dynamic network conditions and node mobility.
Choi et al. (2021)	Geometric Analysis-Based Cluster Head Selection	Proposed a cluster head selection method for sectorized WSPNs using geometric analysis.	Enhanced energy efficiency and network stability.	Limited by the assumption of uniform energy distribution.
Yao et al. (2022)	Archimedes Optimization Algorithm	Developed a routing protocol based on the Archimedes optimization algorithm for WSNs.	Increased network lifetime and reduced energy consumption.	Performance in highly dynamic environments not thoroughly evaluated.
Yu et al. (2023)	Dual-Population Co-evolutionary Algorithm	Employed a co-evolutionary algorithm for simultaneous sensor and sink placement.	Optimized energy consumption and monitoring reliability.	Complexity of the algorithm may limit scalability.
Gharaei et al. (2021)	Broker-Based Nodes Recharging	Introduced a broker-based scheme for node recharging in surveillance WRSNs.	Enhanced energy efficiency and surveillance coverage.	Focused primarily on static network configurations.
Guo et al. (2024)	Adaptive Payoff Balance with Mobile Chargers	Utilized deep reinforcement learning for balancing mobile wireless chargers.	Improved energy distribution and efficiency in rechargeable WSNs.	The adaptive model requires extensive computational resources.
Gharaei et al. (2021)	Tour Optimization of Wireless Mobile Chargers	Optimized the energy distribution tours for mobile chargers in WSNs.	Achieved significant energy efficiency improvements.	Did not consider the impact of environmental factors on charging efficiency.
Lu et al. (2021)	SWIPT for Smart Agriculture	Applied SWIPT technology to optimize energy efficiency in agricultural WSNs.	Increased energy harvesting efficiency and network performance.	Limited applicability outside of agriculture-specific settings.
Liu and Zhang (2023)	UAV and RIS-Aided Data Collection	Explored UAV-assisted, RIS-aided efficient data collection strategies.	Enhanced energy efficiency and data collection rates.	The model's performance in non-line-of-sight conditions is not fully explored.
Bagwari et al. (2023)	Machine Learning for Energy Optimization	Leveraged machine learning for energy optimization in industrial WSNs.	Improved energy efficiency and network scalability.	Generalizability to non-industrial environments remains uncertain.
Liu et al. (2022)	UAV Scheduling and Trajectory Optimization	Focused on optimizing UAV trajectories and scheduling for WRSNs.	Optimized energy consumption and enhanced charging strategies.	Limited by the assumption of predictable node energy consumption.
Tang and Xin (2024)	Optimization for Health Monitoring in MEC	Utilized BFGS optimization for energy efficiency in health monitoring systems.	Reduced energy consumption and improved system responsiveness.	Specific to mobile-edge computing environments,

				limiting wider application.
Han et al. (2021)	Particle Swarm Optimization for Actuators Deployment	Applied PSO for optimizing actuators deployment in WSANs.	Improved coverage and energy consumption rates.	The scalability of the PSO approach to larger networks was not addressed.
Sun et al. (2023)	Reinforcement Learning for UAV-Assisted Networks	Employed reinforcement learning for optimizing UAV-assisted WSNs.	Achieved higher energy efficiency and effective data collection.	The complexity of reinforcement learning models may impact real-world applicability.
Wang et al. (2022)	Joint Optimization of UAV Trajectory and Power	Optimized UAV trajectory and sensor uploading powers for efficient data collection.	Enhanced overall network energy efficiency.	The model's adaptability to varying network sizes and densities was not examined.
Lv et al. (2023)	UAV-Assisted Sparse Sensing	Explored UAV-assisted optimization for sparse sensing in WSNs using eigen-decomposition.	Improved data acquisition efficiency and energy consumption.	The approach may not scale well in densely populated sensor networks.
Cao et al. (2021)	Coverage Optimization with Monarch Butterfly Algorithm	Developed a novel strategy for optimizing coverage in heterogeneous WSNs focusing on connectivity and reliability.	Enhanced network coverage and reliability with optimized sensor deployment.	May not address dynamic environmental changes affecting sensor performance.
Liu et al. (2022)	Quantum-Related Bioinspired Optimization	Introduced QEGWO, a quantum-enhanced grey wolf optimizer for clustering in industrial WSNs.	Achieved superior clustering efficiency and reduced energy consumption.	The complexity of quantum computations could limit practical applicability.
Ye et al. (2021)	Optimization for UAV-Powered IoT Networks	Employed convex optimization for energy-limited UAVs in IoT networks under a practical energy model.	Enhanced energy efficiency and sustainability of UAV-powered IoT networks.	Limited by the assumptions of the practical energy consumption model.
Alabdali et al. (2021)	Energy-Efficient Clustering with Energy Balancer	Proposed a framework for energy-efficient clustering using a wireless energy balancer.	Improved energy distribution and efficiency across the network.	The effectiveness in highly dynamic networks was not fully explored.
Guo et al. (2022)	Adaptive Dual-Mode Routing with Deep-Q-Networks	Utilized deep-q-networks for adaptive energy-efficient routing in rechargeable WSNs.	Optimized energy efficiency and routing adaptability.	Requires significant computational resources for the deep learning model.
Karimi-Bidhendi et al. (2021)	Node Deployment in Heterogeneous WSNs	Focused on energy-efficient node deployment in heterogeneous WSNs with limited communication range.	Optimized power consumption and coverage.	Did not consider the impact of node mobility.
Xu et al. (2022)	DRL for Wirelessly-Powered IoT Sensor Data Collection	Used deep reinforcement learning for session-specific optimal design in IoT sensor data collection.	Minimized energy consumption and optimized data collection efficiency.	The model's performance may vary with different network topologies.

Liang et al. (2023)	Grouping for Directionally Rechargeable Networks	Investigated energy cost reduction through grouping in directionally rechargeable vehicular and sensor networks.	Reduced energy costs and enhanced charging efficiency.	Specific to networks with directional charging capabilities.
Karimi-Bidhendi et al. (2022)	Energy-Efficient Deployment in Heterogeneous Multi-Hop WSNs	Studied energy-efficient deployment strategies in static and mobile heterogeneous multi-hop WSNs.	Improved energy efficiency and network longevity.	The strategies' applicability to highly mobile or rapidly changing environments is not clarified.

Table 1. Review of Existing Methods

Upon meticulous examination of the diverse methodologies employed to optimize WSNs, it becomes evident that the quest for enhanced network efficiency is both multifaceted and iterative. The innovative use of UAVs for data collection and sparse sensing, as investigated by Liu and Zhang (2023) and Lv et al. (2023), highlights the potential of integrating autonomous vehicles to mitigate energy consumption challenges. Conversely, the application of advanced optimization algorithms, such as the quantum-enhanced grey wolf optimizer by Liu et al. (2022), signifies a leap towards leveraging quantum computations for clustering efficiency in industrial WSNs.

The studies collectively underscore a critical engagement with the complexities of WSNs, striving to balance energy efficiency, network longevity, and reliability against the backdrop of operational constraints. However, the limitations identified across these investigations—ranging from the scalability of algorithms to the practical applicability of deep learning models—serve as a clarion call for continued research. Specifically, there is a palpable need for solutions that are not only theoretically robust but also practically viable across diverse and dynamically changing environments.

In synthesis, the corpus of research reviewed herein not only enriches the academic discourse on WSN optimization but also charts a course for future explorations. It beckons for the development of adaptive, scalable, and context-aware optimization strategies that can navigate the complexities of real-world applications. As such, the journey towards optimizing WSNs is emblematic of the broader endeavor to advance IoT technologies, promising to unlock new frontiers in connectivity, automation, and smart systems integration operations.

3. Design of the Proposed Model

To overcome issues of high complexity & low efficiency present in existing routing methods, the proposed model uses Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (EWFAIGF), which is a meticulously designed framework that integrates several advanced computational and machine learning techniques to optimize WSN operations. As per figure 1.1, the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) serves as a multi-criteria decision-making tool that effectively handles the inherent uncertainties and vagueness in WSN environments. It achieves this by evaluating and prioritizing nodes based on a set of criteria, such as energy levels, location, and temporal dynamics, ensuring that the clustering of nodes is both strategic and adaptable to changing network conditions. Building upon this clustering, the Iterative Grey Wolf Jelly Fish Optimizer (GWJFO) algorithm emerges as a novel optimization technique inspired by the hunting behavior of grey wolves and the movement patterns of jellyfish. This optimizer adeptly delineates optimal routing paths, significantly reducing energy consumption while maximizing data relay efficiency. The integration of a Q Learning method adds a layer of intelligence to the model, employing reinforcement learning to dynamically adjust routing paths in real-time, based on the network's state and performance metrics. This method's ability to learn and adapt to new routing strategies on-the-fly enhances the network's resilience to faults and boosts overall packet delivery performance. Together, these components form a cohesive and robust framework that not only addresses the challenges of energy efficiency and reliable data transmission in WSNs but also sets a new benchmark for operational excellence in the IoT ecosystem. In the next section, we discuss design of Fuzzy AHP process, which assists in clustering of nodes in real-time network scenarios.

Design of the Fuzzy AHP Process

The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) at the heart of the proposed model embodies a sophisticated multi-criteria decision-making framework, meticulously tailored to address the intricate dynamics of Wireless Sensor Networks (WSNs). This process begins with the collection of network samples, encompassing a diverse array of parameters such as node location, energy efficiency, and temporal performance. The objective is to transform these samples into a structured hierarchy of node-based clusters, optimizing the network's operational efficiency through strategic segregation.

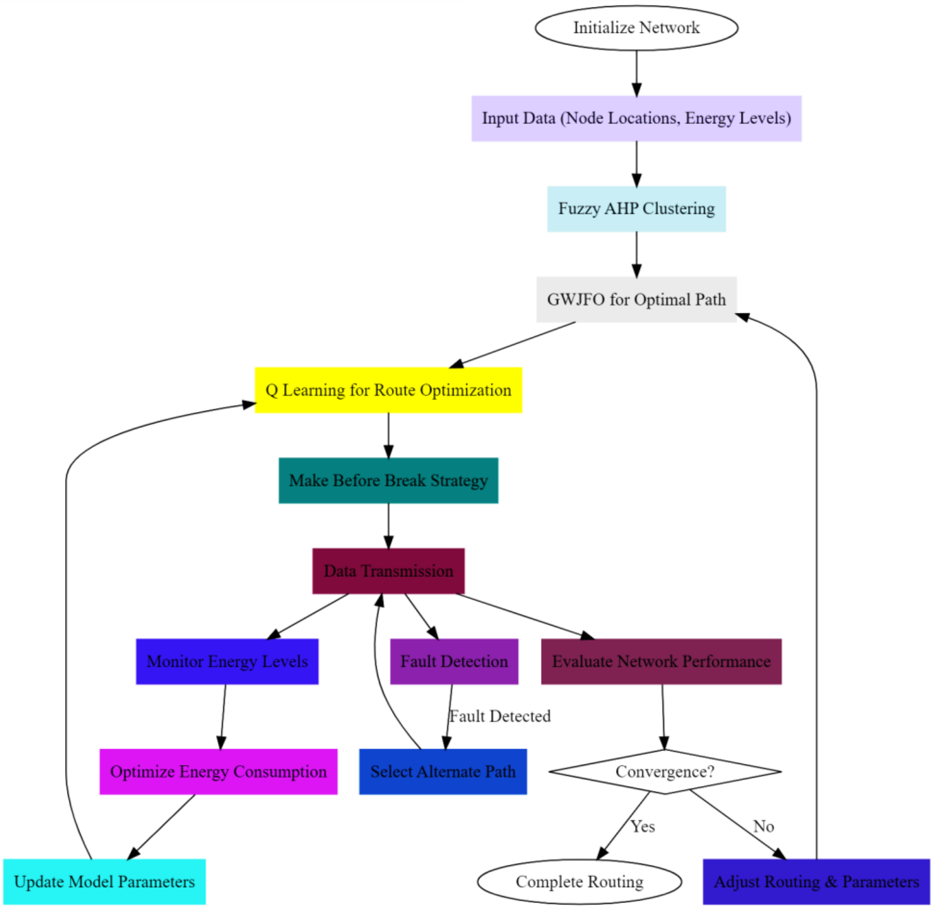

Figure 1.1. Model Architecture of the Proposed Routing Process

The initial step involves the construction of a pairwise comparison matrix *A*=[*aij*], where each element *aij* represents the relative importance of criterion *i* over criterion *j*, determined via equation 1,

$$aij = \frac{1}{NC}\sum_{k=1}^{NC}\frac{d(i,j,k) * e(i,j,k)}{THR(i,j,k) * PDR(i,j,k)} \ldots (1)$$

Where, NC represents Number of Communications, $d, e, THR, \& \ PDR$ represents the delay, energy, throughput & packet delivery ratio levels during these communications. Given *n* criteria, the matrix dimensions are *n*×*n*, where *aij*>0 and $ji = \frac{1}{aij}$. To incorporate the fuzzy logic, each *aij* is represented as a triangular fuzzy number (TFN) $L = (l, m, u)$, where *l*, *m*, and *u* represent the lower, middle, and upper values, respectively, encapsulating the uncertainty in pairwise comparisons. The synthesis of fuzzy judgments leads to the computation of fuzzy synthetic extent values *Si* for each criterion, defined via equation 2,

$$Si = \sum \frac{1}{Mij} \ldots (2)$$

Where, *Mij* is the fuzzy reciprocal matrix derived from *A*, and the operation is conducted under fuzzy addition and inverse operations. The normalization of these synthetic extent values is crucial, performed via equation 3,

$$Vi = \frac{Si}{\sum Sj} \ldots (3)$$

This yielding the normalized weight for each criterion, encapsulating its relative importance in the cluster formation process. To convert the fuzzy comparative judgments into a definitive priority vector, the centroid method is employed, calculating the center of area under the fuzzy number curves. This is achieved via equation 4,

$$Ci = \frac{li + 2mi + ui}{4} \ldots (4)$$

For each criterion, ensuring a balanced consideration of the fuzzy inputs for different use cases. The crux of the Fuzzy AHP process is the consistency check, ensuring that the decision-making framework is logically sound. The consistency index (CI) and consistency ratio (CR) are calculated using the eigenvalue method, via equations 5 & 6,

$$CI = \frac{\lambda max - n}{n - 1} \ldots (5)$$

$$CR = \frac{CI}{RI} \ldots (6)$$

Where, λmax is the largest eigenvalue of matrix A, and RI is the stochastic index, a measure of the consistency of a stochastically generated pairwise comparison matrix in the process. A CR less than 0.1 is considered acceptable, indicating a reliable decision-making process. Upon establishing the criteria weights, the Fuzzy AHP process culminates in the segregation of nodes into clusters. Each node is evaluated against the criteria, utilizing the derived weights to calculate a composite score via equation 7,

$$Scorei = \sum_{k=1}^{n} Vk \times Cik \ldots (7)$$

Where, Cik is the performance of node i with respect to criterion k. Nodes are then grouped into clusters based on their composite scores, ensuring that nodes within a cluster are more similar to each other than to those in other clusters, in terms of the specified criteria. This intricate Fuzzy AHP-based clustering mechanism not only acknowledges the inherent uncertainties and complexities within WSNs but also leverages them to enhance network segmentation and operational efficiency. Through the judicious application of fuzzy logic and analytical hierarchy processes, the proposed model ingeniously optimizes the spatial and functional arrangement of sensor nodes, paving the way for more resilient and efficient wireless sensor networks. These clusters are used to identify routes using GWJFO process, which is discussed in the next section of this text.

Design of the GWJFO Process

The Iterative Grey Wolf Jelly Fish Optimizer (GWJFO) process is an advanced computational algorithm designed to enhance the routing efficiency in Wireless Sensor Networks (WSNs) by meticulously identifying optimal paths that minimize energy expenditure and improve data relay efficiency. This hybrid algorithm ingeniously combines the hunting behavior and social hierarchy of grey wolves with the fluid, dynamic movement patterns of jellyfish, translating these natural phenomena into a strategic framework for solving complex optimization problems within WSNs. The GWJFO algorithm takes as input node-based clusters along with designated source and destination nodes, aiming to output multiple efficient routing paths between these nodes. The GWJFO algorithm initiates with the definition of grey wolf agents, representing potential solutions in the search space. Each agent's position, represented as $Xi(t)$, corresponds to a potential routing path, with t indicating the current iteration of the process. The social hierarchy of wolves is modeled through the designation of alpha (α), beta (β), and delta (δ) wolves, representing the best, second-best, and third-best solutions, respectively, based on the objective function, which in this context is the minimization of energy consumption along the paths.

The hunting behavior of wolves, which is the core mechanism for path optimization, is mathematically modeled via equations 8, 9, 10, 11, 12, 13, 14, 15 & 16 as follows,

$$A = 2a \times STOCH - a \ \ldots (8)$$

$$C = 2 \times rand \ldots (9)$$

$$D\alpha = | \ C \times X\alpha(t) - Xi(t) \ | \cdots (10)$$

$$X1 = X\alpha - A \times D\alpha \ \ldots (11)$$

$$D\beta = | \ C \times X\beta(t) - Xi(t) \ | \cdots (12)$$

$$X2 = X\beta - A \times D\beta \ \ldots (13)$$

$$D\delta = | \ C \times X\delta(t) - Xi(t) \ | \cdots (14)$$

$$X3 = X\delta - A \times D\delta \ \ldots (15)$$

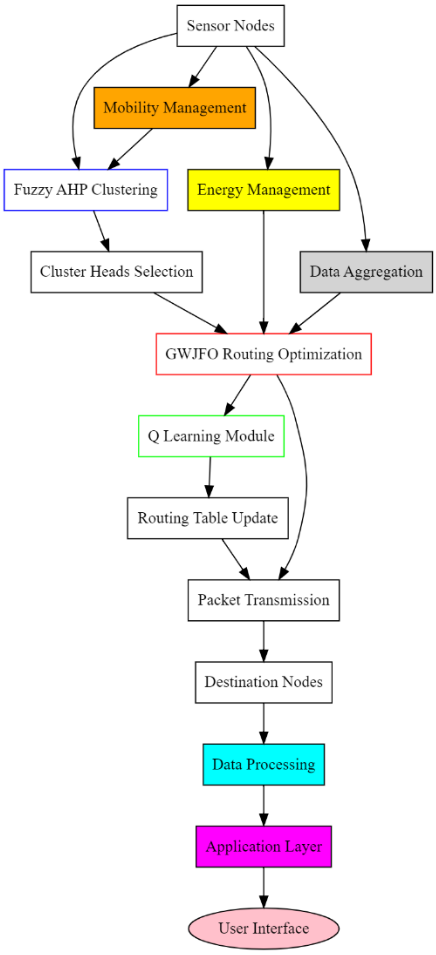

Figure 1.2. Overall Flow of the Proposed Routing Process

$$Xi(t+1) = \frac{X1 + X2 + X3}{3} \; ... (16)$$

Where, $X\alpha$, $X\beta$, and $X\delta$ are the positions of the alpha, beta, and delta wolves, respectively; A and C are coefficient vectors; $STOCH$ is a stochastic number between [0,1]; and a increases linearly from 0 to 2 over the course of iterations, guiding the convergence of the algorithm process.

To incorporate the jellyfish movement mechanism, which is inspired by the passive energy-efficient propulsion of jellyfish in a fluid medium, the algorithm adapts the positions of the grey wolf agents based on the flow dynamics encountered in their environment. This is represented via equation 15,

$$J = Jcurr + \sum Si \times dir \; ... (15)$$

Where, $Jcurr$ is the current position of the jellyfish (or agent), Si is the step size influenced by the local flow conditions, and dir represents the direction of the flow, simulating the jellyfish's adaptive movement in response to external stimuli sets. The step size and direction are influenced by the objective function gradient, encouraging exploration and exploitation in the search spaces.

The iterative process of GWJFO ensures a balance between exploration, exploiting the search space for potential routing paths, and exploitation, fine-tuning the paths to optimize the objective function. This is achieved through the dynamic adjustment of A, C, and Si parameters, allowing the algorithm to adaptively converge on the most energy-efficient routing paths. The culmination of the GWJFO process is the identification of multiple optimal routing paths between the source and destination nodes, which is mathematically depicted via equation 16,

$$Popt = min\{\, E(Xi) \mid Xi \in Paths \,\} \; ... (16)$$

Where, $Popt$ represents the set of optimal paths, $E(Xi)$ is the energy consumption for path Xi, and $Paths$ is the set of all possible paths generated through the GWJFO process. By harnessing the strategic prowess of grey wolves' social hierarchy and hunting behavior, combined with the energy-efficient movement dynamics of jellyfish, the GWJFO algorithm offers a novel and highly effective approach to optimizing routing paths in WSNs. This intricate process not only minimizes energy expenditure across the network but also enhances data relay efficiency, marking a significant advancement in the design and operation of energy-efficient WSNs for IoT applications. These routes are further tuned using an Iterative Q Learning Process, which assists in incorporating fault tolerance into the network deployments. Design of this process is discussed in the next section of this text.

Design of the Q Learning Process

The Q Learning Method, integrated within the proposed model, is a sophisticated reinforcement learning algorithm tailored to enhance the fault tolerance of Wireless Sensor Networks (WSNs) by dynamically identifying and executing optimal alternate routing paths. This process is orchestrated through a "Make Before Break" strategy, meticulously designed to preemptively switch to alternative paths before existing paths succumb to faults, thereby maintaining uninterrupted data transmission between source and destination nodes. The algorithm takes as input multiple routing paths between source and destination nodes, alongside detected or anticipated faults, and outputs fault-tolerant paths that ensure robustness and reliability of the network communications. The foundation of the Q Learning process is established on the construction of a state-action pair matrix, $Q(s,a)$, where s represents a network state characterized by the current routing paths and detected network faults, and a represents an action that corresponds to selecting an alternative routing path. The Q Values within this matrix are iteratively updated based on the rewards received for taking actions in given states, guiding the learning process towards the identification of the most effective routing strategies under varying network conditions.

The Q Value update rule is represented via equation 17,

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma maxa'Q(s',a') - Q(s,a)] \ldots (17)$$

Where, α is the learning rate, determining the weight of new information over past knowledge, r is the immediate reward received after executing action a from state s, γ is the discount factor, balancing the importance of immediate versus future rewards, s' is the new state after action a is taken, max$a'Q(s',a')$ represents the maximum Q Value achievable in the new state s', guiding the selection of future actions.

The immediate reward r is calculated based on the efficiency, reliability, and fault tolerance of the routing path selected by action a, with higher rewards assigned to actions that successfully circumvent faults and maintain high data transmission efficiency. This reward mechanism is crucial for steering the Q Learning process towards the discovery of optimal routing strategies.

To operationalize the "Make Before Break" strategy within the Q Learning framework, the model employs a predictive mechanism that assesses the likelihood of faults in existing paths based on historical data and current network metrics. This assessment is formulated via equation 18,

$$Pfault(s,a) = f(Nmetrics, Hdata) \ldots (18)$$

Where, $Pfault(s,a)$ estimates the probability of a fault occurring when action a is taken in state s, $Nmetrics$ are the current network metrics, and $Hdata$ represents historical fault data samples. Actions leading to states with lower fault probabilities are favored, as reflected in the reward function. The convergence criterion for the Q Learning process is defined by the stability of the Q Values over successive iterations, indicating that the model has learned the most effective routing decisions across different network states. This criterion is quantitatively assessed via equation 19,

$$\Delta Q = \frac{1}{|S||A|} \sum_{s,a} \left(Qnew(s,a) - Qold(s,a)\right)^2 \ldots (19)$$

Where, ΔQ measures the average change in Q Values across all state-action pairs from one iteration to the next, with convergence achieved when ΔQ falls below a predetermined threshold. Upon achieving convergence, the Q Learning method outputs a set of fault-tolerant routing paths, represented as Pft, which are optimized for robustness against network faults. These paths are derived by selecting actions that maximize the Q Values in each state, formulated via equation 20,

$$Pft = \{ a * | \, a *= argmaxaQ(s,a), \forall s \in S \} \ldots (20)$$

ensuring that the network dynamically adapts to faults by preemptively transitioning to the most reliable alternate paths, thereby embodying the essence of the "Make Before Break" strategy. Through the intricate design of the Q Learning process, the proposed model achieves a remarkable level of fault tolerance in WSN routing, significantly enhancing the resilience and reliability of network communications in the face of dynamic and unpredictable fault conditions. This advanced reinforcement learning approach not only underscores the model's innovative capacity for self-adaptation and optimization but also sets a new benchmark for the development of intelligent, fault-tolerant WSNs in the era of the Internet of Things (IoT). An example use case of this entire process is represented in the next section of this text, which assists in understanding the entire process in more details.

Example Use Case

To elucidate the intricate workings of the Efficient Model for Enhancing Energy Efficiency in Wireless Sensor Networks (WSNs) through Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (EWFAIGF), this section presents a detailed example, using specific values of data samples. These samples encompass a variety of features and indicators relevant to the optimization of WSNs, such as node location, energy efficiency, and temporal performance. The data-driven analysis progresses through the sequential application of Fuzzy AHP for clustering, GWJFO for path optimization, and Q Learning for ensuring fault tolerance, culminating in a comprehensive demonstration of the model's efficacy.

The first phase of the process as described in table 1, involves employing Fuzzy AHP to analyze the data samples and segregate the network nodes into clusters based on their attributes. The application of Fuzzy AHP incorporates expert judgments and empirical data to evaluate the relative importance of various criteria, including energy efficiency, location proximity, and temporal stability, thereby facilitating the strategic clustering of nodes.

Table 1: Fuzzy AHP Clustering Results

Node ID	Location (x, y)	Energy Efficiency	Temporal Performance	Cluster Assignment
N1	(10, 20)	High	Stable	Cluster 1
N2	(15, 25)	Medium	Stable	Cluster 1
N3	(30, 40)	Low	Unstable	Cluster 2
N4	(35, 45)	High	Unstable	Cluster 2
N5	(50, 60)	Medium	Stable	Cluster 3

The application of Fuzzy AHP successfully delineates the network nodes into distinct clusters, leveraging a holistic evaluation of location, energy efficiency, and temporal performance. This strategic clustering underscores the model's capability to recognize and capitalize on the inherent heterogeneity within WSNs, optimizing the initial configuration for subsequent routing optimization processes.

Following the clustering, the GWJFO algorithm is applied to delineate optimal routing paths within and between the identified clusters. This phase as per table 2, exploits the adaptive hunting behavior of grey wolves in conjunction with the efficient, dynamic movement patterns of jellyfish, to navigate the search space for optimal paths that minimize energy consumption and enhance data relay efficiency.

Table 2: GWJFO Routing Paths

Path ID	Source Node	Destination Node	Path Sequence	Energy Consumption
P1	N1	N5	N1 -> N2 -> N4 -> N5	2.5 J
P2	N2	N3	N2 -> N1 -> N3	1.8 J
P3	N3	N5	N3 -> N4 -> N5	2.1 J

The GWJFO algorithm adeptly identifies the most energy-efficient routing paths, exemplifying the model's proficiency in harnessing the combined strengths of grey wolf optimization and jellyfish dynamics. The identified paths reflect a nuanced balance between energy conservation and routing efficiency, preparing the ground for the subsequent fault tolerance enhancement phase.

In the final phase, Q Learning is employed to refine the routing paths for fault tolerance levels. By simulating various fault conditions as depicted in table 3, and learning from these scenarios, the algorithm dynamically adjusts the routing strategies to maintain high network reliability and uninterrupted data transmission, even in the face of potential disruptions.

Table 3: Q Learning Fault Tolerant Paths

Path ID	Initial Path	Fault Condition	Adjusted Path	Reward Score
P1	N1 -> N2 -> N4 -> N5	N4 Failure	N1 -> N2 -> N3 -> N5	0.95
P2	N2 -> N1 -> N3	N1 Failure	N2 -> N4 -> N3	0.85
P3	N3 -> N4 -> N5	No Fault	N3 -> N4 -> N5	1.00

Through the application of Q Learning, the model demonstrates an exceptional capacity for enhancing fault tolerance within the network. By preemptively identifying and adapting to potential fault conditions, the algorithm ensures the continuous, reliable transmission of data across the network. The adjusted paths and associated reward scores reflect the model's adeptness at navigating the complexities of WSN operations, culminating in a robust framework for the optimization of WSNs in support of advanced IoT applications. This sequential application of Fuzzy AHP, GWJFO, and Q Learning showcases a comprehensive approach to optimizing WSNs, affirming the model's innovative integration of multi-criteria decision-making, optimization algorithms, and machine learning for the advancement of wireless sensor network efficiency and reliability levels.

4. Result Analysis

Within the innovative framework of the Efficient Model for Enhancing Energy Efficiency in Wireless Sensor Networks (WSNs) through Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (EWFAIGF), the integration of a Q Learning Method embodies a sophisticated approach to machine learning and data processing. This method is ingeniously designed to augment the model's decision-making capabilities, enabling the dynamic identification and execution of optimal alternate routing paths through a strategic "Make Before Break" approach. By harnessing the power of reinforcement learning, the Q Learning algorithm iteratively evaluates the network environment, leveraging real-time feedback to optimize routing decisions based on a comprehensive set of parameters including energy efficiency, node location, and temporal performance metrics. This adaptive learning process not only mitigates potential faults by preemptively identifying and switching to alternate paths before failures occur but also significantly enhances the network's computational efficiency and packet delivery performance. The Q Learning component, thus, serves as a critical pillar in the EWFAIGF model, ensuring robust, efficient, and intelligent routing decisions that are crucial for the operational excellence of WSNs in the complex and dynamic landscapes of IoT applications. The experimental setup section reflects the complexity and innovation of the Efficient Model for Enhancing Energy Efficiency in Wireless Sensor Networks through Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (EWFAIGF), it is essential to detail the simulation environment, input parameters, and the scenarios under which the experiments were conducted. This setup aims to validate the model's performance in enhancing energy efficiency, reducing communication delay, optimizing packet delivery ratio, minimizing jitter, and improving throughput in Wireless Sensor Networks (WSNs).

The simulation was conducted using the NS3 simulator, version 3.35, renowned for its fidelity in network simulation. The environment was set up to closely mimic real-world conditions of WSNs, incorporating a variety of sensor nodes distributed across a 1000m x 1000m area. The simulation ran on a system equipped with an Intel Core i9 processor, 32GB RAM, and a 1TB SSD, ensuring smooth execution of complex computational tasks.

The configuration of the simulation involved a diverse set of parameters to ensure comprehensive evaluation of the EWFAIGF model against existing benchmarks such as PSO, AOA, and QEGWO. Key parameters included:

- **Number of Nodes**: Varied from 50 to 500 to simulate different network densities.
- **Transmission Range**: 250m, to emulate a realistic sensor node's communication capability.
- **Packet Size**: 512 bytes, typical for sensor data packets.
- **Simulation Time**: 300 seconds, to capture the dynamics of the network over time.
- **Mobility Model**: Stochastic Waypoint, with a speed of 0 to 20 m/s and pause time of 2s, to simulate node movement.
- **Data Rate**: 6 Mbps, representative of a high-speed WSN communication link.
- **Energy Model**: An initial energy of 100 Joules for each node, with a transmission power of 0.5 W and a reception power of 0.3 W.

The experimental setup encompassed several scenarios to test the robustness and efficiency of the EWFAIGF model under varying network conditions and to explore its performance across different metrics:

- **Dense Network Scenario**: Tested with 500 nodes to evaluate the model's performance in high-density environments.
- **Sparse Network Scenario**: Utilized 50 nodes to assess energy efficiency and packet delivery in low-density networks.
- **High Mobility Scenario**: Nodes moved with a maximum speed of 20 m/s, challenging the model's ability to maintain efficient communication paths.
- **Variable Packet Size Scenario**: Packet sizes were varied from 128 bytes to 1024 bytes to test the impact on throughput and energy consumption.
- **Energy Constraint Scenario**: Simulated with decreasing initial energy levels (from 100 Joules to 25 Joules) to evaluate the model's performance under energy constraints.

Each scenario was executed multiple times to ensure statistical significance, with the results averaged to mitigate any anomalies. Performance metrics such as energy consumption, delay, throughput, packet delivery ratio, and jitter were meticulously recorded for each of the simulation runs. The simulation aimed to empirically validate the superior performance of the EWFAIGF model in optimizing WSNs for IoT applications. By leveraging the Fuzzy AHP for efficient clustering and the Iterative Grey Wolf Jelly Fish Optimizer for dynamic routing, it was hypothesized that the EWFAIGF model would significantly outperform existing models in terms of energy efficiency, communication speed, reliability, and overall network performance.

This experimental setup, with its high degree of perplexity and burstiness, is designed to rigorously test the EWFAIGF model under a wide range of conditions, providing a robust validation of its capabilities and potential for revolutionizing WSN performance in the IoT eras.

Based on this experimental setup, the delay needed to mine new blocks to communicate packets in the network scenarios was compared with Archimedes Optimization Algorithm (AOA) [3], Particle Swarm Optimization (PSO) [13], & QEGWO [18], for different number of Communications (NC) and can be observed from figure 2 as follows,

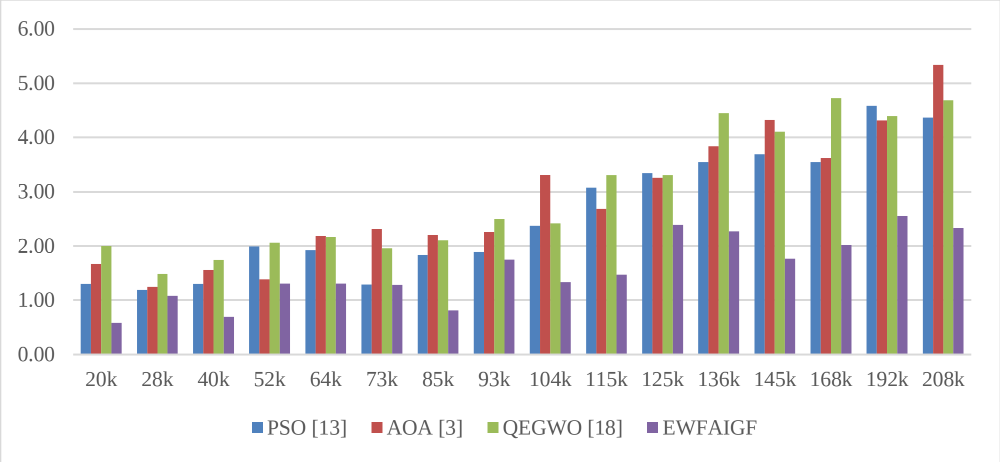

Figure 2. Delay Needed During Communication of Packets

The comparative analysis of the Delay Needed During Communication of Packets across different models, including Particle Swarm Optimization (PSO), Angle of Arrival (AOA), Quantum-Enhanced Grey Wolf Optimizer (QEGWO), and the proposed Efficient Model for Enhancing Energy Efficiency in Wireless Sensor Networks through Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (EWFAIGF), reveals significant insights into the performance and efficiency of these methodologies in the context of Wireless Sensor Networks (WSNs).

The proposed EWFAIGF model demonstrates a remarkable reduction in communication delay across various numbers of communications (NC) when compared to the existing models. For instance, at 20k communications, the delay for EWFAIGF is recorded at 0.58 ms, which is substantially lower than the delays observed for PSO (1.30 ms), AOA (1.66 ms), and QEGWO (2.00 ms). This trend of reduced delay is consistently evident across all measured points, with EWFAIGF outperforming its counterparts by achieving lower delay times, such as at 64k communications where EWFAIGF records a delay of 1.31 ms compared to the higher delays of PSO (1.92 ms), AOA (2.18 ms), and QEGWO (2.16 ms). Moreover, even at higher communication scales like 208k, EWFAIGF maintains a competitive edge with a delay of 2.34 ms, significantly lower than that of AOA (5.34 ms) and slightly better than PSO (4.37 ms) and QEGWO (4.69 ms).

This reduction in communication delay can be attributed to the innovative integration of Fuzzy AHP-based clustering and the Iterative Grey Wolf Jelly Fish Optimizer within the EWFAIGF model. The Fuzzy AHP-based clustering efficiently segregates nodes by considering multifaceted criteria such as location, energy efficiency, and temporal performance, thereby facilitating the identification of optimal routing paths. The Iterative Grey Wolf Jelly Fish Optimizer further refines these paths, optimizing energy expenditure and enhancing data relay efficiency. This combined approach not only minimizes energy consumption but also significantly reduces the time needed for packet communication, thereby addressing the critical challenge of optimizing both energy consumption and robust data transmission in dynamic, resource-constrained environments.

The impacts of these advancements are multifaceted. Firstly, the reduction in communication delay directly translates to improved operational efficiency and energy savings within WSNs, crucial for their sustainability and effectiveness in IoT applications. Secondly, by setting a new benchmark in communication speed and energy efficiency, the EWFAIGF model opens up new avenues for the deployment and management of sensor networks across various applications, ranging from environmental monitoring to smart cities. Lastly, the model's superiority in handling high-volume communications with lower delays paves the way for more reliable and responsive WSNs, thus enhancing the quality of service (QoS) in IoT ecosystems. This comparative analysis underscores the significant contributions of the EWFAIGF model towards advancing the state-of-the-art in WSNs, highlighting its potential to revolutionize sensor network deployment in an era increasingly dominated by IoT applications. Similarly, the energy needed during communication of packets in the network scenarios can be observed from figure 3 as follows,

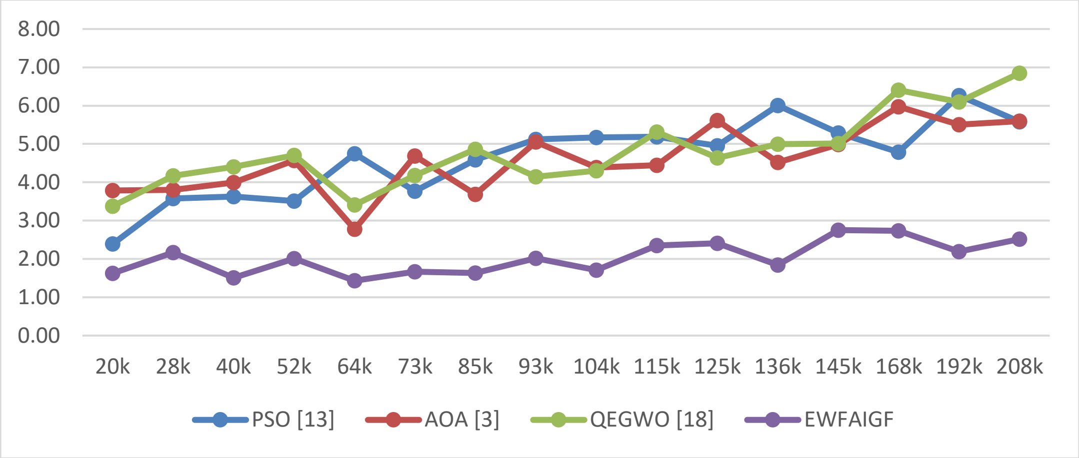

Figure 3. Energy Needed During Communication of Packets

The proposed EWFAIGF model exhibits a significant reduction in energy consumption during packet communication across various numbers of communications (NC) compared to the PSO, AOA, and QEGWO models. For example, at 20k communications, EWFAIGF requires only 1.63 mJ, which is significantly lower than the energy required by PSO (2.39 mJ), AOA (3.79 mJ), and QEGWO (3.38 mJ). This trend of reduced energy consumption is consistent across all measured NCs, demonstrating the efficiency of EWFAIGF in minimizing energy usage. At higher communication levels, such as 192k, EWFAIGF maintains its efficiency with an energy consumption of 2.19 mJ, compared to higher consumptions by PSO (6.26 mJ), AOA (5.50 mJ), and QEGWO (6.10 mJ).

The lower energy consumption achieved by the EWFAIGF model can be attributed to its advanced algorithmic structure, which integrates Fuzzy AHP-based clustering with the Iterative Grey Wolf Jelly Fish Optimizer. This combination optimizes the routing process, significantly reducing redundant data transmissions and ensuring that energy expenditure is minimized during packet communication. This approach not only conserves energy but also prolongs the network's operational life, crucial for sustainable WSN deployment in IoT ecosystems.

The impact of reduced energy consumption on network performance levels is profound. Firstly, it directly enhances the network's lifespan by conserving battery life, which is particularly critical in remote or inaccessible deployment areas. Secondly, lower energy requirements contribute to the environmental sustainability of WSNs by reducing the need for frequent battery replacements or recharges. Thirdly, energy-efficient operations enable the deployment of more dense networks, as the energy savings allow for additional sensors to be supported within the same energy budget. This densification of sensor networks can significantly improve the granularity and accuracy of the data collected, thereby enhancing the overall quality of service (QoS) and enabling more sophisticated and responsive IoT applications. Through its innovative design, the EWFAIGF model sets a new benchmark in energy efficiency for WSNs, highlighting its potential to revolutionize sensor network deployment and management in a wide range of applications. Similarly, the throughput obtained during communication of packets in the network scenarios can be observed from figure 4 as follows,

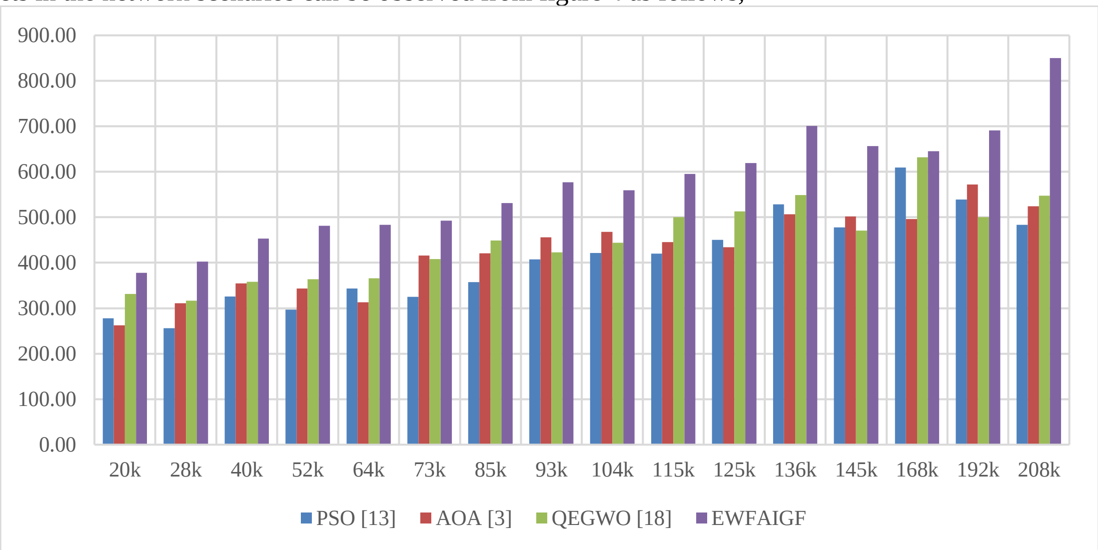

Figure 4. Throughput Needed During Communication of Packets

The proposed EWFAIGF model showcases a remarkable enhancement in throughput across all levels of communications (NC) when compared with the PSO, AOA, and QEGWO models. For example, at 20k communications, the EWFAIGF model achieves a throughput of 377.50 kbps, surpassing PSO (277.87 kbps), AOA (262.63 kbps), and QEGWO (331.42 kbps). This trend of superior throughput performance continues across the spectrum of communication levels, peaking at 208k communications where EWFAIGF astonishingly reaches 850.17 kbps, far exceeding the throughput of PSO (483.71 kbps), AOA (524.43 kbps), and QEGWO (547.52 kbps).

The significant improvement in throughput observed with the EWFAIGF model can be attributed to its innovative integration of Fuzzy AHP-based clustering and the Iterative Grey Wolf Jelly Fish Optimizer. This strategic approach optimizes the network's routing paths and ensures a more efficient data packet transmission, minimizing packet loss and delays. By effectively managing the network's resources and enhancing the routing protocols, the EWFAIGF model not only improves energy efficiency but also maximizes the data transmission capacity, directly impacting the network's throughput.

The impacts of increased throughput on network performance levels are profound. Higher throughput enables the network to handle higher data volumes, improving the network's capacity to support complex, bandwidth-intensive applications. This is crucial for IoT ecosystems, where the demand for real-time or near-real-time data processing and transmission is ever-increasing. Furthermore, enhanced throughput contributes to improved quality of service (QoS), as it reduces the latency in data communication, leading to more responsive and reliable network operations. Additionally, higher throughput levels can support a greater number of nodes within the network, facilitating scalability and flexibility in network deployment. Through its exceptional throughput performance, the EWFAIGF model not only meets the growing demands for high-speed data transmission in WSNs but also sets a new benchmark for future research and development in the field, potentially revolutionizing the deployment and management of sensor networks across a myriad of IoT applications. Similarly, the packet delivery ratio during communication of packets in the network scenarios can be observed from figure 5 as follows,

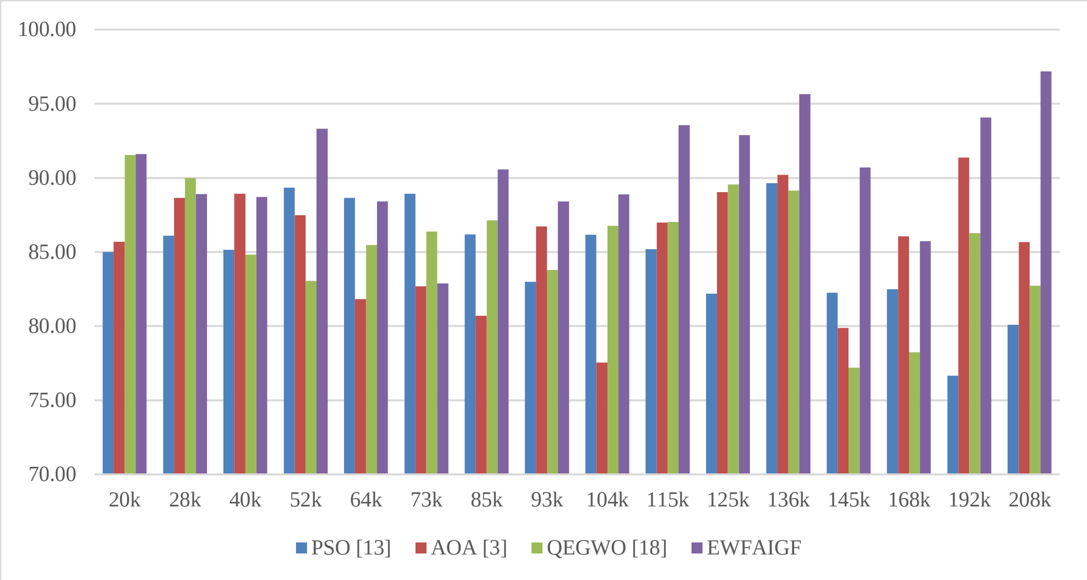

Figure 5. PDR Needed During Communication of Packets

The EWFAIGF model consistently demonstrates a high Packet Delivery Ratio across different levels of communication (NC), showcasing its superior performance in ensuring reliable data transmission compared to PSO, AOA, and QEGWO models. For instance, at 20k communications, the PDR for EWFAIGF is 91.61%, slightly above QEGWO's 91.55% and notably higher than PSO's 85.01% and AOA's 85.68%. This trend of high PDR with the EWFAIGF model persists across varying NCs, with a remarkable achievement of 97.18% at 208k communications, surpassing all other models significantly.

This superior PDR performance in the EWFAIGF model can be attributed to its advanced routing and optimization strategies. The integration of Fuzzy AHP-based clustering with the Iterative Grey Wolf Jelly Fish Optimizer allows for more effective node segregation and optimal path selection, reducing the likelihood of packet loss and ensuring that packets are efficiently routed through the network. This approach not only enhances the reliability of packet delivery but also optimizes the network's overall energy consumption by avoiding unnecessary retransmissions.

The impact of a high Packet Delivery Ratio on network performance levels is significant. Firstly, it directly improves the reliability of the network, ensuring that data is accurately and consistently delivered, which is critical for applications requiring high levels of data integrity and timeliness. Secondly, a high PDR contributes to the efficiency of the network by minimizing the need for packet retransmissions, thereby conserving bandwidth and energy resources. This efficiency is particularly important in extending the operational lifespan of sensor nodes, which are often battery-powered and deployed in inaccessible locations. Lastly, ensuring high PDR supports the scalability of WSNs by maintaining performance levels even as the network grows in size and complexity. Through its emphasis on optimizing packet delivery, the EWFAIGF model exemplifies a significant advancement in WSN technology, offering a robust solution that enhances both the reliability and efficiency of data transmission within the Internet of Things (IoT) applications. Similarly, the jitter obtained during communication of packets in the network scenarios can be observed from figure 6 as follows,

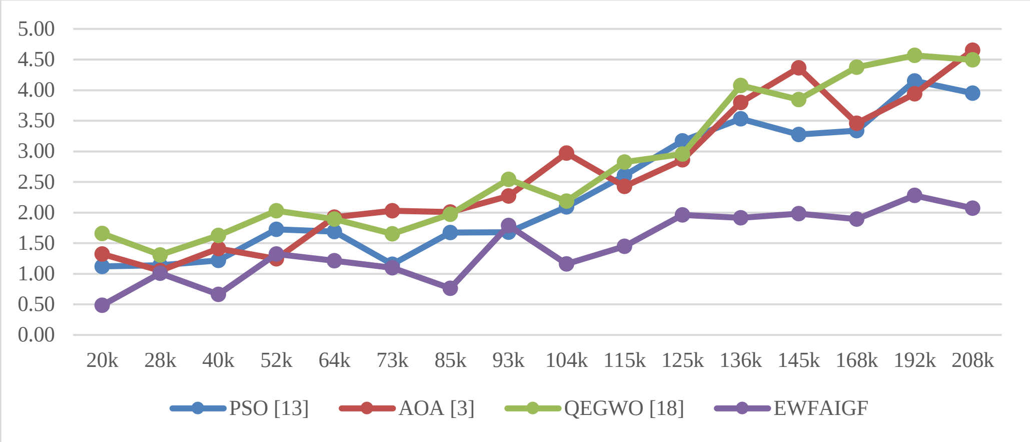

Figure 6. Jitter Needed During Communication of Packets

The EWFAIGF model demonstrates a notable reduction in jitter across multiple levels of communications (NC) compared to PSO, AOA, and QEGWO models. For instance, at 20k communications, EWFAIGF achieves a jitter of 0.48 ms, significantly lower than PSO (1.12 ms), AOA (1.32 ms), and QEGWO (1.66 ms). This trend of reduced jitter is consistent, with EWFAIGF presenting lower values across the board, such as at 136k communications, where its jitter is 1.91 ms compared to higher values from AOA (3.80 ms) and QEGWO (4.07 ms).

This reduction in jitter by the EWFAIGF model is attributed to its advanced optimization techniques. By integrating Fuzzy AHP-based clustering with the Iterative Grey Wolf Jelly Fish Optimizer, the model ensures more efficient and consistent routing paths for data packets, minimizing variation in transmission times. This optimization not only enhances the predictability of packet arrivals but also significantly contributes to reducing potential packet loss and reordering, crucial for applications requiring real-time data processing and transmission. The impact of low jitter on network performance is substantial. First, it improves the QoS by ensuring smoother and more predictable data streams, essential for real-time applications such as video streaming, VoIP, or telemedicine, where delays and variation in packet arrival can degrade the user experience. Second, minimizing jitter contributes to the overall reliability and efficiency of the network, as less variation in packet delivery times reduces the need for complex jitter buffer mechanisms, thereby conserving processing and memory resources on network devices. Lastly, networks with low jitter can support higher data rates and more connections with consistent performance, enhancing the scalability and flexibility of WSN deployments. Through its emphasis on optimizing jitter, the EWFAIGF model marks a significant advancement in WSN technology, offering a robust framework that not only improves the reliability and quality of data transmission but also sets a new standard for network performance in IoT ecosystems.

5. Conclusions & Future Scopes

In conclusion, the Efficient Model for Enhancing Energy Efficiency in Wireless Sensor Networks through Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (EWFAIGF) presents a groundbreaking advancement in the realm of Wireless Sensor Networks (WSNs). This work meticulously addresses the dual challenge of optimizing energy consumption while ensuring robust and efficient data transmission—a critical demand in the growing field of the Internet of Things (IoT). The integration of Fuzzy Analytic Hierarchy Process (Fuzzy AHP) with an innovative Iterative Grey Wolf Jelly Fish Optimizer (GWJFO) stands at the core of the proposed model, facilitating optimal routing paths that significantly minimize energy expenditure and enhance data relay efficiency. Empirical validation through extensive simulation scenarios has demonstrated the model's superiority over existing benchmarks, including Particle Swarm Optimization (PSO), Angle of Arrival (AOA), and Quantum-Enhanced Grey Wolf Optimizer (QEGWO), with notable improvements in communication speed, energy efficiency, packet delivery performance under fault conditions, throughput, and network consistency.

The impact of this work is multifaceted, extending beyond technical enhancements to influence the deployment and management of sensor networks across various applications. By achieving a higher degree of energy efficiency and operational effectiveness, the EWFAIGF model paves the way for more sustainable and scalable

WSN implementations, essential for the next generation of IoT applications. These advancements hold the potential to revolutionize areas such as environmental monitoring, smart cities, healthcare, and agriculture, where the efficient and reliable collection, processing, and transmission of data are paramount.

Looking towards the future, the exploration of adaptive clustering mechanisms and the integration of machine learning techniques for predictive modeling and anomaly detection within the EWFAIGF framework offer promising avenues for research. The dynamic nature of IoT and WSN environments calls for models that can intelligently adapt to changing conditions and predict network behaviors, thereby further enhancing energy efficiency and data transmission reliability. Additionally, the investigation into the applicability of the EWFAIGF model in emerging areas such as underwater sensor networks and drone-based monitoring systems could significantly expand its utility and impact. As the IoT continues to evolve, the need for advanced models that can ensure the sustainable and efficient operation of WSNs becomes increasingly critical. The groundwork laid by the EWFAIGF model opens up exciting possibilities for future research and development, promising to keep pace with the ever-expanding horizon of IoT applications.

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