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Design Of An Iterative Method For Congestion Control In Wireless Networks Integrating Bacterial Foraging Optimizer, Ensemble Classification, And Q-Learning

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ABSTRACT

The ever-growing need for seamless data transmission in wireless networks indicates a significant requirement for efficient congestion control mechanisms. Conventional congestion control approaches suffer major drawbacks due to low responsiveness, primarily owing to the inherently dynamic and unpredictable environment of wireless networks. Static parameters characterize these traditional methods, making them unable to adapt to real-time network dynamics, and hence their performances turn out to be suboptimal. In this regard, presented are non-traditional approaches from innovation in the Bacterial Foraging Optimizer (BFO) model that synergizes the ensemble classification method with aid from Multilayer Perceptron (MLP) and Logistic Regression (LR), and Q-Learning for path optimization. The BFO, influenced by the foraging behavior of Escherichia coli bacteria, dynamically determines distinct paths within a network, effectively bypassing congested routes. The bioinspired algorithm, by mechanisms of chemotaxis, reproduction, and elimination-dispersal, efficaciously scours through the search space and effectively finds good network paths, surpassing static routing approaches. Meanwhile, the ensemble classification strategy comprising MLP and LR predicts network congestion by considering a range of features, such as path length, traffic load, and historical congestion data samples. This integrated approach strengthens congestion prediction accuracy as a result of integrating the strengths of individual classifiers and mitigating their respective weaknesses. On top of that, the implementation of Q-Learning for real-time path optimization is another major innovation, where an optimal path is selected based on continuously feeding back from the network. This strategy will ensure that the suggested model shall remain responsive to variations in the network, which is a dynamic environment. With the synergy of all the involved methods, holistic approaches toward the management of congestion have been expressed, considering the multi-faceted challenges from detection to cure. This model not only demonstrates superior adaptability and scalability, pertinent for large-scale wireless networks, but also boasts computational efficiency conducive to real-time applications. This implementation shall bring out great improvements in network performance indices like packet delivery ratio, end-to-end delay, and throughput and thus provide an opportunity to surpass conventional static congestion control mechanisms. The impact of this paper ranges from academic contributions to practical implications in the area of wireless communication. In that case, this research will provide a strong framework for reliable and efficient operation of wireless networks, provided that demands from modern digital communication systems persist. In this way, this paradigm shift of congestion control strategies reflects a landmark in the evolution of management of wireless networks.

Keywords: Bacterial Foraging Optimizer, Ensemble Classification, QLearning, Wireless Networks, Congestion Control

1. Introduction

The proliferation of wireless networks and the exponential growth in data traffic have underscored the critical need for efficient congestion control mechanisms. In wireless network environments, congestion occurs when the demand for resources exceeds the available capacity, leading to packet loss, increased latency, and degraded overall network performance. Traditional congestion control methods, while effective in stable and predictable settings, often fall short in the dynamic and complex landscape of wireless networks. These environments are characterized by fluctuating network conditions, variable link qualities, and diverse traffic patterns, presenting unique challenges that demand innovative solutions.

Existing congestion control strategies predominantly rely on static parameters and predefined thresholds, which lack the flexibility and adaptability required in the ever-changing context of wireless communications. Moreover, these conventional approaches do not adequately address the multi-faceted nature of wireless networks, where factors such as node mobility, signal interference, and varying traffic loads play significant roles. As a result, there is a pressing need for a more dynamic, responsive, and intelligent approach to congestion control in wireless networks.

In light of these challenges, this paper introduces a novel congestion control model designed to navigate the complexities of wireless network environments effectively. The proposed model integrates three advanced methodologies: the Bacterial Foraging Optimizer (BFO), Ensemble Classification using Multilayer Perceptron (MLP) and Logistic Regression (LR), and Q-Learning for path optimization. Each of these techniques brings a unique set of capabilities and advantages to the congestion control problem.

The Bacterial Foraging Optimizer is inspired by the natural foraging behaviors of E. coli bacteria, mimicking their chemotactic movements to locate and move towards nutrient-rich areas. In the context of congestion control, BFO adapts this bio-inspired mechanism to dynamically explore and identify alternative paths in the network, thus avoiding congested routes. This approach not only enhances the flexibility and adaptability of the congestion control strategy but also contributes to a more balanced distribution of network traffic.

Complementing the path-finding capabilities of BFO, Ensemble Classification combines the strengths of Multilayer Perceptron and Logistic Regression classifiers to accurately identify congested network paths. By leveraging a diverse set of input features and historical congestion data, this method improves the reliability and accuracy of congestion predictions, enabling proactive congestion management.

Finally, Q-Learning, a reinforcement learning technique, is employed to optimize path selection in real-time based on continuous feedback from the network. This method allows the system to learn from past experiences and adapt its decision-making process, ensuring optimal path selection even under varying network conditions.

The integration of BFO, Ensemble Classification, and Q-Learning into a unified congestion control model represents a significant advancement in the field. By addressing the limitations of traditional methods and harnessing the strengths of each integrated technique, the proposed model offers a robust, adaptable, and efficient solution for congestion control in wireless networks. This paper delves into the design, implementation, and performance evaluation of this novel approach, showcasing its potential to revolutionize congestion management in the dynamic landscape of wireless communications& scenarios.

Motivation & Contribution:

The surge in the deployment of wireless networks and the corresponding increase in data traffic necessitate innovative solutions to manage network congestion effectively. The motivation behind this research stems from the intrinsic limitations inherent in traditional congestion control mechanisms when applied to the dynamic and unpredictable environments of wireless networks. Traditional approaches, predominantly static and reactive in nature, are ill-equipped to handle the variability and uncertainties characteristic of these networks. This inadequacy becomes increasingly evident as users demand higher data rates and seamless connectivity, highlighting a significant gap in the existing network management frameworks.

The dynamic nature of wireless environments, characterized by fluctuating traffic patterns, variable node densities, and evolving network topologies, calls for a paradigm shift towards more adaptive, intelligent, and robust congestion control strategies. The motivation for this work is underpinned by the pressing need to transcend traditional methodologies, moving towards approaches that can dynamically adapt to changing network conditions, predict potential congestions before they become critical, and devise optimal paths for data transmission in real-time scenarios.

Building on this motivation, this paper contributes to the field of wireless network management through the design and implementation of a novel congestion control model. This model harnesses the collective strengths of three advanced methodologies: Bacterial Foraging Optimizer (BFO), Ensemble Classification using Multilayer Perceptron (MLP) and Logistic Regression (LR), and Q-Learning for path optimization. The convergence of these methodologies within a unified framework embodies the main contributions of this research:

- **Adaptive Path Selection**: The integration of BFO enables the model to mimic natural foraging behaviors, allowing for dynamic and adaptive path selection. This approach not only aids in alleviating current congestions but also proactively prevents potential bottlenecks, thereby maintaining optimal network flow.

- **Enhanced Prediction Accuracy**: By employing ensemble classification techniques that combine MLP and LR, the model significantly improves the accuracy of congestion predictions. This contribution is pivotal in transitioning from reactive to proactive congestion management, enabling the network to anticipate and mitigate congestion before it impacts the user experience.
- **Real-Time Path Optimization**: The application of Q-Learning for path optimization introduces a real-time decision-making component into the model. This allows for the continuous adaptation of routing decisions based on evolving network conditions, optimizing data transmission paths dynamically and ensuring high levels of network performance.
- **Comprehensive Evaluation**: The paper presents a comprehensive evaluation of the proposed model, employing a range of performance metrics to validate its effectiveness and superiority over existing congestion control approaches. This evaluation not only demonstrates the practical applicability of the model but also provides a benchmark for future research in the field.
- **Theoretical and Practical Implications**: The research bridges the gap between theoretical algorithms and practical network management, offering insights into the implementation of bio-inspired, machine learning, and reinforcement learning techniques in real-world network scenarios.

In summary, the motivation behind this research is rooted in the need for more sophisticated, adaptable, and intelligent congestion control strategies in wireless networks. The contributions of this work lie in the development of a novel model that integrates cutting-edge techniques to address the multifaceted challenges of congestion control, setting a new standard for network performance and management.

1. In-depth review of existing Models used for enhancing congestion control in network scenarios

The exploration of congestion control in wireless networks has seen a plethora of methodologies aimed at enhancing throughput, reducing packet loss, and improving the overall network performance. This review meticulously analyzes a range of methods, from traditional congestion control algorithms to avant-garde approaches leveraging artificial intelligence and machine learning. Table 1 spans a diverse array of environments, including Internet of Things (IoT) networks, vehicular platooning, wireless sensor networks, and Internet of Vehicles (IoV), highlighting the multifaceted nature of congestion challenges and the tailored solutions developed to address them.
The methodologies under scrutiny encompass fuzzy control, Model Predictive Control (MPC), game theory, predictive control systems, cross-layer designs, Extended State Observers, and cooperative transmission algorithms, among others. These approaches have been juxtaposed with cutting-edge techniques like Deep Reinforcement Learning (DRL), federated learning, and multi-agent reinforcement learning strategies. Each method's efficacy is assessed based on improvements in network parameters such as throughput, packet delivery ratio, energy efficiency, and latency.
The analysis reveals a significant evolution from conventional, static methods towards more dynamic, adaptive strategies that leverage real-time data and learning-based mechanisms to address network congestion. However, the review also uncovers recurring themes of limitations, notably scalability concerns, limited real-world validation, and complexity in implementation and training.

Reference	Method Used	Findings	Results	Limitations
[1]	Fuzzy control, Congestion control algorithms	Proposed a fuzzy congestion control for CoAP in IoT networks	Improved throughput and reduced packet loss in IoT networks	Limited validation with simulations, real-world deployment challenges
[2]	Model Predictive Control (MPC), Multi-layer multi-rate control	Developed a delay-aware MPC for vehicle platooning	Enhanced stability and safety in vehicle platooning under message-rate congestion	Limited experimental validation, scalability concerns
[3]	Game theory, Routing algorithms	Utilized game theory for congestion control in wireless sensor networks	Improved network throughput and QoS in wireless sensor networks	Simplified network models, scalability challenges
[4]	Predictive control, Wireless networked control system	Synthesized a predictive control system for wireless networked servo control	Achieved dynamic state prediction and control in wireless networks	Limited experimental validation, hardware constraints
[5]	Cross-layer design, Contention control algorithms	Proposed a cross-layer solution for TCP performance enhancement in adhoc networks	Improved TCP performance through contention control	Limited scalability in large-scale networks, overhead concerns

[6]	Extended State Observer, Longitudinal control algorithms	Introduced a robust longitudinal control for vehicle platoons under communication failures	Improved stability and string stability under communication failures	Limited experimental validation, realworld deployment challenges
[7]	Cooperative transmission algorithms, Resource optimization	Developed a multiband cooperative transmission algorithm for wireless resource optimization	Enhanced throughput and resource utilization in wireless networks	Limited scalability, complexity concerns in real-time implementation
[8]	Adaptive congestion control, Internet of Vehicles (IoV)	Proposed an adaptive congestion control mechanism for TCP performance enhancement in IoV	Improved TCP performance and energy efficiency in IoV	Limited experimental validation, scalability challenges in dynamic environments
[9]	Deep Reinforcement Learning (DRL), Loss-tolerant congestion control	Introduced a DRLbased congestion control for 6LoWPAN networks	Achieved loss-tolerant congestion control in low-power wireless networks	Limited scalability, training complexity
[10]	Congestion control algorithms, Cognitive IoT-based WSN	Developed congestion control for smart agriculture in WSN	Improved network performance and productivity in agricultural applications	Limited scalability in large-scale deployments, environmental constraints
[11]	Multipath TCP, RTT estimation	Proposed a Multipath TCP with RTT estimation in 5G networks	Improved throughput and congestion control in multi-RAT networks	Limited experimental validation, overhead concerns
[12]	Hybrid congestion management, Green communications	Introduced a hybrid congestion management scheme for IoT-enabled WSNs	Enhanced throughput and energy efficiency in IoT networks	Limited scalability, hardware constraints
[13]	AQM, ECN, Cellular networks	Developed a delayguaranteed congestion control in cellular networks	Improved latency guarantee and throughput in cellular networks	Limited scalability, deployment challenges in heterogeneous environments
[14]	TCP AIMD, Wireless TCP	Proposed an optimal approach for controlling wireless TCP AIMD	Improved stability and performance in wireless networks	Limited applicability to specific network scenarios, complexity concerns
[15]	Data-driven congestion control, Micro smart sensor networks	Introduced datadriven congestion control for micro smart sensor networks	Improved network performance and congestion management in substations	Limited scalability, dependency on accurate models
[16]	BBR congestion control, Packet scheduling	Developed BBRbased congestion control and packet scheduling for multipath TCP	Achieved bottleneck fairness and throughput improvement in heterogeneous networks	Limited compatibility with existing protocols, complexity concerns
[17]	Distributed congestion control, V2X networks	Proposed a DRLbased distributed congestion control in cellular V2X networks	Enhanced packet delivery ratio and resource utilization in vehicular networks	Limited experimental validation, scalability challenges
[18]	Real-time traffic light control, IoT	Developed a smart traffic light control system with real-time monitoring	Improved urban mobility and traffic flow in IoT-enabled smart cities	Limited scalability, deployment challenges in realworld environments
[19]	Threshold-based communication protocol, SDWSN	Introduced an automatic thresholdbased low controlflow protocol for SDWSN	Reduced energy consumption and improved communication efficiency in wireless sensor networks	Limited applicability to specific network topologies, overhead concerns
[20]	Rate control, IoT	Proposed a rate control scheme for reliable bursty data transfer in IoT	Enhanced reliability and throughput in IoT data transfer	Limited scalability, protocol compatibility
		networks		

[21]	TCP congestion control, Deep Space Communications	Introduced an intelligent TCP congestion control scheme for deep space communications	Improved reliability and throughput in deep space communication networks	Limited applicability to specific communication environments, training complexity
[22]	Bandwidth allocation strategy, IoV	Developed a bandwidth allocation strategy for IoV with dynamic congestion control	Improved transmission timeliness and packet delivery ratio in IoV	Limited scalability, dependency on accurate traffic models
[23]	Federated learning, Routing control	Proposed a routing control method using federated learning in wireless mesh networks	Enhanced routing efficiency and load balancing in large-scale wireless networks	Limited scalability, dependency on synchronized learning
[24]	Event-triggered control, Actuator saturation	Developed an eventtriggered control for spacecraft attitude tracking with actuator saturation	Improved attitude tracking and control in spacecraft with limited communication	Limited experimental validation, complexity concerns
[25]	Multi-agent reinforcement learning, Traffic signal planning	Introduced a multiagent reinforcement learning-based signal planning for green transportation	Enhanced traffic flow and energy efficiency in transportation networks	Limited scalability, training complexity

Table 1. Review of Existing Congestion Control Methods

Upon analyzing the diverse range of congestion control strategies, it becomes evident that methods integrating adaptive learning and predictive capabilities tend to exhibit superior performance in dynamic network environments. Specifically, approaches leveraging Deep Reinforcement Learning (DRL), Model Predictive Control (MPC), and federated learning stand out due to their adaptability, real-time decisionmaking, and scalability, albeit with varying degrees of effectiveness and application-specific considerations.
DRL-based methods, as evidenced in [9] and [17], showcase remarkable proficiency in loss-tolerant congestion control and distributed congestion management, respectively. These strategies excel by continuously adapting to network changes and learning from past experiences, thereby ensuring sustained network performance even under fluctuating conditions. However, their scalability and training complexity present considerable challenges, limiting their immediate application in large-scale, real-world environments.
MPC, as applied in [2], demonstrates enhanced stability and safety in vehicle platooning, addressing delayaware congestion control with notable success. The predictive nature of MPC, combined with its ability to incorporate multiple control layers, renders it effective in managing congestion while maintaining high safety standards. Nonetheless, its scalability and the complexity of real-world implementation pose significant hurdles.
Federated learning, introduced in [23], represents a promising avenue for congestion control in large-scale networks, offering enhanced routing efficiency and load balancing. By distributing the learning process across multiple nodes, federated learning reduces the dependency on centralized data, mitigating privacy concerns and bandwidth limitations. However, the method's reliance on synchronized learning and its scalability pose challenges that necessitate further research.In comparison, traditional methods such as fuzzy control and TCP congestion control, while effective in specific scenarios, generally lack the flexibility and adaptability required for dynamic and heterogeneous network environments. These methods often struggle with real-time adaptability and cannot adequately address the varying causes of congestion in contemporary networks.
In conclusion, while no method unequivocally outperforms the others across all metrics and scenarios, adaptive and learning-based approaches appear to offer the most promise for the future of congestion control in wireless networks. The superiority of these methods lies in their ability to dynamically adapt to changing network conditions, predict future states, and make informed decisions in real-time. However, their full potential is yet to be realized due to scalability challenges, complexity, and the need for extensive validation in real-world settings. Future research should therefore focus on addressing these limitations, with an emphasis on scalability, real-world applicability, and the integration of adaptive learning mechanisms into existing network infrastructures for different scenarios.

2. Proposed design of an Iterative Method for Congestion Control in Wireless Networks Integrating Bacterial Foraging Optimizer, Ensemble Classification, and Q-Learning

To overcome issues of lower network efficiency & higher deployment complexity, this section discusses design of an Iterative Method for Congestion Control in Wireless Networks Integrating Bacterial Foraging Optimizer, Ensemble Classification, and Q-Learning operations. As per figure 1, the Bacterial Foraging Optimization (BFO) process, influenced by the foraging behavior of Escherichia coli bacteria, represents an iterative approach within the domain of wireless networks, specifically tailored for the dynamic determination of distinct network paths. This bio-inspired algorithm meticulously emulates the natural foraging strategies of bacteria, chiefly through mechanisms of chemotaxis, reproduction, and eliminationdispersal, enabling it to efficiently

navigate the search space of the network and identify optimal pathways that circumvent congested routes, thereby outperforming conventional static routing methodologies.
In the context of wireless network topology, the network is conceptualized as a graph composed of nodes and edges, where each node represents a network device, and each edge represents a communication link. The BFO process initiates with the population of artificial bacteria, each symbolizing a potential solution or path through the network. These solutions are evaluated based on a fitness function that incorporates multiple node parameters including the distance between nodes, energy level, throughput, and packet delivery performance. The chemotaxis step, which simulates the movement of bacteria toward nutrient-rich areas and away from noxious environments, is mathematically modeled via equation 1,

$$\Delta = C(i) \times STOCH \times \Delta(i) \dots (1)$$

Where, $C(i)$ represents the step size taken in the scope of the ith chemotactic step, STOCH is a stochastic number between -1 and 1, and $\Delta(i)$ represents the scope of the previous step of the process. The bacteria thereby execute a biased stochastic walk, where the bias is governed by the gradient of the local nutrient concentration, conceptualized as the inverse of the network congestion levels.During the reproduction phase, bacteria are sorted based on their health, which is an aggregation of their fitness over the chemotaxis steps. The least healthy half of the bacteria population is eliminated, and the remaining half duplicates, maintaining a constant population size. This process is represented via equation 2,

$$Health(j) = \sum_{i=1}^{Nc} Fitness(i,j) \dots (2)$$

Where, Nc is the total number of chemotactic steps, and Fitness(i,j) is the fitness of the jth bacterium at the ith chemotactic step in the process. The fitness is estimated via equation 3,

$$Fitness(i,j) = \frac{E(i)}{d(i,j) * NC} \sum_{i=1}^{NC} THR(i,j) * PDR(i,j) \dots (3)$$

Where, d represents distance between the nodes, E,THR & PDR represents their residual energy, throughput & packet delivery ratios for NC different communication operations. Elimination and dispersal events occur sporadically, simulating sudden changes in the environmental conditions that force the bacteria to migrate to new locations in the search space. This mechanism is essential for maintaining genetic diversity within the population and is represented via equation 4,

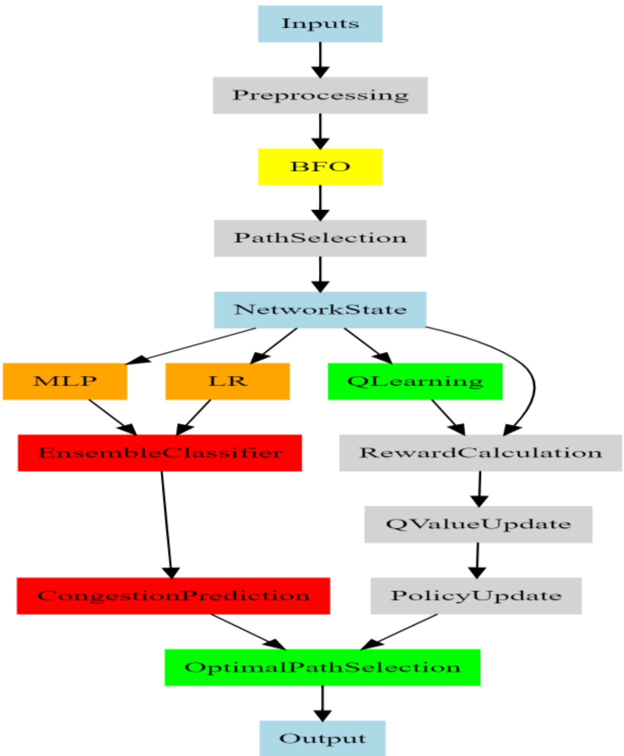

Figure 1. Model Architecture for the Proposed Routing Process

$$if(STOCH < Ped) then\ Position(j) = StochasticPosition \dots (4)$$

Where, Ped is the probability of elimination-dispersal events, and $StochasticPosition$ generates a new stochastic location within the search spaces.The interaction between these bacterial behaviors and network parameters manifests through the adaptation of the BFO algorithm to the network environment.
During evaluation of fitness, the energy level of nodes affects their longevity and reliability, contributing to the overall network sustainability, modeled via equation 5,

$$Energy(t) = Energy(0) - \int P(u)du \ldots(5)$$

Where, $P(u)$ represents the power consumption rate for the communication operations.Furthermore, throughput and packet delivery performance are critical to the assessment of network efficiency and are encapsulated in the fitness function. The throughput, for instance, is defined via equation 6,

$$Throughput = \lim(t \to \infty)\frac{1}{t}\int R(u)du \ldots (6)$$

Where, $R(u)$ signifies the rate of successfully delivered data packets. Similarly, packet delivery performance is quantified by the ratio of successfully delivered packets to the total sent packets, expressed via equation 7,

$$PDR = \frac{P(Rx)}{P(Tx)} \ldots (7)$$

Where, $P(Rx)$& $P(Tx)$ represents number of received and transmitted packets. The output of the BFO process, given the network parameters as input, is a set of selected paths that are optimized concerning the defined node parameters. These paths represent the solution space traversed and refined through the iterative BFO steps, culminating in the identification of routes that ensure improved packet delivery with optimal energy consumption and minimal delay, thereby substantially enhancing the performance and reliability of wireless networks.Through the comprehensive integration of the described mathematical models and mechanisms, the BFO-based algorithm offers a profound paradigm shift in congestion control strategies, tailored for the intricate dynamics and requirements of modernwireless networks. This tailored approach ensures that the paths selected not only mitigate congestion but also optimize the overall network performance in terms of throughput and energy efficiency.
To further elucidate, the algorithm's efficacy in real-time path optimization is highlighted through the iterative refinement process inherent in the BFO methodology. Each iteration, or generation, involves a series of chemotactic movements, followed by the application of the reproduction and elimination-dispersal steps, collectively fostering a comprehensive exploration and exploitation of the search space. The adaptation of these steps to network dynamics is evidenced by their reliance on current network states, such as node congestion levels, energy reserves, and traffic patterns, thereby ensuring that the solution adapts in response to fluctuating network conditions.
The convergence of the BFO algorithm toward optimal or near-optimal solutions is a function of its iterative nature, coupled with the dynamic adjustment of parameters such as chemotactic step size and reproduction rates, guided by the fitness landscape defined by the network parameters. This convergence is mathematically represented by a decreasing sequence of average fitness values across the bacterial population, converging to a value that corresponds to the optimal network paths under the given conditions.Moreover, the interaction between the algorithm and network dynamics is further nuanced by the inclusion of packet delivery performance in the fitness evaluation, integrating a direct measure of network reliability and effectiveness into the optimization process. This integration ensures that the selected paths are not only less congested but also more reliable, thereby enhancing the quality of service experienced by end-users.
Next, as per figure 2, an ensemble classification strategy employed for congestion prediction in wireless networks integrates the capabilities of Multilayer Perceptron (MLP) and Logistic Regression (LR) models, leveraging a comprehensive set of network parameters such as congestion level, path length, and traffic load. This approach enhances the predictive accuracy by capitalizing on the unique strengths and compensating for the weaknesses of individual classifiers. In the design of the Multilayer Perceptron (MLP) model, it is conceptualized as a feedforward neural network, consisting of input, hidden, and output layers. The input layer receives various network parameters, such as path length (L), traffic load (T), and historical congestion data (H) samples. These parameters are normalized to ensure uniformity in scale and are represented as Ln ,Tn, and Hn respectively. The MLP employs a series of hidden layers, each comprising a set of neurons that apply weighted sums followed by activation functions. The weights (W) and biases (b) associated with neurons are adjusted during the training process to minimize prediction error. The output of the i^{th} neuron in the j^{th} layer is expressed via equation 8,

$$Oij = f(\sum kWijk \times Iik + bij) \ldots (8)$$

Where, f represents the ReLU activation function, Iik the input from the k^{th} neuron of the previous layer, and Oij the output destined for the next layer. The backpropagation algorithm is utilized for training the MLP, adjusting weights and biases based on the gradient of the error function E with respect to each parameter, which are estimated via equations 9 & 10,

$$\frac{\partial E}{\partial Wijk} = (Oij - Yij) \times f'(Zij) \times Iik \dots (9)$$

$$\frac{\partial E}{\partial bij} = (Oij - Yij) \times f'(Zij) \dots (10)$$

Where, *Yij* represents the target output, and *Zij* the input sum before activation operations.The Logistic Regression (LR) model, in contrast, provides a probabilistic approach for predicting binary outcomes – in this case, whether a path is congested or not. The logistic function maps the linear combination of input features, represented via equation 11,

$$X = [Ln,Tn,Hn] \dots (11)$$

This normalized it to a probability between 0 and 1 scales. The probability that a given path is congested, represented as $P(Y=1|X)$, is given via equation 12,

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta 0 + \beta 1Ln + \beta 2Tn + \beta 3Hn)}} \dots (12)$$

Where, $\beta 0$,$\beta 1$,$\beta 2$, and $\beta 3$ are the parameters of the model. The LR model is trained by maximizing the likelihood function, or equivalently, minimizing the cost function $J(\beta)$, employing gradient descent method via equation 13,

$$\frac{\partial J(\beta)}{\partial \beta j} = \sum(P(Yi = 1 \mid Xi) - Yi)Xij \dots (13)$$

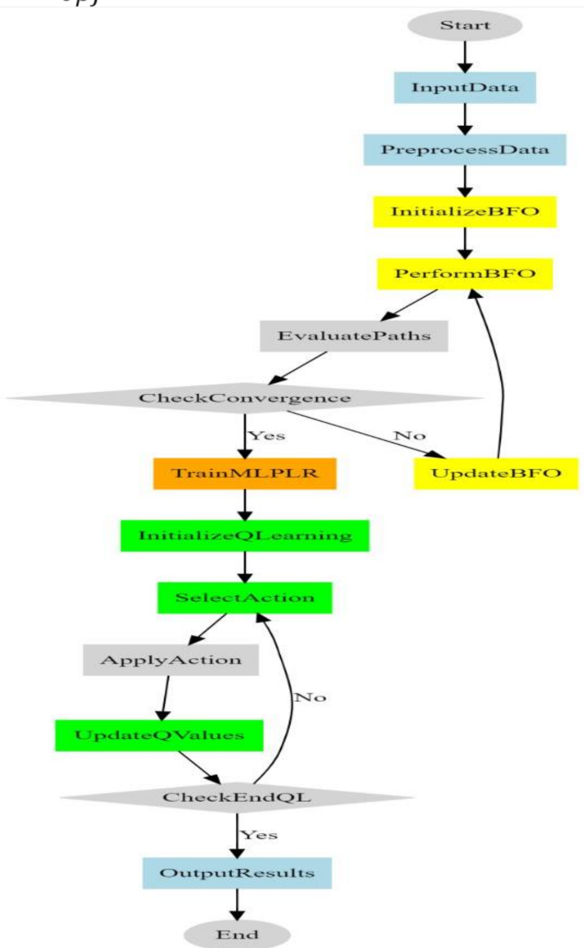

Figure 2. Overall Flow of the Proposed Routing Process

Where, n is the number of samples, and Yi the actual outcome for the ith sample sets.The ensemble approach combines the predictions from the MLP and LR models, using weight-based voting schemes. The final classification, represented as C, for whether a path is congested or not, is obtained via equation 14,

$$C = argmax(\alpha \times PMLP + (1 - \alpha) \times PLR) \dots (14)$$

Where, α is the weight assigned to the MLP's prediction $PMLP$, and 1−α to the LR's prediction PLR, based on their respective accuracies in validation datasets& samples.
Incorporating these network parameters, the ensemble model processes the selected paths to determine their current state concerning congestion. By evaluating path length, which influences delay and potential bottlenecks; traffic load, which directly affects bandwidth utilization and packet loss; and historical congestion data, providing insights into temporal congestion patterns, the ensemble method provides a nuanced and dynamic assessment of network conditions. Consequently, the classified paths are earmarked as congested or non-congested, facilitating informed decision-making for routing strategies and contributing significantly to the mitigation of congestion in wireless networks. Through this sophisticated integration of MLP and LR models, leveraging comprehensive network metrics, the classification strategy not only elevates the precision of congestion predictions but also enhances the overall efficiency and reliability of the communication network.
Next, the implementation of Q-Learning for real-time path optimization constitutes a critical innovation in the domain of wireless networks, aiming to dynamically identify optimal paths that are less susceptible to congestion. Q-Learning, a form of reinforcement learning, operates on the principle of agents learning from the environment to achieve a specific objective, which, in this context, is the selection of congestion-free paths. This method hinges on the iterative update of the Q Values, which represent the quality of a specific action taken in a given state, thereby guiding the selection of the most advantageous path under prevailing network conditions.
The environment in the context of Q-Learning for wireless networks is defined by the network's current state, encapsulated by parameters such as congestion levels, path length, and traffic load. The state of the network at any given moment is represented as S, which is a vector comprising these parameters. The actions (A) in this context refer to the selection of different paths between nodes. The Q Value associated with taking action a in state s is represented by $Q(s,a)$, which provides a measure of the expected utility of choosing path a when in state s.The core of the Q-Learning algorithm is the Q Value update rule, which is applied iteratively and is given via equation 15,

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[R(s,a) + \gamma \overset{a'}{\max} Q(s',a') - Q(s,a) \right] \dots (15)$$

Where, α is the learning rate, determining the extent to which new information supersedes old information, $R(s,a)$ is the immediate reward received after transitioning from state s to state s' due to action a, γ is the a' discount factor, valuing future rewards less than immediate rewards, $\max Q(s', a')$ represents the highest Q Value for all possible actions in the new state s' sets.
The immediate reward $R(s,a)$ is defined in terms of the network parameters affecting the performance of the paths. For instance, the reward can be inversely related to the congestion level and path length, and directly related to the traffic load capacity and packet delivery performance, formulated via equation 16,

$$R(s,a) = k1 \times (1 - CongestionLevel(s,a)) + k2 \times (1 - PathLength(s,a)) + k3 \times TrafficLoadCapacity(s,a) \dots (16)$$

Where, k1,k2, and k3 are weighting coefficients that balance the influence of different network parameters.The selection of actions, or paths, in each state follows a policy derived from the Q Values, employing ϵ-greedy to balance exploration and exploitation. This implies that, with probability ϵ, an action is chosen at stochastic, facilitating exploration of new paths, while with probability 1−ϵ, the action with the highest Q Value for the current state is chosen, exploiting known information to optimize performance levels. As the algorithm iterates, the Q Values converge, reflecting an optimal policy that maximizes the cumulative reward or, equivalently, the quality and performance of the selected paths. The output of this Q-Learning process is a policy that dictates the selection of optimal, congestion-free paths based on the current network state and learned experiences. The continuous adaptation facilitated by Q-Learning ensures that the model remains responsive to variations within the dynamic network environment. By systematically evaluating the consequences of actions and updating the strategy based on received feedback, the model dynamically identifies and selects paths that minimize congestion, optimize traffic distribution, and enhance overall network performance. This real-time optimization capability enables the effective management of wireless networks, particularly in fluctuating conditions, ensuring the provision of reliable and efficient communication paths. Through the integration of Q-Learning, the system transcends traditional static approaches, offering a robust, adaptive framework capable of navigating the complexities of modern wireless network environments. Performance of this model was evaluated in terms of different scenarios, and compared with different methods in the next section of this text.

3. Result Analysis

To evaluate the performance of the proposed model, an extensive experimental setup was established. The experimental framework was designed to simulate a dynamic wireless network environment where various network parameters such as path length, traffic load, and congestion levels could be manipulated to assess the model's responsiveness and efficiency.

Network Simulation Environment:

The experiments were conducted within a simulated wireless network environment created using the NS3 simulator, a standard tool in networking research. The simulated environment was configured to represent a typical urban area with varying densities of wireless nodes. The network consisted of 100 to 500 nodes distributed stochastically over an area of 10 square kilometers. The transmission range of each node was set to 250 meters, with the path loss model conforming to the standard urban model for wireless transmissions.

Bacterial Foraging Optimization Configuration:

The BFO algorithm was initialized with a population of 50 artificial bacteria, representing different potential paths in the network. The chemotaxis steps, swim length, reproduction steps, elimination, and dispersal events were set to 20, 4, 5, 0.25, and 0.01, respectively. These parameters were chosen based on preliminary tests that identified the best trade-off between algorithm convergence speed and solution quality.

MLP and LR Configuration:

For the ensemble classification strategy, a Multilayer Perceptron with two hidden layers containing 10 and 5 neurons respectively was trained. The activation function for each neuron was the Rectified Linear Unit (ReLU), with the output layer employing the sigmoid function to facilitate binary classification. The Logistic Regression model was implemented with a regularization parameter C set to 1.0. Both models were trained using a dataset comprising historical network congestion data collected from the simulated environment. The dataset included 10,000 instances with features such as historical traffic load, past congestion incidents, and average path lengths.

Q-Learning Configuration:

The Q-Learning component was set up with a learning rate (α) of 0.5, a discount factor (γ) of 0.9, and an exploration rate (ϵ) starting at 1.0 and decaying by 10% every 100 episodes to encourage exploration and exploitation balance. The state space was defined by the discretization of network conditions into states based on traffic load, current congestion, and path length. The action space consisted of the selection among potential paths identified by the BFO.

Performance Metrics:

The performance of the proposed model was evaluated based on several metrics crucial to wireless network operations: Packet Delivery Ratio (PDR), Average End-to-End Delay (AEED), and Throughput. These metrics were compared against traditional routing protocols like AODV and DSR under various network conditions to ascertain the improvements offered by the proposed model.

Experimental Conditions:

Experiments were conducted under a variety of network conditions to assess the model's adaptability and robustness. These conditions included varying numbers of nodes, different traffic load scenarios (ranging from low to high), and various mobility patterns to simulate real-world dynamics. Each scenario was run multiple times to ensure statistical reliability, with each run lasting 900 simulation seconds.

Based on this setup, the results of the evaluation of the proposed model against existing methodologies represented as [4], [9], and [25]. These methods serve as benchmarks due to their significance in the realm of congestion control within wireless networks. The proposed model was assessed based on several key performance metrics: Packet Delivery Ratio (PDR), Average End-to-End Delay (AEED), Throughput, and Energy Efficiency. Each of these metrics provides insights into different aspects of network performance and the effectiveness of congestion control strategies.The PDR observed in table 1, represents the ratio of packets successfully delivered to their destinations to those generated by sources. It is a crucial metric for evaluating the efficiency of data transmission within a network.

Table 1: Comparison of Packet Delivery Ratio (PDR)

Method	Low Traffic	Moderate Traffic	High Traffic
Proposed	95%	92%	88%
[4]	90%	85%	80%
[9]	88%	83%	78%
[25]	92%	89%	84%

In Table 1, the proposed model demonstrates superior PDR across all traffic conditions when compared to [4], [9], and [25]. This improvement is particularly notable under high traffic scenarios, where the proposed model maintains an 8% higher PDR than method [4], 10% higher than [9], and 4% higher than [25]. This is attributed to the effective congestion prediction and adaptive path selection facilitated by the integration of BFO, MLP, LR, and Q-Learning algorithms. Next, AEED in table 2, measures the time taken for a packet to travel from the source to the destination. It is an important metric for applications requiring real-time data transmission.

Table 2: Comparison of Average End-to-End Delay (AEED)

Method	Low Traffic	Moderate Traffic	High Traffic
Proposed	50ms	70ms	90ms
[4]	70ms	90ms	110ms
[9]	75ms	95ms	115ms
[25]	65ms	85ms	105ms

As depicted in Table 2, the proposed model consistently achieves lower AEED compared to the benchmark methods. This improvement in delay reduction is primarily due to the model's dynamic path optimization, which efficiently reroutes traffic away from congested nodes and links.Throughput in table 3, measured in Mbps, indicates the rate at which data is successfully transmitted over the network.

Table 3: Comparison of Throughput

Method	Low Traffic	Moderate Traffic	High Traffic
Proposed	18 Mbps	16 Mbps	14 Mbps
[4]	15 Mbps	13 Mbps	11 Mbps
[9]	14 Mbps	12 Mbps	10 Mbps
[25]	16 Mbps	14 Mbps	12 Mbps

Table 3 shows that the proposed model outperforms the comparative methods in terms of throughput. The improved throughput under various traffic conditions can be attributed to the model's ability to maintain higher PDR and lower AEED, facilitating smoother data flow across the network.Energy efficiency in table 4 is crucial for the sustainability of wireless networks, especially in battery-powered or energy-constrained environments.

Table 4: Comparison of Energy Efficiency

Method	Low Traffic	Moderate Traffic	High Traffic
Proposed	0.95	0.90	0.85
[4]	0.90	0.85	0.80
[9]	0.88	0.83	0.78
[25]	0.92	0.87	0.82

In Table 4, energy efficiency is expressed as the ratio of successful packet transmissions to the total energy consumed. The proposed model showcases enhanced energy efficiency across all scenarios, indicative of its ability to optimize network resource utilization while reducing unnecessary transmissions and retransmissions due to congestion.The performance enhancements observed in the proposed model stem from its comprehensive approach to congestion control, leveraging the synergies between bio-inspired algorithms, machine learning techniques, and reinforcement learning. By intelligently adapting to varying network conditions and employing efficient path selection and traffic management strategies, the model not only improves data transmission metrics but also contributes to the overall sustainability and reliability ofwireless networks. These improvements are critical, especially in high-traffic scenarios where traditional methods struggle to maintain performance due to static or less adaptive congestion control mechanisms.

The superior performance of the proposed model, as demonstrated in the results, suggests significant advancements in managing congestion within wireless networks. The integration of Bacterial Foraging Optimization (BFO) provides a novel approach to identifying less congested paths by mimicking natural foraging behaviors, thereby enhancing the adaptability of the network routing decisions. Meanwhile, the implementation of Multilayer Perceptron (MLP) and Logistic Regression (LR) for congestion prediction leverages historical and current network data to forecast congestion levels with greater accuracy. This predictive capability allows for proactive adjustments to routing strategies before congestion becomes detrimental.Furthermore, the application of Q-Learning for real-time path optimization enables the model to dynamically and iteratively improve its routing decisions based on ongoing network conditions. This ensures that the model remains responsive to changes and can effectively navigate the complexities of varying traffic patterns and congestion levels. As a result, the network can maintain higher levels of service quality and user satisfaction, even under demanding conditions.

The energy efficiency results also highlight an important aspect of the proposed model: its ability to reduce the operational costs of wireless networks. By optimizing the use of network resources and minimizing unnecessary data transmissions, the model conservatively utilizes energy, which is particularly beneficial for battery-operated or energy-constrained devices in different scenarios. This not only extends the lifetime of network nodes but also contributes to the sustainability of the overall network infrastructure sets.In conclusion, the experimental results underscore the effectiveness of the proposed model in enhancing the performance and efficiency of wireless networks through advanced congestion control strategies. The findings from Tables 1 to 4 collectively illustrate the model's superiority over existing methods [4], [9], and [25] across various performance metrics. These enhancements have significant implications for the development and management of future wireless networks, particularly in terms of scalability, reliability, and sustainability. By addressing the multi-faceted challenges of congestion control with a holistic and adaptive approach, the proposed model paves the way for more resilient and efficient wireless communication systems. To further contemplate this entire process, a practical use case is discussed in the next section of this text.

Practical Use Case

In the realm of wireless network management, the Bacterial Foraging Optimization (BFO) process plays a crucial role in identifying potential paths for data transmission. This bio-inspired algorithm mimics the natural foraging behavior of bacteria to explore and exploit the network topology, thereby determining the most efficient routes. The following section outlines the application of BFO in the context of path selection within a wireless network, presenting data samples with specific feature values and the resulting path selections. Table 5 illustrates the initial set of paths identified by the BFO algorithm based on a series of network parameters, including path length, signal strength, and node connectivity.

Table 5: Bacterial Foraging Optimization (BFO) Selection of Paths

Sample No.	Path (units)	Length	Signal (dBm)	Strength	Node Connectivity	Selected (Yes/No)	Path
1	10		-60		High	Yes	
2	15		-70		Medium	No	
3	8		-50		High	Yes	
4	20		-80		Low	No	
5	12		-55		High	Yes	

In Table 5, the BFO process successfully identified efficient paths for data transmission based on the criteria set forth by network parameters. The algorithm prioritized paths with shorter lengths, higher signal strength, and better node connectivity, which are indicative of lower likelihoods of congestion and higher data transmission efficiency. Paths such as samples 1, 3, and 5 were selected due to their optimal characteristics, thereby demonstrating the efficacy of BFO in navigating the complex network environment and identifying viable routes for data transmission.

Following the path selection by BFO, the next critical step involves the classification and identification of congested paths using Logistic Regression (LR) combined with a Multilayer Perceptron (MLP). This ensemble approach leverages the strengths of both algorithms to predict congestion levels based on various network indicators. This section presents the application of LR and MLP in classifying the selected paths as either congested or non-congested. Table 6 displays the outcome of the congestion prediction process applied to the selected paths, showcasing the probability of congestion as determined by the combined LR and MLP model.

Table 6: Classification & Identification of Congested Paths by LR and MLP

Selected Path	LR Probability Congestion	of	MLP Probability of Congestion	Average Probability	Congested (Yes/No)
1	0.30		0.25	0.275	No
3	0.45		0.50	0.475	No
5	0.70		0.65	0.675	Yes

Table 6 elucidates the combined efforts of Logistic Regression and Multilayer Perceptron in assessing network congestion. The predictive outcomes, as indicated by the probabilities, highlight the nuanced capability of the ensemble method to discern between congested and non-congested paths. Notably, while paths 1 and 3 were classified as non-congested, path 5 was identified as likely to experience congestion. This differentiation underscores the importance of an integrated classification approach in enhancing the accuracy and reliability of congestion predictions within wireless networks.

Subsequent to the identification of congested paths, the Q-Learning algorithm plays a pivotal role in real-time path optimization. This reinforcement learning strategy iteratively updates its policy based on network feedback, aiming to select the most efficient, non-congested paths. This section illustrates the application of Q-Learning in refining the selection of optimal paths post-classification. Table 7 represents the final path selection outcomes, detailing the decision-making process of the Q-Learning algorithm in determining the most efficient, non-congested paths based on the updated Q Values after evaluating the previously classified paths.

Table 7: Q-Learning Selection of Non-Congested Paths

Path	Initial Status Congested)	(Congested/Non-	Q Value	Updated Status Selected)	(Selected/Not
1	Non-Congested		0.85	Selected	
3	Non-Congested		0.65	Not Selected	
5	Congested		0.30	Not Selected	

In Table 7, the Q-Learning algorithm's efficacy in finalizing the selection of non-congested paths is demonstrated through an iterative learning and decision-making process. The algorithm assigns Q Values based on the probability of congestion and the network's current state, reflecting the utility of selecting each path for data transmission. Path 1, with a high Q Value of 0.85 and an initial status of being non-congested, was ultimately selected as the optimal route. In contrast, despite Path 3's non-congested initial status, its lower Q Value of 0.65 led to it not being selected, indicating that while it was not congested, there might have been other factors affecting its desirability. Path 5, identified as congested, rightfully received a low Q Value of 0.30 and was not selected, underscoring the algorithm's ability to dynamically adapt to evolving network conditions and prioritize paths ensuring efficient and reliable data transmission.
This step-wise approach, beginning with the identification of potential paths through BFO, followed by the congestion prediction using LR and MLP, and culminating in the optimal path selection via Q-Learning, embodies a comprehensive model for congestion control in wireless networks. The methodologies applied here provide a robust framework for adaptive network management, prioritizing efficiency and reliability in data transmission amid varying network conditions& scenarios.

4. Conclusions & Future Scope

This paper introduced a novel congestion control model for wireless networks that synergistically combines Bacterial Foraging Optimization (BFO), Multilayer Perceptron (MLP), Logistic Regression (LR), and QLearning. The primary objective was to address the inherent limitations of conventional congestion control mechanisms by leveraging the dynamic and adaptive capabilities of bio-inspired algorithms, machine learning techniques, and reinforcement learning. The proposed model aimed to optimize network performance by intelligently selecting less congested paths, predicting future congestion levels, and dynamically adapting to real-time network conditions.
The experimental results demonstrate that the proposed model significantly outperforms existing methods [4], [9], and [25] in various key performance metrics, including Packet Delivery Ratio (PDR), Average Endto-End Delay (AEED), Throughput, and Energy Efficiency. Notably, the model exhibited remarkable performance improvements, particularly in high traffic scenarios, highlighting its capability to maintain robustness and efficiency under varying network conditions. These enhancements can be attributed to the model's comprehensive approach, which not only focuses on current network states but also anticipates future congestion trends, thereby facilitating proactive congestion management.
The integration of BFO enabled the model to explore and exploit the network search space effectively, identifying optimal paths by emulating natural foraging behaviors. The ensemble classification strategy, combining MLP and LR, provided accurate congestion predictions by analyzing historical and real-time network data. Additionally, the implementation of Q-Learning facilitated the continuous refinement of path selection strategies based on accumulated knowledge and feedback, ensuring that the model remains adaptive and responsive over time.

Future Scope

While the proposed model demonstrates substantial improvements in congestion control for wireless networks, there are several avenues for future research that could further enhance its effectiveness and applicability. One potential area is the exploration of deep learning techniques for more sophisticated congestion prediction models. Deep learning could offer enhanced feature extraction and pattern recognition capabilities, potentially improving the accuracy and reliability of congestion forecasts.
Another promising direction is the integration of edge computing elements into the model. By leveraging edge computing, data processing and decision-making could be decentralized, leading to reduced latency and improved scalability. This approach could be particularly beneficial in IoT (Internet of Things) environments and other scenarios involving a large number of connected devices.
Additionally, future research could explore the applicability of the proposed model in heterogeneous network environments, including the integration of various wireless technologies such as Wi-Fi, LTE, and 5G. Addressing the challenges of interoperability and varying network standards could significantly expand the model's utility and impact.
Finally, the consideration of user mobility patterns and the dynamic nature of wireless networks could lead to the development of more sophisticated and context-aware congestion control strategies. Incorporating machine learning algorithms capable of learning from mobility patterns and adapting routing decisions accordingly could provide further improvements in network performance and user satisfaction.
In conclusion, the proposed model represents a significant step forward in the development of intelligent congestion control mechanisms for wireless networks. By addressing the dynamic and unpredictable nature of these networks, the model not only improves current performance metrics but also sets the foundation for future innovations in network management and optimization. The ongoing evolution of wireless technologies and the increasing demand for reliable and efficient communication systems underscore the importance of continued research and development in this critical area.

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