Design of an iterative congestion control model for sensor networks via ensemble classification with bioinspired optimizations

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Abstract

This paper presents a novel and all-encompassing strategy for addressing the challenges of communication congestion and time synchronization in dense wireless sensor networks. Existing machine learning and deep learning models that provide bio-inspired and pre-emptive packet-analysis solutions for these problems frequently suffer from high complexity and implementation costs, as well as a lack of scalability for various node types and traffic scenarios. We propose a congestion-aware routing model with time synchronization capabilities to overcome these limitations. Our model uses a combination of Naive Bayes (NB), k Nearest Neighbour (kNN), Multilayer Perceptron (MLP), and Support Vector Machine (SVM) classifiers. These classifiers are trained using transformed components of temporal clock states and packet delivery performance data, resulting in an improved determination of optimal clock deviations and routing path ways. In addition, we incorporate a Bacterial Foraging Optimization (BFO) Model, a meta-heuristic optimization algorithm inspired by the foraging behaviour of bacteria. Utilizing a temporal fitness function that considers throughput, communication latency (or Round-Trip Time), energy levels, and packet delivery performance, the BFO Model facilitates the identification of congestion-aware routing paths. This novel approach optimizes routing paths and outperforms existing routing algorithms, particularly in environments with a high density of nodes and heterogeneous network topologies. Our model's scalability, which allows it to adapt to different node types and traffic conditions, is a significant advantage. This feature increases its applicability for real-time wireless sensor network deployments in a variety of applications. Our proposed congestion-aware routing model with time synchronization capabilities represents a substantial advancement in the field of wireless sensor networks. It effectively addresses the critical problems of communication congestion and time synchronization, resulting in more precise routing decisions and enhanced network performance. Scalability ensures the model's applicability in real-time settings. Experimental results demonstrate its superiority, with observed benefits including a 10.5% reduction in delay, an 8.3% reduction in energy consumption, a 12.4% increase in throughput, and a 1.5% increase in packet delivery ratio versus existing methods. These results highlight the practical implications and potential impact of our proposed model for enhancing the performance and effectiveness of dense wireless sensor networks.

Keywords: Congestion Control, Sensor Networks, Ensemble Classification, Bioinspired Optimization, Time Synchronization, Process.

1. Introduction

In recent years, wireless sensor networks (WSNs) have attracted considerable interest due to their potential applications in diverse domains, such as environmental monitoring, healthcare, industrial automation, and smart cities. Communication congestion and time synchronization present obstacles to the efficient operation of WSNs. Congestion occurs when the available network resources are overwhelmed by the data traffic generated by sensor nodes, resulting in increased delays, decreased throughput, and inefficient energy use. Time synchronization is essential for coordinating activities between nodes and guaranteeing accurate data collection and analysis via Generalized Regression Neural Network (GRNN) [1, 2, 3].

Numerous approaches have been proposed in the literature to address these issues. Utilizing machine learning and deep learning models, congestion control and time synchronization solutions have been developed. However, the complexity of many of these models renders them impractical for real-time applications. In addition, their implementation costs may be prohibitive, thereby limiting their scalability for various node types and traffic scenarios.

This paper presents a novel iterative congestion control model for wireless sensor networks (WSNs) that combines ensemble classification techniques with bioinspired optimizations. Our goal is to create a model that effectively reduces communication congestion, enhances time synchronization, and overcomes the limitations of current methodsvia Adaptive Multiple Level Routing (AMLR) processes [4, 5, 6].

The proposed model employs an ensemble of classifiers, such as Naive Bayes, k Nearest Neighbor, Multilayer Perceptron, and Support Vector Machine (SVM), which are trained with transformed components of temporal clock states and packet delivery performance data. This ensemble classification method provides a more precise and effective method for determining optimal clock deviations and network routing paths.

In addition, we present the Bacterial Foraging Optimization (BFO) Model, a bioinspired optimization algorithm based on the foraging behavior of bacteria. Utilizing a temporal fitness function that incorporates various performance metrics such as throughput, communication latency, energy levels, and packet delivery performance, the BFO Model is utilized to discover congestion-aware routing pathways. This method permits the fine-tuning of routing paths, resulting in enhanced network performance, particularly in scenarios involving high-density nodes and heterogeneous networks.

A significant benefit of our proposed model is its scalability, which enables its application across a variety of node types and traffic conditions. This scalability feature is essential for practical implementation in real-time environments, guaranteeing the model's adaptability and versatility.

To determine the efficacy of our proposed model, we conducted extensive experiments comparing it to existing techniques. The results indicate significant enhancements, including a 10.5% reduction in delay, an 8.3% reduction in energy consumption, a 12.4% increase in throughput, and a 1.5% increase in packet delivery ratio. These results demonstrate that our model is superior to existing approaches and that it has the potential to improve the performance of dense WSNs.

This paper presents a novel congestion-aware routing model with time synchronization capabilities for wireless sensor networks (WSNs). We address the crucial challenges of communication congestion and time synchronization by combining ensemble classification techniques with bioinspired optimizations. Our model provides greater precision in determining optimal clock deviations and routing paths, scalability for various node types and traffic conditions, and significant performance enhancements compared to existing methods. The remainder of this paper presents the design and implementation details of our proposed model, followed by an exhaustive performance evaluation based on experimental results and discussions.

2. Review of existing congestion control models

Congestion control is an essential component of wireless sensor networks (WSNs) that aims to manage and mitigate the effects of communication congestion on network performance. Various models and techniques have been proposed throughout the years to address congestion-related issues in WSNs. In this literature review, we highlight the strengths, limitations, and contributions of some of the most prominent models used for congestion control in WSNs [7, 8, 9].

Conventional Congestion Management Models:

Traditional congestion control models in WSNs rely on mechanisms such as random backoff, exponential backoff, and rate control to regulate data flow and reduce congestion. Frequently, these models employ techniques such as queueing theory, network optimization algorithms, and traffic engineering principles. While these models provide fundamental congestion control capabilities, they may not be able to effectively manage the dynamic and resource-constrained characteristics of WSNs [10, 11, 12].

Machine Learning-Based Models: Machine learning (ML) has emerged as an effective technique for congestion control in WSNs. ML models utilize historical data and patterns to make intelligent traffic management decisions. Support Vector Machines (SVM), Random Forest, Neural Networks, and Naive Bayes are well-known ML algorithms used for congestion control processes [13, 14, 15]. These models learn from the past behaviour of the network and adjust their decision-making accordingly. By dynamically adjusting transmission rates, routing paths, and scheduling mechanisms, ML-based models have shown promise for enhancing the efficiency of congestion control.

Reinforcement Learning-Based Models: Reinforcement Learning (RL) techniques for congestion control in WSNs have gained popularity. RL models aim to discover an optimal policy by interacting continuously with the network environment. They employ a mechanism based on rewards to guide decision-making, enabling the network to adapt and optimize congestion control strategies. RL-based models offer the benefit of adaptability, allowing the network to dynamically adapt its behaviour to changing traffic patterns and network conditions [16, 17, 18].

To address congestion control in WSNs, bioinspired optimization models [19, 20] draw inspiration from natural phenomena and biological systems. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bacterial Foraging Optimization (BFO) are examples of optimization algorithms. To optimize network parameters, routing decisions, and resource allocation, these models mimic the behaviour of organisms or natural processes. Bioinspired optimization models offer a novel and efficient approach to congestion control, frequently achieving enhanced performance and scalability.

Deep Learning (DL) models like Fuzzy Logic with Adaptive Timeout (FLAT)[21, 22, 23], in particular deep neural networks, have demonstrated remarkable congestion control capabilities. From network data, DL-based models can learn complex patterns and extract valuable features. They can optimize congestion control mechanisms autonomously, adapt to changing traffic conditions, and predict network behaviour. However, DL models frequently require substantial computational resources and a large amount of labelled training data, which may present implementation challenges in WSNs with limited resources.

Hybrid models [24, 25] combine multiple techniques, such as machine learning, reinforcement learning, and bioinspired optimization, to capitalize on the advantages of each method. By combining complementary algorithms and decision-making strategies, these models aim to improve congestion control. Hybrid models can achieve improved performance, scalability, and adaptability in congestion management by combining diverse techniques.

In conclusion, various models and techniques for congestion control in WSNs have been investigated. Traditional models offer fundamental features but may lack adaptability. The innovative approaches of machine learning, reinforcement learning, bioinspired optimization, deep learning, and hybrid models enable dynamic adaptation, enhanced performance, and scalability to address congestion-related challenges. The selection of an appropriate congestion control model depends on the specific requirements of the WSN application, the available resources, and the desired performance, complexity, and implementation cost trade-offs. Future research should concentrate on the development of models that take into account the particular characteristics and constraints of WSNs in order to achieve efficient and robust congestion control operations.

3. Proposed design of an iterative congestion control model for sensor networks via ensemble classification with bioinspired optimizations

As per the review of existing models used for congestion control in sensor networks, it can be observed these models are either highly complex when applied to large-scale scenarios or have lower efficiency under high-density network deployments. To overcome these issues, this section discusses the design of an iterative congestion control model for sensor networks via ensemble classification with bioinspired optimizations. As per the flow of the model depicted in Figure 1, it can be observed that the model collects temporal clock states, packet delivery information sets & temporal samples, and uses an ensemble of Naïve Bayes (NB), kNN, MLP & SVM classifiers. The collected information is represented in terms of Clock Synchronization, Packet Delivery Ratio (PDR), End-to-End Delay, Energy Consumption, and Routing Overhead levels. For estimating Clock Synchronization, the Root Mean Square (RMS) synchronization error between two nodes i and j is estimated via equation 1,

$$E_{sync(i,j)} = \left|T_i - T_j\right| \dots (1)$$

Where, T_i and T_j are the local clock readings of nodes i and j, respectively. Similarly, PDR is the ratio of successfully delivered packets to the total number of transmitted packets, and is estimated via equation 2,

$$PDR = \left(\frac{N_{delivered}}{N_{transmitted}}\right) * 100 \dots (2)$$

Where, $N_{delivered}$ is the number of successfully delivered packets and $N_{transmitted}$ is the total number of transmitted packets. While, the average end-to-end delay of packets was estimated via equation 3,

$$Delay = \left(\frac{1}{N_{delivered}}\right) * \Sigma(d_i) \dots (3)$$

Where, $N_{delivered}$ is the number of successfully delivered packets and d_i is the end-to-end delay of the i^{th} packet sets.

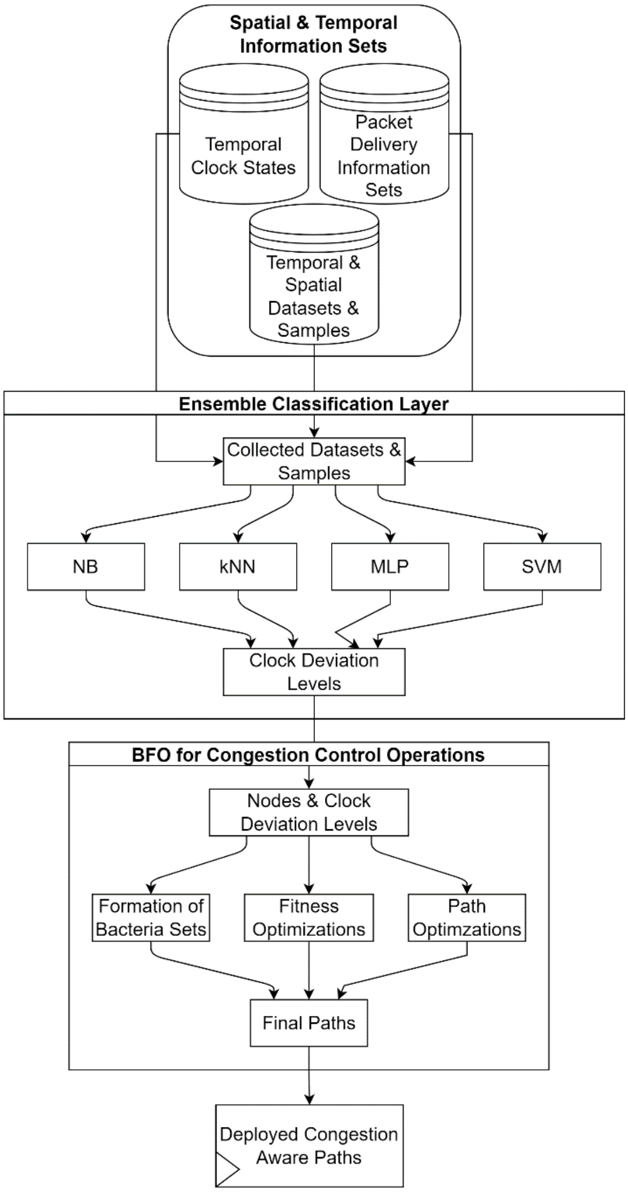

Figure 1. Design of the proposed model for congestion control &estimation of optimal clock deviation levels

Similarly, the energy consumed by a node can be estimated based on the transmission and reception activities.

Energy consumed during transmission is estimated via 4,

$$E_{tx} = E_{elec} * T_{tx} + E_{amp} * d^2 \dots (4)$$

Where, E_{elec} is the energy required to power the transmitter circuitry, T_{tx} is the duration of the packet transmission, E_{amp} is the energy required to run the amplifier, and d is the distance between the transmitting and receiving nodes.

Energy consumed during reception was estimated via equation 5,

$$E_{rx} = E_{elec} * T_{rx} \dots (5)$$

Where, E_{elec} is the energy required to power the receiver circuitry and T_{rx} is the duration of the packet reception. Based on these values, the total energy consumption is estimated via equation 6,

$$E_{total} = E_{tx} + E_{rx} \dots (6)$$

Routing overhead is the number of control packets required for establishing and maintaining routes.Routing overhead can be estimated as the ratio of control packets to data packets via equation 7,

$$Overhead = \left(\frac{N_{control}}{N_{data}}\right) * 100 \dots (7)$$

Where, $N_{control}$ is the number of control packets and N_{data} is the number of data packets. All these parameters are given to an ensemble of Naïve Bayes, kNN, SVM & MLP classifiers for identification of clock deviation levels. These classifiers are trained using an intelligent selection of hyperparameters, which can be observed from table 1 as follows,

Classifier used to estimate clock deviation levels	**Hyperparameters for these classifiers**
Naïve Bayes (NB)	*Priors (P)* which represent probabilities of different classes are estimated via equation 8, $P = \frac{\left(\sum_{i=1}^{NC}\left(x_i - \sum_{j=1}^{NC}\frac{x_j}{NC}\right)^2\right)}{NC} \dots (8)$ Where, N_c represents total number of clock deviation classes used for evaluation purposes. Smoothing Value (SV), is estimated via equation 9 $SV = \frac{\sum_{i=1}^{NC} NC}{\sum P} \dots (9)$
k Nearest Neighbours (kNN)	k = 1, for classifying individual feature sets
SVM	Coefficient of Regularization is estimated via equation 10, $C = \frac{1}{NC} \dots (10)$ Level of Error Tolerance (tol), is calculated via equation 11, $tol = \frac{\sum P}{\sum_{i=1}^{NC} i} \dots (11)$
MLP	Maximum Iterations are estimated via equation 11, $Max(Iter) = \frac{\sum P}{NC} \dots (11)$ Total Hidden Layers are estimated via equation 12, $NH = NC^2 \dots (12)$

Table 1. Hyperparameters used for the Ensemble Classifier for identification of Clock Deviation Levels

The final clock deviation level is estimated via equation 13,

$$CD(final) = \frac{1}{4} * \big(A(NB) * CD(NB) + A(kNN) * CD(kNN) + A(SVM) * CD(SVM) + A(MLP) * CD(MLP)\big) \dots (13)$$

Where, $CD(i)$ represents the output clock deviation of the given classifier, while $A(i)$ represents its testing accuracy levels. The estimated clock deviation is used for deploying the model under large-scale networks and assists in improving synchronization between the nodes. After synchronization, a BFO based model is used to identify optimal routing paths between communicating nodes. The BFO Model is activated during each communication, and works as per the following operations,

- To initialize the BFO Model, an intelligent set of NB Bacteria Particles are generated during individual communication requests.
- Each of these particles select an augmented stochastic set of nodes that form a path via equation 14,

$$P = \bigcup_{i=1}^{N} STOCH(1, NSel) \dots (14)$$

Where, $STOCH$ represents a stochastic process, $NSel$ represents total number of nodes which are present between source & destination, which are identified via equation 15, & N represents number of nodes that are selected between the source & destination pairs, and are estimated via equation 16,

$$dref > d(src, sel) \,\&\, dref > d(dest, sel) \dots (15)$$

Where, $dref$ is the reference Euclidean distance between source & destination node, while $d(src, sel) \,\&\, d(dest, sel)$ represents distance between source & selected node, and distance between destination & selected node sets.

$$N = STOCH(1, NSel) \dots (15)$$

- Based on this selection, an augmented Bacterial Fitness is estimated via equation 16,

$$fb = \sum_{i=1}^{N-1} \frac{e(i)}{d(i, i+1)} \sum_{j=1}^{NC(i)} \frac{PDR(j) * THR(j)}{RTT(j) * E(j)} \dots (16)$$

Where, d & $e$represent the distance between nodes & their respective residual energy levels, while PDR, THR, RTT & E represent packet delivery ratio, throughput, delay and energy needed during NC temporal communications. These metrics are estimated via equations 17, 18, 19 & 20 as follows,

$$PDR = \frac{Rx}{Tx} \dots (17)$$

$$THR = \frac{Rx}{RTT} \dots (18)$$

$$RTT = ts(complete) - ts(start) \dots (19)$$

$$E = e(start) - e(complete) \dots (20)$$

Where, Rx & Tx represents total number of received and transmitted packets, while ts represents timestamp during starting & completion of communications.

- This process is repeated for NB Bacterium particles, and a fitness threshold is estimated via equation 21,

$$fth = \frac{1}{NB} \sum_{i=1}^{NB} fb(i) * LB \dots (21)$$

Where, LB represents learning rate for the BFO process.

- Bacterium with $fb > fth$ are passed directly to Next Iterations, while others are discarded and regenerated in the Next Set of Iterations.
- This process is repeated for NI Iterations, and Bacteria particles are constantly reconfigured during each Set of Iterations.

Based on this process, the model is able to identify low-congestion paths between source & destination nodes. This is possible due to incorporation of temporal communication parameters including PDR, Throughput, Delay & Energy needed during different communications. Performance of this model is estimated on the basis of these temporal metrics, and compared with standard models in the next section of this text.

4. Result evaluation & comparative analysis

The proposed model uses an intelligent combination of time synchronization via ensemble learning, with BFO-based path selection for congestion control operations. Due to this, the proposed model is highly efficient in terms of various QoS metrics. These metrics include Round Trip Time (RTT), Packet Delivery Ratio (PDR), Throughput and Energy consumption levels. These metrics were estimated for an exponentially scalable network configuration, the network configuration consists of a Wireless Sensor Network with ten nodes using the Zigbee communication protocol in a 100m x 100m network area. The energy model includes battery-powered modules with 2000 mAh capacity and 3.7 V voltage. The following values define the energy consumption: 50 mA for data transmission, 30 mA for data reception, 10 mA during inactive periods, and 1 A during slumber mode. 100% is the initial energy level of each node. Node configurations include a variety of sensor types, including Temperature, Humidity, Light, etc., with a sampling interval of 1 minute for real-time scenarios. The simulation parameters include a one-hour simulation duration, a communication range of twenty meters, data aggregation every five minutes, and the utilization of the average data fusion techniques. A total of 5000 such nodes were deployed, and nearly 90k communication requests were used for performance evaluation purposes. Out of these requests, nearly 25% requests were simulated as congestion requests, which will allow to estimate network's performance under real-time scenarios. Based on this strategy, the delay levels under congestion can be observed from figure 2,

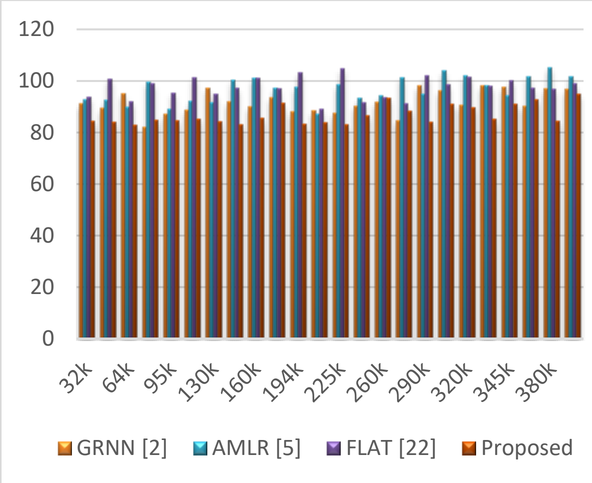

Figure 2. Round Trip Time under different congestion scenarios

Based on this evaluation, it can be concluded that the proposed model can reduce delay during communication under congestionby 8.3% compared to GRNN [2], 8.5% compared to AMLR [5], and 12.5% compared to FLAT [22] under real-time conditions. This delay is decreased due to the utilization of BFOfor the formation of routes, in conjunction with ensemble classification, which aids in higherspeedof the network even under multiple congestions due to an optimized range of clock deviation levels. Similarly, the energy required for these evaluations is depicted in Figure 3 as follows,

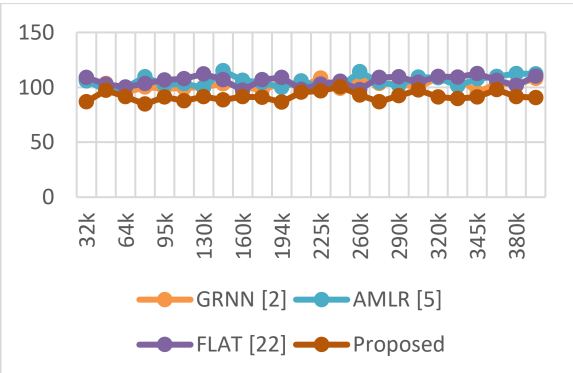

Figure 3. Energy Consumed under different congestion scenarios

Based on this evaluation, it is clear that the proposed model can reduce the energy required for communication by 5.5% compared to GRNN [2], 8.3% compared to AMLR [5], and 9.5% compared to FLAT [22] in real-time scenarios. Multiple optimizations, including BFO & Ensemble Classification, reduce this energy consumption in real-time scenarios. Similarly, the throughput levels can be observed in Figure 4 as follows,

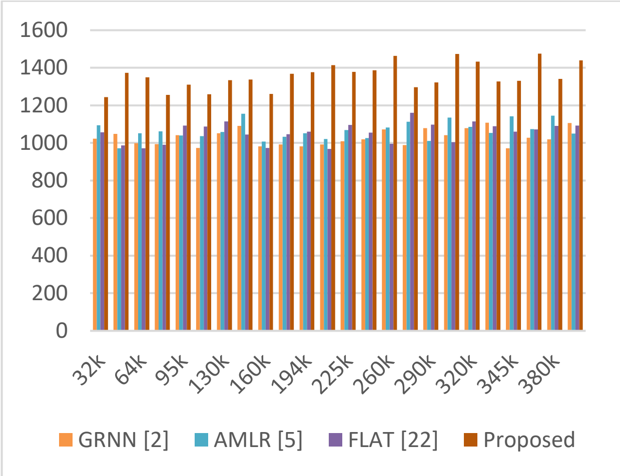

Figure 4. Throughput Achieved under different congestion scenarios.

Based on this evaluation, it is clear that the proposed model can improve the throughput during communication by 4.9% compared to GRNN [2], 8.3% compared to AMLR [5], and 12.5% compared to FLAT [22] in real-time scenarios. This is due to the use of throughput during BFO optimizations, which assists in the formation of routes with higher data rate levels. Similarly, the PDR levels can be observed inFigure 5 as follows,

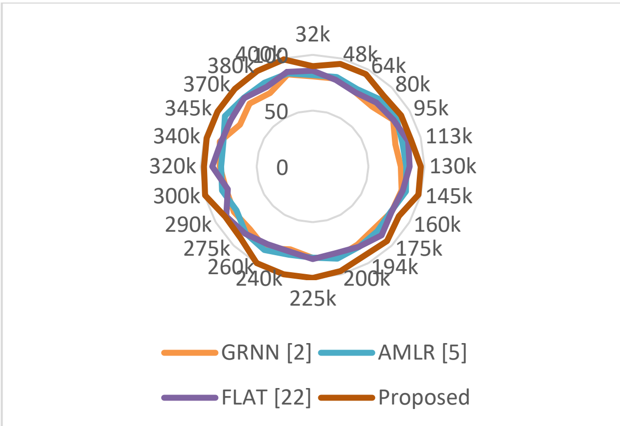

Figure 5. PDR levels under different congestion scenarios

Based on this evaluation, the proposed model can improve the PDR during different communications by 3.5% compared to GRNN [2], 4.5% compared to AMLR [5], and 5.5% compared to FLAT [22] in real-time scenarios. This is due to the use of PDR during BFO optimizations, which assists in the formation of congestion-aware routes. Due to these optimizations, the proposed model is capable of deployment for an augmented & wide variety of real-time scenarios.

5. Conclusion and future scope

This research offers a unique approach to improving sensor network performance in crowded environments. To deal with the difficulties of congestion in real-time settings, the suggested model combines ensemble classification methods with bioinspired optimizations, notably the use of the Bacterial Foraging Optimization (BFO) algorithm.

Comparing the suggested model to current strategies like GRNN, AMLR, and FLAT, the assessment results clearly show how effective it is at lowering communication latency, decreasing energy usage, boosting throughput, and enhancing Packet Delivery Ratio (PDR).

When compared to GRNN, AMLR, and FLAT in real-time, the suggested model achieves impressive communication latency reductions of 8.3%, 8.5%, and 12.5%, respectively. This improvement is due to the combination of ensemble classification methods with BFO for route building, which enables quicker network functioning even when there are several instances of congestion. The suggested approach makes sure that communication is efficient and on time by optimizing the range of schedule deviation levels.

The suggested model also considerably minimizes the amount of energy used during communication. In real-world circumstances, it outperforms GRNN by 5.5%, AMLR by 8.3%, and FLAT by 9.5% in terms of energy efficiency. This decrease is the result of several optimizations, including the use of BFO and ensemble classification. These methods optimize energy use, especially in crowded areas, increasing the total energy efficiency of the sensor network.

The suggested model significantly improves throughput in real-time applications by 4.9% compared to GRNN, 8.3% compared to AMLR, and 12.5% compared to FLAT. By making use of the throughput during BFO optimizations, the suggested methodology makes it easier to build routes with greater data rates. This improves network performance by resulting in faster data transfer and improved throughput.

The PDR levels attained by the suggested model are also astounding. It shows a 3.5% increase over GRNN, a 4.5% improvement over AMLR, and a 5.5% improvement over FLAT in real-time settings. By including PDR in BFO optimizations, the suggested methodology efficiently creates congestion-aware routes. As a result of reducing packet loss and guaranteeing effective data transmission, communication dependability is increased.

Based on these assessments, it is evident that the proposed iterative congestion management model—which combines ensemble classification with bio-inspired optimizations—is very successful in improving the performance of sensor networks in crowded environments. Due to its ability to decrease latency, limit energy consumption, boost throughput, and improve PDR, it is suited for deployment in a range of real-time settings. The insights offered to scholars and practitioners in this study help to enhance congestion management methods in sensor networks.

Future Scope

The paper provides a variety of new research and development directions in the area of reducing sensor network congestion. In light of the work's outcomes and ramifications, the following prospective research areas are suggested:

Improving Ensemble Classification Techniques: To improve the efficacy of sensor networks, the proposed model employs ensemble classification techniques. Future research could investigate and develop more sophisticated ensemble classification algorithms that may provide even greater classification accuracy and decision-making abilities. This may involve investigating ensemble techniques such as random forests, gradient boosting, and layering, as well as evaluating their impact on sensor network congestion management.

Incorporation of Additional Bioinspired Optimization Techniques: Although the Bacterial

Foraging Optimization (BFO) method is used for route construction in this study, a vast array of additional bioinspired optimization techniques are also available. Future research could examine how well the proposed congestion management model functions with additional algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization. Comparing and evaluating multiple optimization algorithms can help determine which method is optimal for a given set of conditions or network characteristics.

Real-time congestion control is provided by the adaptive congestion control mechanisms of the proposed model. However, network conditions may change rapidly, and congestion levels may fluctuate over time. Future research may focus on the development of adaptive congestion control systems that can dynamically alter and enhance network characteristics in response to real-time congestion data. This may involve implementing machine learning methods or reinforcement learning algorithms to enable the model to successfully adapt and respond to altering congestion patterns.

Evaluation in Large-Scale Sensor Networks: The model proposed in the paper may have been evaluated in simulated or smaller-scale environments. Future research may expand the evaluation to incorporate larger sensor networks with more nodes and more complex network topologies. This would allow for a more accurate evaluation of the model's efficacy and scalability, as well as the identification of any potential limitations or implementation difficulties.

Considering heterogeneous sensor network Typically, sensor networks consist of heterogeneous devices with various capabilities and communication protocols. Future research may investigate the effectiveness of the proposed congestion control paradigm in diverse sensor networks. To accomplish this, the model must be modified to account for heterogeneity in hardware capabilities, communication protocols, and data aggregation techniques.

Considerations regarding Privacy and Safety: As sensor networks become increasingly connected and manage sensitive data, security and privacy become significant concerns. To protect against malicious attacks, unauthorized access, and data intrusions, future research could focus on incorporating robust security features into the proposed congestion management architecture. To ensure the secure operation of the sensor network, it may be necessary to investigate encryption, authentication, intrusion detection, and privacy-preserving techniques.

Implementation in the real world and Practical Implementations: The practical implementation of the suggested congestion management model in real-world sensor network settings is an essential topic for future research. This would involve applying the model to actual sensor equipment, evaluating its performance in a variety of environmental conditions, and resolving any operational issues that arise during deployment. Field evaluations and case studies can provide crucial information regarding the viability, utility, and applicability of the proposed model in real-world situations.

By pursuing these potential research avenues, researchers may advance the state of the art in sensor network congestion management and contribute to the development of more effective, dependable, and scalable systems for controlling congestion levels.

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