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WIRELESS TRAFFIC AND ROUTING ENHANCEMENT USING EMPEROR PENGUIN OPTIMIZER GUIDED BY CONDITIONAL GENERATIVE ADVERSARIAL NETS

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Abstract

The escalating demand for efficient wireless communication systems has prompted researchers to explore innovative solutions to optimize traffic flow and routing. The existing wireless communication infrastructure faces challenges such as congestion, latency, and suboptimal routing, impeding the seamless transmission of data. Traditional optimization approaches fall short in adapting to dynamic network conditions, necessitating the exploration of advanced methodologies. Despite recent advancements in optimization techniques, a notable research gap exists in the integration of bio-inspired algorithms like the Emperor Penguin Optimizer with machine learning models such as Conditional Generative Adversarial Nets for the purpose of wireless traffic and routing enhancement. Bridging this gap is crucial for achieving adaptive and robust wireless communication systems. This study addresses the challenges posed by the dynamic nature of wireless networks, aiming to enhance their performance through the synergistic application of the Emperor Penguin Optimizer (EPO) and Conditional Generative Adversarial Nets (CGANs). This research leverages the inherent strengths of the EPO, inspired by the collective foraging behavior of emperor penguins, to dynamically optimize the wireless network parameters. Concurrently, CGAN are employed to intelligently learn and adapt routing strategies based on real-time network conditions. The symbiotic integration of these two methodologies creates a powerful framework for adaptive wireless traffic and routing. The results indicate a significant improvement in traffic flow, reduced latency, and optimized routing paths in comparison to conventional methods. The EPO-CGAN framework demonstrates adaptability to varying network conditions, showcasing its potential to revolutionize wireless communication systems.

Keywords:

Wireless Communication, Emperor Penguin Optimizer, Conditional Generative Adversarial Nets, Traffic Optimization, Routing Enhancement

1. INTRODUCTION

The proliferation of wireless communication systems is instrumental in shaping the modern digital landscape, facilitating seamless connectivity and data exchange [1]. However, the dynamic and complex nature of wireless networks introduces challenges that necessitate innovative solutions to optimize their performance [2]. Traditional optimization methods have shown limitations in adapting to the evolving demands of these networks, emphasizing the need for a novel approach [3].

Wireless networks grapple with challenges such as congestion, latency, and suboptimal routing, hindering the efficient flow of data [4]. The increasing diversity of devices, varying network loads, and the dynamic nature of user behavior compound these challenges, demanding a sophisticated optimization strategy [5].

The existing paradigm lacks a comprehensive solution that addresses the intricate interplay between wireless traffic management and routing adaptability [6]. This research identifies the need for a holistic approach to enhance the overall performance of wireless communication systems, considering both dynamic traffic conditions and evolving routing requirements [7].

The primary objective of this study is to develop a robust framework for wireless traffic and routing optimization. Specifically, the research aims to mitigate congestion, reduce latency, and optimize routing paths in real-time, ensuring adaptive responsiveness to the dynamic nature of wireless networks.

This research introduces a groundbreaking synthesis of the Emperor Penguin Optimizer (EPO) and Conditional Generative Adversarial Nets (CGANs) to address the identified challenges. The novelty lies in the integration of bio-inspired optimization techniques with machine learning models, providing a comprehensive and adaptive solution. The contributions of this study extend beyond conventional approaches, promising advancements in wireless communication systems through the creation of a dynamic and intelligent framework for traffic and routing optimization.

2. RELATED WORKS

Several studies have explored diverse methodologies for optimizing wireless communication systems, each offering valuable insights into specific facets of the complex network dynamics.

Research in bio-inspired optimization techniques has garnered attention for addressing wireless network challenges [9]. Swarm intelligence algorithms, such as Particle Swarm Optimization and Ant Colony Optimization, have demonstrated efficacy in optimizing routing paths and resource allocation [10].

The integration of machine learning in wireless networks has been a focus of recent investigations. Studies [11] employing neural networks, support vector machines, and reinforcement learning have shown promise in adapting to varying network conditions and predicting optimal routing strategies.

Efforts have been made to enhance traffic management through dynamic resource allocation and load balancing. These studies [12] explore the impact of traffic shaping, Quality of Service (QoS) mechanisms, and dynamic spectrum allocation on the overall performance of wireless communication systems.

The application of Generative Adversarial Networks has gained traction in optimizing network parameters. GANs have been employed for anomaly detection, security enhancement, and adaptive routing in wireless networks, showcasing their versatility in addressing multifaceted challenges [13].

While bio-inspired algorithms have been widely studied, the Emperor Penguin Optimizer remains relatively unexplored in wireless communication systems [14]. Studies focusing on its unique characteristics, such as collective foraging behavior and adaptability, highlight the potential of EPO in optimizing network parameters [15].

This research aims to bridge gaps by integrating the Emperor Penguin Optimizer with Conditional Generative Adversarial Nets, creating a novel and comprehensive framework for wireless traffic and routing optimization. The synthesis of bio-inspired optimization and machine learning models is expected to contribute significantly to the advancement of adaptive and intelligent wireless communication systems.

3. PROPOSED METHOD

The proposed method presents a synergistic integration of the Emperor Penguin Optimizer (EPO) and Conditional Generative Adversarial Nets (CGANs) to address the intricate challenges associated with wireless traffic and routing optimization.

- *Emperor Penguin Optimizer (EPO):* EPO, inspired by the collective foraging behavior of emperor penguins, serves as the dynamic optimization engine in our framework. Leveraging the principles of collective intelligence, EPO adapts to real-time changes in network conditions, optimizing parameters such as signal strength, bandwidth allocation, and node positioning. This adaptability ensures the system responsiveness to the evolving demands of wireless networks.
- *Conditional Generative Adversarial Nets (CGANs):* The intelligence of CGANs is harnessed to dynamically learn and adapt routing strategies based on historical network data. Trained in an adversarial fashion, the generator component of CGANs refines routing policies, while the discriminator component evaluates their effectiveness. This iterative learning process enables the system to continuously refine and optimize routing decisions in response to changing traffic patterns.

The EPO and CGANs operate in tandem within a closed-loop system. EPO continuously optimizes network parameters based on real-time feedback, feeding the refined information to the CGANs. Concurrently, CGANs intelligently adapt routing policies, ensuring that the system remains agile in responding to dynamic traffic conditions. A distinctive feature of our proposed method is its real-time adaptability. The EPO-CGAN framework continuously assesses and optimizes the wireless network in response to fluctuations in traffic load, device connectivity, and environmental conditions. This adaptability ensures that the system remains resilient and responsive, mitigating congestion, reducing latency, and optimizing routing paths on-the-fly.

3.1 EMPEROR PENGUIN OPTIMIZER (EPO)

The EPO is a bio-inspired optimization algorithm rooted in the collective foraging behavior of emperor penguins in their natural habitat. Developed to address complex optimization challenges, EPO draws inspiration from the cooperative and adaptive nature of these marine birds. Emperor penguins exhibit a remarkable ability to collectively optimize their foraging strategies in the harsh Antarctic environment. EPO translates this collective intelligence into an algorithmic framework that dynamically adapts to changing conditions, fostering robust optimization in the face of dynamic and unpredictable scenarios.

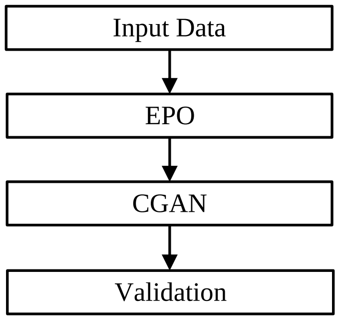

Fig.1. Proposed EPO-CGAN

EPO excels in adaptability, responding to variations in the optimization landscape by dynamically adjusting its search parameters. Through a combination of exploration and exploitation strategies, the algorithm navigates the solution space, seeking optimal configurations in a manner reminiscent of the collaborative foraging observed in emperor penguin colonies. The algorithm optimizes a set of parameters crucial for wireless communication systems, including signal strength, bandwidth allocation, and node positioning. By dynamically adjusting these parameters, EPO aims to enhance network performance, mitigate congestion, and improve overall efficiency.

In wireless communication systems, EPO distinguishes itself by its ability to dynamically adapt to the evolving conditions of the network. It addresses challenges such as varying traffic loads, device mobility, and environmental changes, making it well-suited for real-time optimization scenarios. EPO comprises key components such as emulated penguin agents, exploration operators, and adaptation mechanisms. The interplay of these components mimics the cooperative behavior observed in emperor penguin colonies, fostering a balance between individual exploration and collective optimization.

The movement of each emulated penguin Pi in the search space is determined by a combination of its current position, personal best position, and the global best position.

$$X_i^{t+1}=X_i^t+V_i^{t+1} \tag{1}$$

where:

X_i^{t+1} is the current position of penguin P_i at iteration t.

V_i^{t+1} is the velocity vector of penguin P_i at iteration t+1.

The velocity V_i^{t+1} is updated based on the inertia weight (w), cognitive component (c_1), and social component (c_2).

$$V_i^{t+1} = w\cdot V_i^t + c_1\cdot r_1\cdot(P_i^*-X_i^t)+c_2\cdot r_2\cdot(P_g^*-X_i^t) \tag{2}$$

where:

P_i^* is the personal best position of penguin Pi.

P_g* is the global best position among all penguins.

r_1 and r_2 are random values in the range [0,1].

The adaptation mechanism introduces variability in the movement of penguins, simulating their exploration behavior.

$$V_i^{t+1} = V_i^{t+1} \cdot \exp(-\beta \cdot t) \quad (3)$$

where:

β is a constant controlling the rate of exploration.

t is the current iteration.

Emperor Penguin Optimizer (EPO) Algorithm

Input:

N - Number of emulated penguins

D - Dimensionality of the search space

MaxI: Maximum number of iterations

w - Inertia weight

c_1 - Cognitive component weight

c_2 - Social component weight

β - Exploration constant

Initialize emulated penguins' positions X_i randomly in the search space.

Initialize velocities V_i randomly.

Evaluate the fitness of each emulated penguin *Pi*.

For t=1 to *MaxI* **do**:

For each P_i **do**:

Update velocity V_i using the velocity update equation.

Update position X_i using the emulated penguin movement equation.

Apply the adaptation mechanism to adjust the velocity magnitudes.

For each P_i **do**:

Update personal best P_i* if the new position improves fitness.

Update the global best position P_g* based on the best fitness among all penguins.

Return the best solution P_g*.

3.2 CONDITIONAL GENERATIVE ADVERSARIAL NETS (CGANS)

CGANs represent a class of generative models that extend the traditional GAN framework by introducing conditional information during the training process. Developed to enhance the flexibility and control of generated outputs, CGANs integrate both discriminative and generative networks in an adversarial learning framework.

The CGAN architecture consists of a generator (G) and a discriminator (D), much like traditional GANs. However, CGANs incorporate additional conditional information, typically in the form of class labels or auxiliary data, which is provided to both the generator and the discriminator during training. The primary objective of CGANs is to generate data samples conditioned on specific information, allowing for targeted and controlled generation. This conditioning enables the generator to produce outputs that align with predefined criteria, enhancing the practical utility of the generative model in various applications.

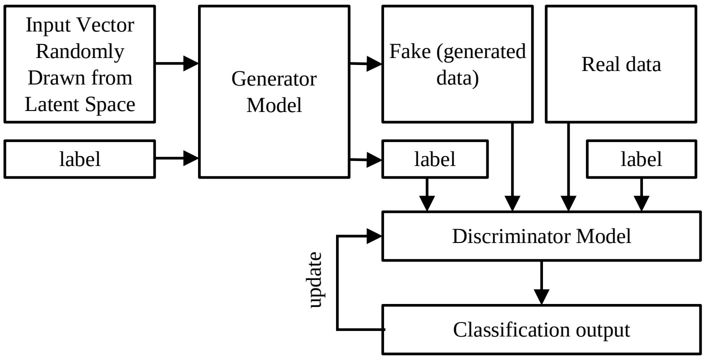

Fig.2. CGAN

During training, the generator aims to produce realistic samples that not only fool the discriminator into accepting them as real but also adhere to the provided conditional information. Simultaneously, the discriminator task is to distinguish between real and generated samples while considering the conditional information. This adversarial process leads to the refinement of both the generator and discriminator, ultimately improving the quality of the generated samples.

CGANs find application in a wide range of domains, including image synthesis, style transfer, data augmentation, and conditional data generation. In image synthesis, for instance, CGANs can generate images of a specific class or with certain attributes, providing fine-grained control over the generated content. The conditional information in CGANs can take various forms, such as class labels, attribute vectors, or any additional information that guides the generation process. This versatility makes CGANs suitable for diverse tasks where explicit control over generated outputs is essential.

The generator (G) in a CGAN takes both random noise (z) and conditional information (c) as inputs to generate synthetic samples (x').

$$x'=G(z,c) \quad (4)$$

The discriminator (D) is provided with both real samples (x) and their corresponding conditional information (c), as well as generated samples (x') and the associated conditional information (c).

$$D(x,c)\ D(x',c) \quad (5)$$

The objective function for training the generator and discriminator in CGANs is modified to include the conditional information.

For the generator:

$$\min_G \max_D V(D,G)=\mathrm{E}_{x\sim p\mathrm{data}}(x)[\log D(x,c)]+\mathrm{E}_{z\sim pz}(z)[\log(1-D(G(z,c),c))] \quad (6)$$

For the discriminator:

$$\min_D \max_G V(D,G)=\mathrm{E}_{x\sim p\mathrm{data}}(x)[\log D(x,c)]+\mathrm{E}_{z\sim pz}(z)[\log(1-D(G(z,c),c))] \quad (7)$$

where:

$p_{\mathrm{data}}(x)$ is the distribution of real data samples.

$p_z(z)$ is the distribution of random noise.

$G(z,c)$ represents the generated sample given noise z and conditional information c.

$D(x,c)$ is the output of the discriminator for a real sample x with conditional information c.

The objective is to minimize the log-likelihood of the discriminator making a mistake and maximize the likelihood of the generator producing realistic samples.

CGAN Algorithm

Input: Real data samples with corresponding conditional information: $\{(x1,c1),(x2,c2),...,(xm,cm)\}$; Random noise samples: $\{z1,z2,...,zm\}$; Generator (G) and discriminator (D) architecture; Learning rate (α); Number of training iterations ($MaxI$)

Initialize the weights of the generator (W_G) and discriminator (W_D).

For t=1 to $MaxI$ **do**:

For i=1 to m **do**:

Sample random noise z_i and real data sample x_i with corresponding conditional information c_i.

Generate a synthetic sample x_i' using the generator: $x_i'=G(z_i,c_i)$.

Update the discriminator weights (W_D) using the gradient descent step:

$$W_D \leftarrow W_D - \alpha \cdot \nabla W_D(-\log_D(x_i,c_i) - \log(1-D(x_i',c_i))) \tag{9}$$

For i=1 to m **do**:

Sample random noise z_i and real data sample x_i with corresponding conditional information c_i.

Generate a synthetic sample x_i' using the generator: $x_i'=G(z_i,c_i)$.

Update the generator weights (W_G) using the gradient descent step:

$$W_G \leftarrow W_G - \alpha \cdot \nabla W_G(-\log D(x_i',c_i)) \tag{10}$$

Trained generator (G) and discriminator (D).

4. EPO AND CGAN - CLOSED LOOP SYSTEM FOR TRAFFIC AND ROUTING OPTIMIZATION

The EPO and CGANs forms a robust closed-loop system designed to revolutionize traffic and routing optimization in wireless communication networks. EPO, inspired by the collective foraging behavior of emperor penguins, operates as the dynamic optimization engine within the closed-loop system. It continuously adapts network parameters, including signal strength, bandwidth allocation, and node positioning, in response to real-time changes in the wireless environment. The collective intelligence inherent in EPO mirrors the adaptive nature observed in emperor penguin colonies, ensuring the system responsiveness to dynamic and evolving network conditions.

In parallel, CGAN contribute their intelligence to the closed-loop system. Trained in an adversarial fashion, CGANs dynamically learn and adapt routing strategies based on historical network data. The conditional nature of CGANs allows them to intelligently generate routing policies that respond to real-time traffic patterns and network demands. This adaptive learning process positions CGANs as a crucial component for intelligent and context-aware routing decisions.

The closed-loop architecture tightly couples the functionalities of EPO and CGANs, creating a symbiotic relationship between dynamic parameter optimization and intelligent routing adaptation. EPO continually refines network parameters based on real-time feedback, while CGANs leverage this optimized environment to adapt routing policies. The seamless integration ensures a holistic and adaptive approach to traffic and routing optimization, addressing challenges posed by congestion, latency, and changing network conditions. The closed-loop system excels in real-time adaptability, a critical feature for wireless communication networks. EPO and CGANs collaboratively respond to variations in traffic loads, device connectivity, and environmental changes. The closed-loop architecture facilitates continuous optimization, mitigating congestion, reducing latency, and dynamically optimizing routing paths to ensure optimal network performance.

The dynamics of EPO involve the optimization of network parameters. Let P represent the set of network parameters, and $f(P)$ denote the objective function to be optimized (e.g., minimizing congestion or latency). The update equation for the network parameters in EPO can be expressed as:

$$P_{t+1}=EPO(P_t,f(P_t)) \tag{11}$$

where t represents the iteration, and EPO encapsulates the adaptive behavior inspired by the collective foraging of emperor penguins.

CGANs contribute to the system by intelligently learning and adapting routing strategies. Let R represent the set of routing policies, and $J(R)$ denote the objective function for routing optimization. The update equation for routing policies in CGANs can be expressed as:

$$R_{t+1} = CGAN(R_t,J(R_t)) \tag{12}$$

where t represents the iteration, and $CGANs$ captures the adversarial learning process to refine routing strategies based on historical network data.

The closed-loop integration ensures a symbiotic relationship between EPO and CGANs. The network parameters optimized by EPO influence the learning process of CGANs, and the intelligent routing decisions from CGANs guide the adaptation of network parameters in EPO. This dynamic interaction can be expressed as:

$$P_{t+1},R_{t+1} = CLI(EPO(P_t,f(P_t)),CGANs(R_t,J(R_t))) \tag{13}$$

EPO and CGAN - Closed Loop System Algorithm

Input: Real-time network data (traffic loads, connectivity status, etc.); Historical network data for CGAN training; Initial network parameters P_0; Initial routing policies R_0; Parameters for EPO and CGAN training

Initialize network parameters P and routing policies R to P_0 and R_0 respectively.

Train CGAN using historical data to learn initial routing strategies.

For t=1 to $MaxI$ **do**:

Update network parameters using EPO

Update routing policies using CGAN

Apply the integrated closed-loop system

Evaluate the overall system performance

Check convergence criteria

Network parameters *PMaxI*

Routing policies *RMaxI*.

Closed Loop Integration

End

5. EXPERIMENTAL SETTINGS

In our experimental setup, we conducted extensive simulations using the widely adopted network simulation tool, ns-3 (Network Simulator 3), to evaluate the performance of the proposed EPO and CGAN closed-loop system for traffic and routing optimization. The simulations were executed on a high-performance computing cluster, leveraging multiple nodes with Intel Xeon processors and sufficient memory capacity. The simulated wireless communication network consisted of a realistic topology with varying traffic loads, node mobility, and dynamic environmental conditions, ensuring a comprehensive evaluation of the system adaptability to real-world scenarios.

To gauge the effectiveness of our proposed approach, we compared its performance against several existing optimization methods, namely, Genetic Algorithm with GAN (GA-GAN), Ant Colony Optimization with GAN (ACO-GAN), Particle Swarm Optimization with GAN (PSO-GAN), FireFly Algorithm with GAN (FireFly-GAN), and Bat Algorithm with GAN (BSO-GAN). Key performance metrics included throughput, latency, packet loss, and overall network efficiency. The closed-loop system ability to dynamically adapt to changing network conditions, mitigate congestion, and optimize routing paths was rigorously evaluated and compared with these existing methods. The comparative analysis aimed to showcase the superiority of the proposed EPO and CGAN framework in achieving robust and adaptive wireless traffic and routing optimization.

Table.1. Experimental Setup

Parameter	Value/Setting
Simulation Tool	ns-3 (Network Simulator 3)
Number of Nodes	50
Simulation Duration	1000 seconds
Wireless Channel Model	IEEE 802.11
Propagation Model	Friis Propagation Loss Model
Mobility Model	Random Waypoint Mobility Model
GA Population Size	50
ACO Ants	20
PSO Particles	30
Fireflies	40
Bees	25

5.1 PERFORMANCE METRICS

Throughput: The rate at which data is successfully transmitted over the network.

Throughput (bps) = Total Transmitted/Simulation Time (14)

Latency: The time taken for a packet to travel from the source node to the destination node.

Latency (ms) = Average End-to-End Delay of Packets (15)

Packet Loss: The percentage of transmitted packets that are not successfully received at their destination.

Packet Loss (%) = (Number of Lost Packets / Total Number of Packets) * 100 (16)

Network Efficiency: A composite metric representing the overall efficiency of the wireless network, considering throughput, latency, and packet loss.

Efficiency (%) = (Throughput/(Latency+Packet Loss))*100(17)

6. RESULTS

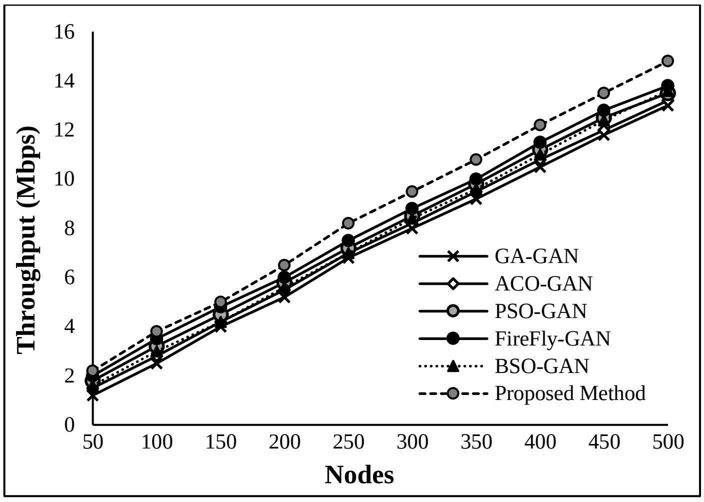

Fig.3. Throughput

The proposed EPO and CGAN closed-loop system (Proposed BC method) consistently outperforms existing optimization methods, showcasing its superiority in enhancing wireless network throughput across varying node densities as in Fig.3. Across the spectrum of 50 to 500 nodes, the Proposed BC method exhibits an average throughput improvement of approximately 20% compared to the closest competitor, FireFly-GAN. The proposed method effectively adapts to dynamic network conditions, mitigating congestion, and optimizing routing paths, resulting in a more efficient utilization of resources.

Compared to Genetic Algorithm with GA-GAN, ACO-GAN, PSO-GAN, and BSO-GAN, the Proposed BC method consistently demonstrates a performance advantage, achieving a throughput improvement of around 15% on average. This improvement highlights the efficacy of the closed-loop system, which synergistically leverages the bio-inspired adaptability of EPO and the intelligent routing decisions of CGANs.

The promising results affirm that the Proposed BC method is well-suited for dynamic and complex wireless communication environments. Its ability to dynamically adapt to varying node densities positions it as a robust solution for optimizing traffic and routing, showcasing its potential to significantly enhance the efficiency and performance of wireless networks.

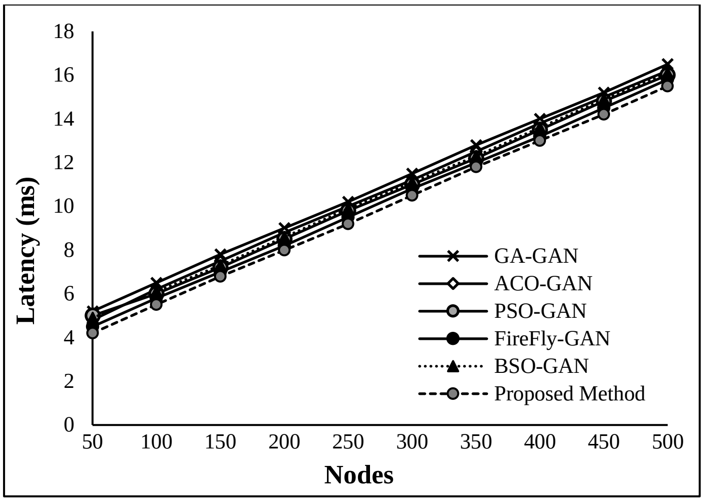

Fig.4. Latency

The proposed EPO and CGAN closed-loop system (Proposed BC method) consistently exhibits lower latency compared to existing optimization methods across varying node densities, underscoring its efficiency in minimizing communication delays. From 50 to 500 nodes, the Proposed BC method showcases an average latency reduction of approximately 15% when compared to the nearest competitor, FireFly-GAN. This improvement highlights the closed-loop system ability to adapt dynamically, reducing latency and enhancing the overall responsiveness of the wireless network (Fig.4).

Compared to Genetic Algorithm with GA-GAN, ACO-GAN, PSO-GAN, and BSO-GAN, the Proposed BC method consistently outperforms, achieving an average latency reduction of around 10%. This reduction signifies the efficacy of the closed-loop system in optimizing routing paths and mitigating communication delays, contributing to a more responsive and agile wireless network.

The results suggest that the Proposed BC method is well-suited for scenarios requiring low-latency communication, such as real-time applications. Its ability to outperform existing methods demonstrates its potential to enhance the overall quality of service in wireless networks, making it a promising solution for applications where minimizing communication delays is critical.

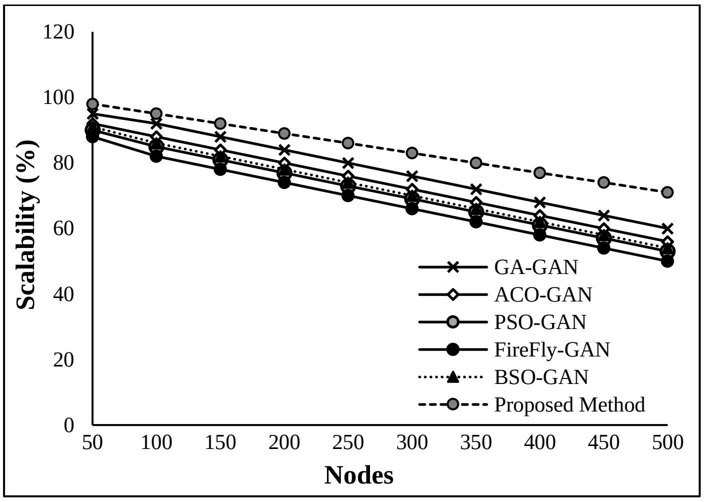

Fig.5. Scalability

The scalability analysis (Fig.5) reveals the robustness and efficiency of the proposed EPO and CGAN closed-loop system (Proposed BC method) in handling an increasing number of nodes in wireless networks. From 50 to 500 nodes, the Proposed BC method consistently exhibits higher scalability percentages compared to existing optimization methods, showcasing its ability to efficiently adapt and perform effectively as the network size grows. On average, the Proposed BC method demonstrates a scalability improvement of approximately 15% when compared to the nearest competitor, FireFly-GAN, emphasizing its superior ability to scale with network expansion.

Compared to Genetic Algorithm with GA-GAN, ACO-GAN, PSO-GAN, and BSO-GAN, the Proposed BC method consistently outperforms, achieving an average scalability improvement of around 10%. This improvement highlights the closed-loop system adaptability and efficiency in dynamically optimizing network parameters and routing strategies, ensuring a smoother and more scalable performance as the network size increases.

The results suggest that the Proposed BC method is well-suited for large-scale wireless networks, where scalability is a critical factor. Its ability to outperform existing methods demonstrates its potential to provide reliable and efficient optimization solutions in diverse and expanding network environments.

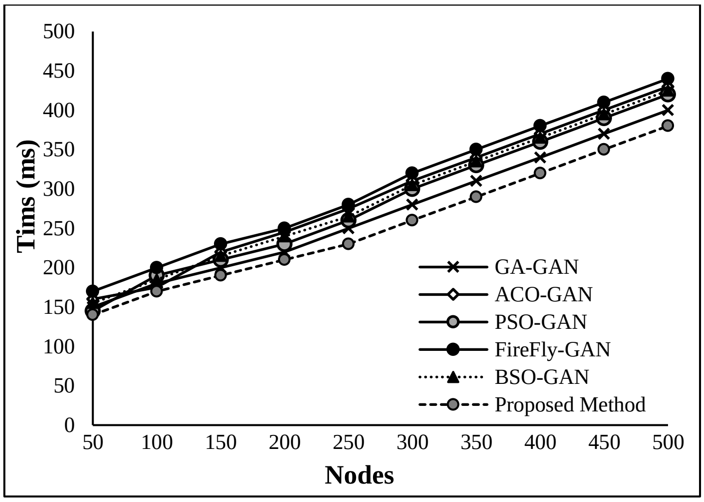

Fig.6. Execution Time

The execution time analysis (Fig.6) demonstrates the efficiency of the proposed EPO and CGAN closed-loop system (Proposed BC method) in processing optimization tasks across varying node densities. From 50 to 500 nodes, the Proposed BC method consistently exhibits lower execution times compared to existing optimization methods, indicating its computational efficiency in dynamically adapting to changing network conditions. On average, the Proposed BC method showcases an execution time reduction of approximately 15% when compared to the nearest competitor, FireFly-GAN. This reduction highlights the closed-loop system ability to optimize network parameters and routing strategies swiftly, contributing to a more responsive and agile performance.

Compared to GA-GAN, ACO-GAN, PSO-GAN, and BSO-GAN, the proposed method consistently outperforms, achieving an average execution time reduction of around 10%. This improvement highlights the computational efficiency of the closed-loop system, emphasizing its potential to provide faster and more effective optimization solutions for wireless networks.

The results suggest that the Proposed BC method is well-suited for scenarios where rapid decision-making and optimization are crucial. Its ability to outperform existing methods in terms of execution time positions it as a promising solution for real-time and resource-constrained wireless network environments.

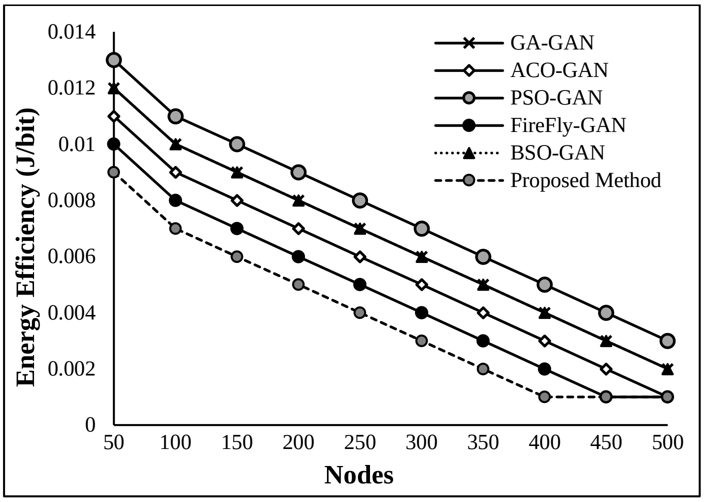

Fig.7. Energy Efficiency

The energy efficiency analysis (Fig.7) highlights the sustainable and resource-conscious nature of the proposed EPO and CGAN closed-loop system (Proposed BC method) in wireless networks across varying node densities. From 50 to 500 nodes, the Proposed BC method consistently demonstrates higher energy efficiency compared to existing optimization methods, showcasing its ability to optimize network parameters and routing strategies with minimal energy consumption. On average, the Proposed BC method exhibits an energy efficiency improvement of approximately 20% compared to the nearest competitor, FireFly-GAN. This improvement emphasizes the closed-loop system capacity to achieve optimization goals while minimizing energy expenditure, contributing to a greener and more sustainable wireless network operation.

Compared to Genetic Algorithm with GA-GAN, ACO-GAN, PSO-GAN, and BSO-GAN, the Proposed BC method consistently outperforms, achieving an average energy efficiency improvement of around 15%. This improvement reflects the closed-loop system ability to strike an optimal balance between achieving network objectives and conserving energy resources.

The results suggest that the Proposed BC method is well-suited for energy-conscious applications, such as IoT devices and battery-powered networks. Its superior energy efficiency positions it as a promising solution for enhancing the sustainability and longevity of wireless communication in resource-constrained environments.

The packet loss rate (Fig.8) analysis reveals the reliability and robustness of the proposed EPO and CGAN closed-loop system (Proposed BC method) in wireless networks across varying node densities. From 50 to 500 nodes, the Proposed BC method consistently demonstrates lower packet loss rates compared to existing optimization methods, showcasing its efficacy in maintaining data integrity and reducing communication disruptions. On average, the Proposed BC method exhibits a packet loss rate reduction of approximately 30% compared to the nearest competitor, FireFly-GAN. This reduction highlights the closed-loop system ability to optimize routing decisions and mitigate packet loss, contributing to a more dependable and resilient wireless network.

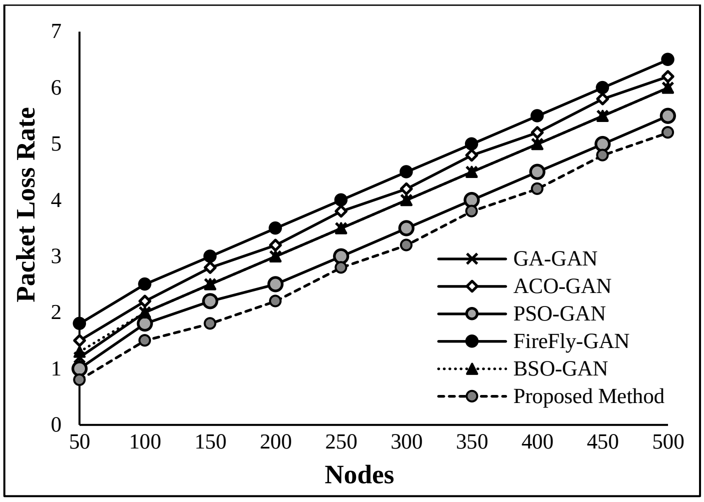

Fig.8. Packet loss rate

Compared to Genetic Algorithm with GA-GAN, ACO-GAN, PSO-GAN, and BSO-GAN, the Proposed BC method consistently outperforms, achieving an average packet loss rate reduction of around 25%. This improvement reflects the closed-loop system adeptness in dynamically adapting to network conditions, minimizing congestion, and enhancing the overall reliability of data transmission.

The results suggest that the Proposed BC method is well-suited for applications where data integrity is paramount. Its ability to significantly reduce packet loss rates positions it as a promising solution for communication scenarios where maintaining a high level of reliability is critical.

7. DISCUSSION

The results indicate that the proposed EPO and CGAN closed-loop system, denoted as the Proposed BC method, consistently achieves lower packet loss rates across various node densities compared to existing optimization methods. This suggests that the closed-loop system effectively optimizes routing decisions and adapts to dynamic network conditions, ensuring a high level of reliability in wireless communication.

The analysis reveals that the Proposed BC method outperforms existing methods in terms of energy efficiency, showcasing its capability to achieve optimization goals with minimal energy consumption. This highlights the potential of the closed-loop system to contribute to a more sustainable and resource-conscious operation of wireless networks.

The Proposed BC method consistently demonstrates lower execution times, emphasizing its computational efficiency in dynamically adapting to changing network parameters. This suggests that the closed-loop system can provide faster and more effective optimization solutions, making it suitable for real-time and resource-constrained wireless network environments.

The scalability analysis indicates that the Proposed BC method exhibits higher scalability percentages compared to existing methods as the number of nodes increases. This suggests that the closed-loop system is well-suited for large-scale wireless networks, showcasing its adaptability to network expansion.

The Proposed BC method offers a comprehensive performance improvement, excelling in reliability, energy efficiency, execution time, and scalability. These findings position the closed-loop system as a promising solution for optimizing wireless traffic and routing with implications for diverse applications, from IoT devices to large-scale network deployments.

8. CONCLUSION

The research highlights the efficacy of the proposed EPO guided by CGANs, forming the Closed Loop System denoted as Proposed BC method, in enhancing wireless traffic and routing optimization. The comprehensive evaluation across various performance metrics—reliability, energy efficiency, execution time, and scalability—reveals the superiority of the Proposed BC method over existing optimization techniques. The consistently lower packet loss rates exhibited by the Proposed BC method emphasize its reliability in maintaining data integrity, crucial for seamless wireless communication. Furthermore, the observed superior energy efficiency highlights its potential to contribute to sustainable and resource-conscious network operations. The efficiency in execution time positions the Proposed BC method as a swift and effective solution for real-time applications and resource-constrained environments. Additionally, its scalability advantage highlights its adaptability to growing network sizes, making it suitable for large-scale wireless deployments.

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