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A Fuzzy Congestion Control in Wireless Sensor Networks based on Spider Monkey Optimization Algorithm

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ABSTRACT

Wireless Sensor Networks (WSN) have been broadly applied in various fields, such as medicine and agriculture. A network is likely to experience information congestion when many sensors initiate sending data concurrently. This could lead to maximizing in the packet loss ratio, thereby reducing efficiency and affecting the total system performance, so congestion control is an utmost challenge. To solve this problem, a Fuzzy Congestion Control in WSN based on the Spider Monkey Optimization Algorithm (FCC-WSN-SMOA) is proposed. The proposed method combines random early detection with the fuzzy proportional integral derivative controller. The proportional integral derivative (PID) and fuzzy logic conjointly together to help control the target buffer queue. FLC regulates the transmitting rate of every node. Then, FLC input and output parameters are optimized by SMOA. The simulation is activated in MATLAB. The FCC-WSN-SMOA method attains 21.28%, 32.20%, and 17.42% lower packet loss ratio and 16.25%, 26.07%, and 23.38% lower packet loss probability compared with existing methods, such as progressive fuzzy PSO-PID congestion control approach for WSN (FCC-WSN-PSO), optimized fuzzy clustering utilizing moth-flame optimization approach in WSNs (FCC-WSN-MFOA), and time synchronization depending on Improved Wolf Colony Algorithm-Cuckoo Search Optimized Fuzzy PID Controller for Smart Grid (FCC-WSN-IWCA-CSO), respectively.

KEYWORDS

Congestion control; Fuzzy logic controller; PID controller; Spider monkey optimization algorithm (SMOA); Wireless sensor networks (WSN)

1. INTRODUCTION

1.1 Background

Nowadays, WSN is the most notable technology due to their widespread applications, like military, smartphones, disaster management, and health care monitoring [1]. Network congestion is the main issue that WSNs may encounter in these widely used applications. WSN can link network nodes in series to convey data in a “carry-send” mode, in which each node is capable of independent data collection, transmission, and receiving [2]. WSNs may be able to increase the network’s throughput and transmission data volume. Furthermore, the number of nodes and the deployment area are typically relatively large in WSN [3]. Since there is no time limit for data transmission or acquisition, the network nodes may instantly receive much data [4,5]. There will be a significant load on the receiving nodes if such a large amount of data comes to each receiving node instantly [6]. The message queue at the node will quickly fill up if the data transmission and receiving rates are not synchronized, which may cause network congestion [7]. Congestion in WSNs can occur due to various reasons, such as high traffic load, limited bandwidth, nodes’ energy constraints, or routing issues [8].

1.2 Literature Review

This subsection reviews some related papers based on fuzzy congestion control in WSN which aregiven below, Bhatti and Asghar [9] have presented a progressive fuzzy PSO-PID congestion control approach for WSNs. Fuzzy logic was used to define the reference particle’s beginning position, which accelerated PSO convergence by reducing the number of initial iterations. It provides a low packet loss ratio and high mean queue length.

Trinh *et al.* [10] have suggested optimized fuzzy clustering using moth-flame optimization algorithms in wireless sensor networks. A distributed fuzzy clustering scheme was presented that uses two fuzzy logic controllers (FLCs). The moth-flame optimization algorithm was employed to increase the effectiveness of the suggested method. It provides low mean end-end delay, but high packet loss probability.

Zhang *et al.* [11] have presented a time synchronization approach for a smart grid under an improved Wolf Colony-Cuckoo Search Optimized Fuzzy PID Controller. The presented algorithm dynamically adjusts the parameters of the fuzzy PID controller to decrease the master-slave clock fault. It provides a low mean queue length and a high mean end-to-end delay.

Faisal *et al.* [12] have presented a prediction mode utilizing a fuzzy logic system for controlling the congestion in WSN. Fuzzy logic congestion controller was separated into four phases, (1) identifying with estimating the congestion, (2) regulating the traffic rate (3) tuning the active nodes rate, and (4) reporting it through their new rate. It provides a low packet loss ratio and high packet loss probability.

Bhatti *et al.* [13] have presented multiple objective fuzzy krill herd congestion control approaches for optimizing the source sending rate. Network performance was enhanced by the presented multi-objective outflow rate optimization approach. It provides low packet loss probability and high mean end-end delay.

1.3 Research Gap and Motivation

One of the most significant problems with WSNs is congestion since it results in packet loss, it wastes sensors' limited energy. The procedures involved in rate adjustment, congestion notification, and congestion detection are distinct from the existing approaches for controlling congestion. Under congestion conditions, the transmission rate of every traffic source is reduced with respect to the priority index of the source nodes. The existing approaches perform badly in assigning relative priority in various congestion scenarios. These disadvantages are motivating to do this work.

1.4 Challenges

One of the most important problems that must be solved in systems for reducing congestion is the queuing length of the node. Certain packets are prone to overflow when malicious node isolation occurs.

1.5 Contribution

The proposed method in the paper introduces a novel approach to addressing congestion in WSNs. The key novelty lies in the integration of the random early detection (RED) method with a Fuzzy PID and SMOA approach to effectively manage congestion and lessen packet loss in WSNs.

The primary contributions of this article are abridged below:

- Fuzzy congestion control in WSN utilizing SMOA is proposed.
- An innovative active queue management model is proposed that incorporates the RED and FuzzyPID approach.
- FLC [14] is utilized to detect congestion and controlling in WSN.
- Spider Monkey Optimization algorithm [15] is proposed to optimize input and output parameters of FLC.

1.6 Paper Organization

The remaining of the article is organized as, Section 2 describes the basic concepts of the proposed method, Section 3 describes the proposed technique, Section 3 determines the results and discussion, and Section 4 concludes this article.

2. BASIC CONCEPTS OF PROPOSED METHOD

RED method, PID controller, fuzzy logic concept, and congestion control protocols are described in this section.

2.1 Random Early Detection Method (RED)

In wireless sensor networks, RED is used for managing the queues. This method finds the congestion problems in the network and detects them. If it identifies one, it decreases the arriving packet. Random early detection utilizes the average weight length of the queue (l_{avg}). If (l_{avg}) is lesser than the threshold limit ($\min_{th}$), the packet is located in the queue or if (l_{avg}) is greater than the ($\max_{th}$), it drops the packets. If the (l_{avg}) is between ($\max_{th}$) and ($\min_{th}$) then R_b sign is marked in each packet. The probability for marking or dropping the packets is expressed below

$$R(b) = \begin{cases} 0 & l_{avg<\min_{th}} \\ \dfrac{l_{avg} - \min_{th}}{\max_{th} - \min_{th}} \times \max & \min_{th} <= l_{avg} < \max_{th} \\ 1 & \max_{th} <= q_{avg} \end{cases} \quad (1)$$

2.2 PID Controller

It is used for maintaining the average queue length and reducing the fluctuation in queue length. The proportional term and integral term arecombined to form a PID controller. The nonlinear effect limits their performance in the PID controller. With the help of the control

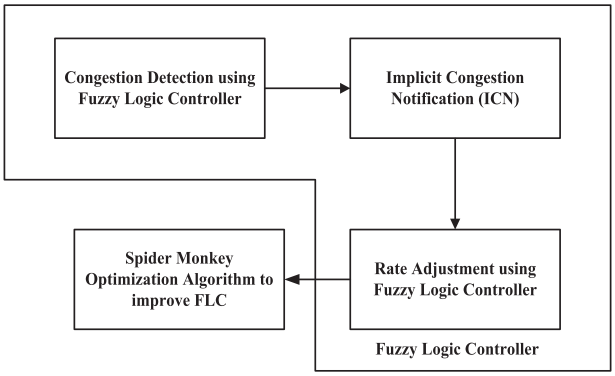

Figure 1: Block diagram of FCC-WSN-SMOA

function, the PID controller detects initial congestion. The objective of this controller is to sustain the queue length and prevent congestion. The transfer function is expressed in Equation (2)

$$H_f(D) = o_r + \frac{o_j}{D} + o_s D \tag{2}$$

In the above equation, o_r, o_j and o_s denote the proportion gain, integral gain, and derivative gain, and D is an initial congestion. The scattered time equation is as follows:

$$z(o) = o_r f(O) + o_j V_d \int_0^{\alpha} f(v)\mathrm{d}v + \frac{o_s}{V_d}\Delta f(O) \tag{3}$$

$$\Delta f(O) = f(o) - f(o-1) \tag{4}$$

where v_d represents the time taken and $\Delta f(o)$ is the bias rate between o and o-1.

2.3 Fuzzy Controller

Making decisions and acting appropriately in unpredictable situations are extremely difficult tasks. Here, decision making based upon certain rules and conditions is applied. The system must select a suitable measure from the set of accessible rules. The system is called the fuzzy logic controller. To get a better decision, a controller uses four processes: fuzzification, rule base, inference, and defuzzification. Making better decisions and using fewer resources are two benefits of using FLC.

3. PROPOSED METHOD OF FUZZY LOGIC CONTROLLER WITH SMO ALGORITHM

The proposed fuzzy logic controller with SMO algorithm is discussed here. Figure 1 represents the block diagram of FCC-WSN-SMOA.

3.1 Fuzzy Logic Controller

When congestion arises, the FLC goal is to identify it and take appropriate action. The proposed method comprises CDU, CNU, and RAU.

3.1.1 Congestion Detection Unit

It determines the traffic in each network node's queue. The proposed method shows congestion using RED. Fuzzy controller provided the error between the input rate and capacity link as well as the input variable queue length.

- When $|f| \approx 0$ and $|\Delta f| \approx 0$, the controller works as a linear proportional integral derivative
- When the error value is high, the controller works as a saturated PD
- When the error value is reduced to low and high, the controller works as a steady-state PID

The difference between the current and upcoming queue length is measured by the first input variable of fuzzy CDU $f(m)$. It can be expressed as

$$f(m) = l(n) - z_v \tag{5}$$

The variation of error among different time slots is expressed as

$$\Delta f(m) = f(m) - f(m-1) \tag{6}$$

Then the output system $r(m)$ is formulated by

$$r(m) = r(m-1) + r \tag{7}$$

$$r = \alpha f + \beta \Delta f + \Gamma \int_0^{\alpha} f \mathrm{d}v \tag{8}$$

In the above equation, $l(n)$ indicates a running queue length, z_V represents target queue length, r represents packet drop probability, and $\Delta f(m)$ represents the bias rate between m and m-1, and $f(m)$ is perceived from present queue length $l(n)$ subtracted from anticipated queue length z_V.

There are three membership functions for each input and output variable. Every input along output variable has a triangle membership function. Figure 2 portrays the membership functions for inputs and output.

The input (e, De) physical domain represents $\{-1, -0.8, -0.6, -0.4, -0.2, 0, 0.2, 0.4, 0.6, 0.8, 1\}$, output (p) represents $\{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$. Fuzzy variables determined under the following rule: (De) = error, error variant, NL (NegativeLarge), NM (NegativeMedium), NS (NegativeSmall), ZR(Zero), PS (PositiveSmall), PM (PositiveMedium), PL (PositiveLarge),

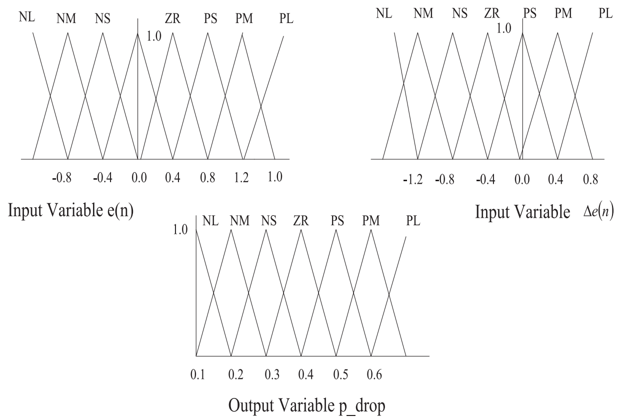

Figure 2: Membership functioning for inputs and output

Table 1: Fuzzy logic rules

Input1	NL	NM	NS	ZR	PS	PM	PL
NL	ZR	ZR	ZR	ZR	ZR	ZR	ZR
NM	NL	NM	NM	NS	ZR	ZR	PS
NS	NL	NM	NM	NS	ZR	ZR	ZR
ZR	NM	NS	NS	ZR	PS	PS	PM
PS	ZR	ZR	ZR	PS	PM	PM	PL
PM	NS	ZR	ZR	PS	PM	PM	PL
PL	ZR	ZR	ZR	ZR	ZR	ZR	ZR

[_1, 1], l. P(n) = control factors, NL, NM, NS ZR, PS, PM, PL, [0,1], l. Table 1 depicts the fuzzy logic rules.

3.1.2 Congestion Notification Unit

Two methods are used in this task, implicit congestion notification and explicit congestion notification. If the congestion is detected, then notification is sent to nodes. It reduces the package loss and gives better efficiency.

3.1.3 Rate Adjustment Unit

The main aim is to handle the sensor node transfer ratio and increase the network performance. RAU uses the fuzzy controller. If the congestion notification is received, then it reduces the congestion. This unit has some advantages such as increasing conductivity, efficiency, reduce package loss, and increasing system performance. To optimize the input and output parameters e, De and p, SMO algorithm is utilized.

3.2 Optimization Using Spider Monkey Optimization Algorithm

In this section, SMOA is proposed to optimize input and output parameters e, De and p of FLC. In congestion control, WSNs often deal with multiple conflicting objectives (*e.g.* minimizing delay, maximizing throughput, reducing energy consumption). SMO's ability to handle multiple objectives can aid in finding trade-off

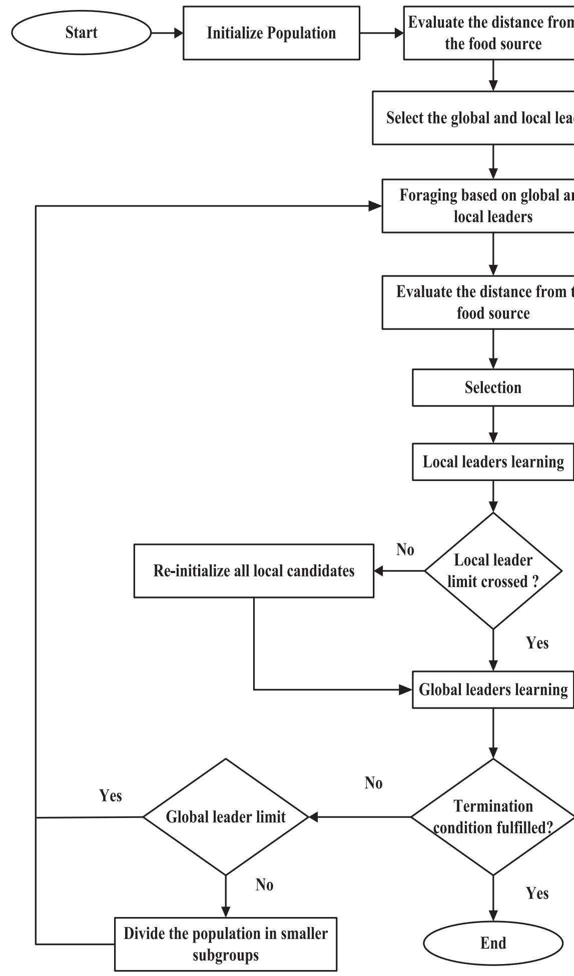

Figure 3: Flow chart of the SMO algorithm

solutions effectively. This algorithm is related to foraging activities of spider monkeys. Figure 3 portrays the flow chart of SMOA. The stepwise procedure of SMOA is given below,

Step 1: Initialization

SMOA creates evenly distributing first swarm of N SM, here sm_i epitomizes the ith SM at swarm. All sm_i is initialized using Equation (9)

$$SM_{ij} = SM_{\min j} + U(0,1) \times (SM_{\max j} - SM_{\min j}) \tag{9}$$

where $SM_{\min j}$, $SM_{\max j}$ denotes lower as well as upper bounds for search space at the jth dimension, $U(0,1)$ symbolizes evenly distributing random count at $(0,1)$ range.

Step 2: Random Generation

After the initialization, the input parameters are generated randomly. The generated population of SMs is based on the behavior of spider monkey.

Step 3: Fitness Function

Create the random count of solution through initialization. Each solution is examined. Hence, the objective function is recurring on every spider monkey, which is given below

$$Fitnessfunction = Optimizing[\text{e.De andp }] \quad (10)$$

Step 4: Local leader phase (LLP)

All spider monkeys have the opportunity for updating themselves. The fitness value is determined in its new location; if it is more than it was at its previous location, it is updated; if not, it is not. The position updation is exhibited in Equation (11)

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1) \quad (11)$$

Step 5: Global Leader Phase (GLP)

The procedure transfers to the GLP after completing the LLP. The likelihood of selection determines the solution update. SM updates the position based on its own stability, the experience of neighboring SM, and the expertise of world leaders. The position updation is given in Equation (12):

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij})$$
$$U(-1,1) \times (SM_{rj} - SM_{ij}) \quad (12)$$

here GL_j specifies positioning of global leader at the jth dimension.

Step 6: Local Leader Decision phase

Both the global and local leaders have been determined prior to this stage. If no local leader is reconfigured to a certain threshold called the local leader limit, each member updates their positions depending on random initialization or global leader experience. The probability pr implies perturbation rate is exhibited in Equation (13)

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij})$$
$$U(0,1) \times (SM_{rj} - LL_{kj}) \quad (13)$$

Step 7: Global leader learning (GLL) phase

When the swarm does not reorganize to a certain boundary termed as the global leader limit, the global leader separates as small groups in a manner akin to the local leader decision. GLL verifies regarding if it is any premature convergence, then varies at $N/2$ to $2 \times N$ range.

Table 2: Simulation parameters

Parameter	Value
Network size	$300 \times 400\,m^2$
Packet size	512 Bytes
Simulation duration	1 min
Sensor node count	21
Sink count	1

Table 3: Control parameters of SMOA

Size of population	$N = 20$
Problem dimension	$D = 2$
Global Leader Limit	$GLL \in \left\{\frac{N}{2}, 2N\right\} \Rightarrow GLL \in \{10, 40\}$ Let $GLL = 30$
Local Leader Limit	$LLL = D \times N = 40$
Perturbation rate	$pr = [0.1, 0.8]$ Let $pr = 0.7$

Step 8: Termination

The input and output parameters of FLC for congestion control is optimized with the help of SMOA, will repeat step 3 iteratively until fulfilling the halting criteria $u = u + 1$.

4. RESULTS AND DISCUSSION

The result of FCC-WSN-SMOA is described in this section. The MATLAB simulation is run in PC along Intel Core, 2.50 GHz CPU, 8GB random access memory, Windows 8. The obtained outcomes of the FCC-WSN-SMOA method are analyzed with existing FCC-WSN-PSO, FCC-WSN-MFOA, and FCC-WSN-IWCA-CSO models. Table 2 tabulates the simulation parameters, likewise Table 3 tabulates the control parameters of SMOA.

4.1 Performance Measures

4.1.1 Packet Loss Ratio

This is determined by Equation (14)

$$\text{Loss Rate } = \text{Packet\_loss/Time} \quad (14)$$

4.1.2 Packet Loss Probability

This is scaled by Equation (15)

$$\text{Ploss} = PLN/PLN + PR \quad (15)$$

where PLN implies count of data packets lost and PR implies count of received packet.

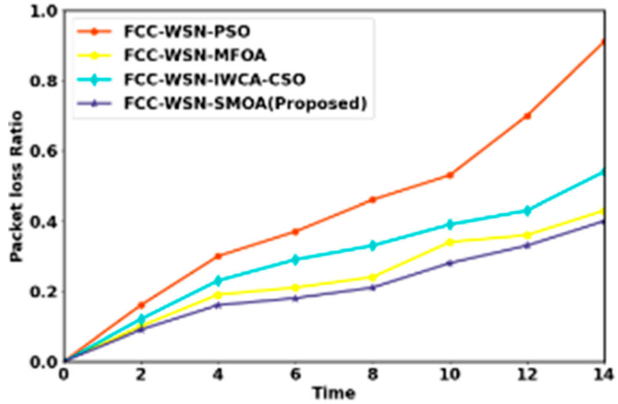

Figure 4: Performance of the packet loss ratio

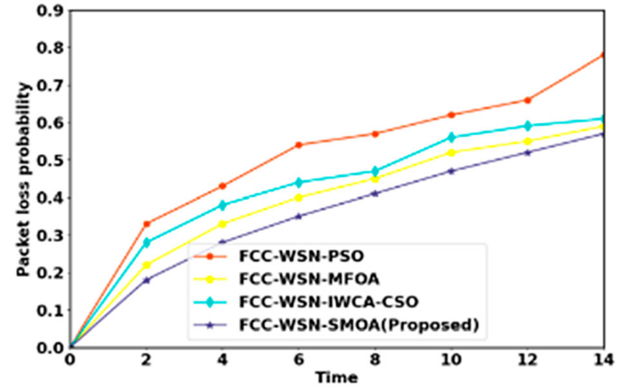

Figure 5: Performance of packet loss probability

4.1.3 Mean End-to-End Delay

The time passes amid the creating data packets and arriving at their destination.

4.1.4 Mean Queue Length

Managing queue length effectively can help reduce packet delay and improve overall network performance.

4.2 Performance Comparison of Various Methods

Figures 4–7 depict the simulation result for the proposed FLC system.

Figure 4 depicts packet loss ratio analysis. Here, the FCC-WSN-MFOA attains nearly least packet loss ratio, the FCC-WSN-IWCA-CSO attains moderate packet loss ratio, and the FCC-WSN-PSO attains high packet loss ratio. But, the proposed FCC-WSN-SMOA method attains 21.28%, 32.20%, and 17.42% lower packet loss ratio compared with the existing methods FCC-WSN-PSO, FCC-WSN-MFOA, and FCC-WSN-IWCA-CSO, respectively. The proposed method attains a low packet loss ratio.

In Figure 5, the FCC-WSN-MFOA attains nearly least packet loss probability, the FCC-WSN-IWCA-CSO attains moderate packet loss probability, and the FCC-WSN-PSO attains high packet loss probability. But, the proposed FCC-WSN-SMOA method attains 16.25%, 26.07%, and 23.38% lower packet loss probability compared with existing methods FCC-WSN-PSO, FCC-WSN-MFOA, and FCC-WSN-IWCA-CSO, respectively. The proposed method attains low packet loss probability.

In Figure 6, the FCC-WSN-PSO attains nearly least delay, the FCC-WSN-MFOA attains moderate delay and the FCC-WSN-IWCA-CSO attains high delay. But, the proposed FCC-WSN-SMOA method attains 20.86%, 23.57%, and 24.04% less mean end-to-end delay analyzed to the existing methods FCC-WSN-PSO, FCC-WSN-MFOA, and FCC-WSN-IWCA-CSO, respectively. The proposed method attains low mean end-end delay.

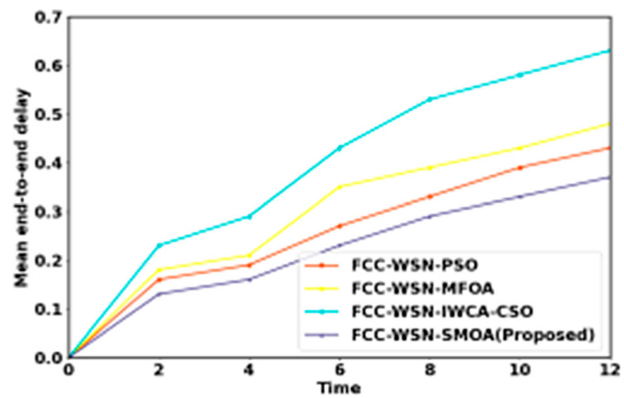

Figure 6: Performance of mean end-to-end delay

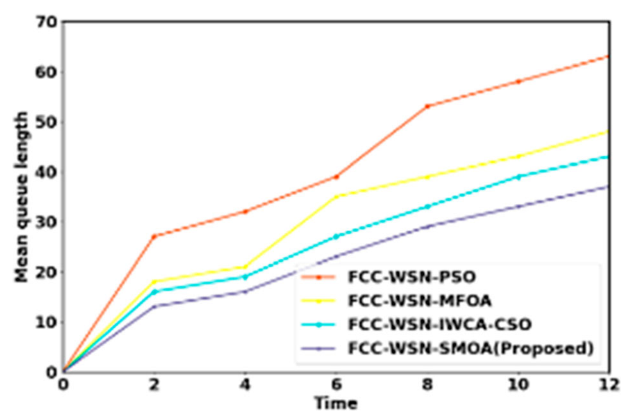

Figure 7: Performance of mean queue length

Figure 7 depicts mean queue length analysis. Here, the FCC-WSN-IWCA-CSO attains nearly least mean queue length, the FCC-WSN-MFOA attains moderate mean queue length, and the FCC-WSN-PSO attains high mean queue length. But, the proposed FCC-WSN-SMOA method attains 24.09%, 16.57%, and 22.72% lower mean queue length compared with existing methods FCC-WSN-PSO, FCC-WSN-MFOA, and FCC-WSN-IWCA-CSO, respectively. The proposed method attains low mean queue length.

5. CONCLUSION

In this article, a fuzzy congestion control in WSN depending on Spider Monkey Optimization Algorithm is implemented. By integrating SMO with fuzzy logic, this model holds promise in revolutionizing congestion control strategies in WSNs. The FCC-WSN-SMOA method attains 20.86%, 23.57%, and 24.04% lower mean end-to-end delay and 24.09%, 16.57%, and 22.72% lower mean queue length compared with existing methods FCC-WSN-PSO, FCC-WSN-MFOA, and FCC-WSN-IWCA-CSO, respectively. In future, this study requires further enhancements and combines fuzzy logic with deep learning techniques to enhance decision-making in congestion control.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

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APPENDIX

Symbols	Explanation	Symbols	Explanation
(l_{avg})	Average weight length of queue	o_r	the proportion gain
$(\min_{th})$	Threshold limit	o_j	integral gain
$(\max_{th})$	Maximum threshold	o_s	derivative gain
R_b	Derivative gain	e, De	Input parameters
$\Delta f(m)$	Bias rate between time slots m and m-1	p	Output parameter of FLC
z_V	Target queue length	D	initial congestion
sm_i	ith spider monkey on swarm	v_d	time taken
$SM_{\min j}$	Lower bounds of search space at jth dimension	$\Delta f(o)$	bias rate between o and o-1
$SM_{\max j}$	Upper bounds of search space at jth dimension	r	packet drop probability
GL_j	Global leader positioning on jth dimension	$f(m)$	noticed from the length of current queue $l(n)$ subtract anticipated queue length z_V.
$U(0,1)$	uniformly distributed random number	$l(n)$	running queue length

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