A fuzzy logic and cross-layered optimization for effective congestion control in wireless sensor networks to improve efficiency and performance


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Abstract. Wireless Sensor Networks (WSNs) are a fundamental component of the Internet of Things (IoT), used in diverse applications to detect environmental conditions and send information to the Internet. WSNs are susceptible to congestion issues, leading to increased packet loss, extended delays, and reduced throughput. This research introduces a Fuzzy Logic-based Cross-Layered Optimization Model (FL-CLOM) for WSNs to tackle the problem. FL-CLOM is developed by including the signal-to-noise ratio of the wireless channels in the Transmission Control Protocol (TCP) approach, bridging the transmission layer and Media Access Control (MAC) layer. A fuzzy logic system is created by integrating fuzzy control with congestion control to dynamically manage the queue size in crowded nodes and minimize the effects of external uncertainties. Various simulations were conducted using MATLAB and NS-2.34 to compare the suggested FL-CLOM to conventional methods. The results indicate that FL-CLOM efficiently adjusts to queue size changes and demonstrates rapid convergence, reduced average delay, reduced packet loss, and increased throughput.
1 Introduction to wireless sensor networks and congestion control

Over 8 billion devices are part of the Internet of Things (IoT) system [1]. These devices mostly conduct sensing and tracking activities and transmit their data to a cloud-based system for analysis utilizing big data technologies. One crucial technology driving this development is Wireless Sensor Networks (WSNs) [2]. WSNs consist of several sensor nodes linked using wireless communication, such as radio frequency, to avoid the constraints of wired infrastructure. These Sensor Nodes (SN) can create an impromptu network via multi-hop transmissions using relays or intermediary nodes [3]. This network is autonomous, self-sufficient, and self-arranged and communicates with nodes beyond the system towards the gateway (sink nodes or base stations).

While sensor nodes have several functions, including sensing, processing, storage, and distribution, their primary constraint is energy usage. The battery's self-power source dictates the lifespan of the SN. WSNs have several benefits but face various issues, including routing, localizing, quality of service, and safety [4]. The high volume of network activity in large-scale WSNs creates challenges in transferring data, path optimization to a destination node, and managing diverse traffic in different topologies, particularly nonuniform traffic in randomly used areas like forests and disaster zones. This situation leads to a shortened network lifespan and Congestion Control (CC) issues in WSNs [5]. It impacts such as tracking conductors, heating ratings in power structures, healthcare sensor tracking, and earthquake alert systems.

Congestion is a significant problem that often impacts network efficiency, especially in high-density nodes ranging from wired to wireless networks, including WSN. WSN stands out because of its unique features, including minimal energy consumption via battery power and limited bandwidth, which are significant factors in congestion issues. Traffic and resource control are two primary methods often used to alleviate congestion in WSNs. For example, the initial is employed to modify the transmission speed by Additive Increase Multiple Decrease (AIMD) [6]. This method continuously monitors the current bandwidth and adapts the rate according to the sent SNs' existence, taking fairness into account. The primary benefit of Transmission Control Protocol (TCP) is its immediate congestion relief by reducing shipping rates. However, it resulted in poor bandwidth utilization and lost packets at the onset of congestion. There are three main types of congestion: congestion at the origin node due to concurrent data transmission by nearby SNs, congestion at a middle node resulting from data collection and buffer overload, and congestion at the sink node due to numerous children delivering traffic simultaneously to the single sink node. These congestion forms result in packet loss, latency, and reduced data transfer rate.

This paper's contributions are as follows, based on the current understanding: The research provides a mathematical framework for cross-layer congestion management that integrates the data transfer layer and Medium Access Control (MAC) layer by using the Signal-to-Noise Ratio (SNR) of the wireless channels in the TCP framework [7]. The research develops a Fuzzy Logic-based Cross-Layered Optimization Model (FL-CLOM) by integrating fuzzy and slide modal control. Fuzzy dynamically controls the buffer size in congested nodes and mitigates the effects of unknown disturbances, reducing the chattering phenomena of buffer size.

The rest of the article is arranged in this manner: Section 2 of the paper discusses the background and congestion management mechanisms in WSN. The Fuzzy Logic-based Cross-Layered Optimization Model (FL-CLOM) is introduced and detailed in Section 3. Section 4 presents the simulation analysis and its results. Section 5 comprises the research's findings and prospects.
2 Background and literature survey of congestion control algorithms

Recent research has focused on CC in WSNs, categorized into two primary types: traffic-based control and resource-based control. Traffic-based congestion management systems change the data rate of incoming streams from descending nodes dependent on the forwarding capability of the originating node(s). Singh et al. introduced a Traffic-Aware CC (TACC) that functions based on the end-to-end concept at the transportation layer of WSN [9]. TACC utilizes burst loss data to identify congestion at the point of origin and instructs source nodes to modify their reporting rate appropriately. TACC needs enhancements to provide prioritized event transfer across different flows. Vijayalakshmi et al. created a novel transport protocol, RT-CaCC, incorporating a cache-aware CC method [10]. RT-CaCC uses cache management strategies such as cache inserting, cache deletion, and cache size management to reduce the loss of packets in WSNs while optimizing cache use and bandwidth management. However, another important measure of WSNs must be considered when evaluating energy use. Dalal et al. studied how CC affects data accuracy and developed a Congestion-Adaptive Data Collection (CADC) to address congestion while ensuring data correctness effectively [10]. CADC reduces congestion by using adaptive lossy compression to maintain a specified overall data estimate error limit in a distributed fashion. Sonmez et al. introduced a fuzzy-based image-transmitting sensor for WSN. It dynamically reduces picture quality to enhance video streaming consistency. It does not employ acknowledgment; hence, the receiving device can only detect packet loss based on packet number sequences. Yang et al. developed a standard Particle Swarm Optimisation (PSO)-neural Proportional Integral Differentiator (PID) (PNPID) CC system by integrating conventional PSO with single-neuron PID management [11]. The PNPID control system demonstrated superior performance in resolution and accuracy compared to the classic PID controller. The efficacy of PNPID in various situations must be confirmed.

Resource-based congestion management utilizes unused network resources to distribute the traffic burden during congestion [12]. Menci et al. adopted a hierarchical tree and grid structure to create an initial structure and then applied Prim's method to identify suitable neighbors [13]. The suggested technique used a hierarchy of trees to generate network layouts and implemented a resource management mechanism to manage congestion in WSNs. Additional tests of greater persuasiveness should be conducted to validate their approach further. Aceituno et al. developed an effective CC-based scheduling method called REFIACC (Reliable, Effective, Fair, and Interference-Aware CC) protocol [14]. REFIACC eliminates interferences and guarantees equitable bandwidth consumption across sensor nodes via communication planning. Congestion and disturbance in contention areas on inter- and intra-paths are reduced by considering the differences in link capacity during the planning phase.

3 Proposed fuzzy logic-based cross-layered optimization model

This section proposes the FL-CLOM method, a network, energy model, fuzzy-based controller design, and CC methods using MAC information.

3.1 Network models

Like other recent studies on congestion management in WSN, this study involves a single base station or sink node positioned at the network's endpoint that links to the Internet. A power source is located at this node's location. At a designated time, sensors triggered by
particular events (including detecting and preparing for data transfer), called source nodes, would transmit data to the sinking node via the following or nearby nodes (depending on hops) in nonuniform installations. The research assumes the subsequent network conditions:

- Source nodes and the sink node are distributed arbitrarily and uniformly in a network rectangular area, each with identical beginning energy levels.
- After the sensor nodes are placed, there is no movement or specific position data.
- All SNs have identical communication ranges.
- All nodes in the system have been provided with the time-synchronization standard to facilitate interaction.
- A sensor node exits the system only after its energy is used up, indicating it is no longer functioning.

![Fig. 1. WSN network model](image)

Fig. 1 displays the network approach, including a sink, a source, and additional SNs. The dashed line delineates each SN's signaling range and connection to its adjacent node. The arrowhead is decided by the transmitted message. The system will be segmented into layers according to the hop count. After establishing the route, the originating node will transmit the information to the sink node by following the sequence and ultimately reaching the sinking node.

### 3.2 Energy models

Communication in WSNs uses the IEEE 802.15.4 Low-rate Wireless Personal Area Network (LoRa-WPAN) protocols. The energy consumption is directly related to the quantity of packets transmitted and received by a particular sensor node. Equation (1) represents the power model for WSN. It defines the transmission power $E_{tr}$ (measured in Joules per bit) for the $x$th bit traveling a length $d$ in the free space propagating scenario.

$$E_{tr}(x, l) = xE_{el} + xE_{trans}l^2$$  \hspace{1cm} (1)

$E_{el}$ denotes represents the energy used during data processing, whereas $E_{trans}$ is the energy required to transmit 1 bit across a distance $l$. Similar to delivery, Equation (2) represents the power $E_{tr}$ (Joules/bit) received for $x$ bits, with $E_{rr}(x)$ being the power needed to receive 1 bit.

$$E_{rr}(x) = xE_{rcv}$$  \hspace{1cm} (2)
3.3 Optimized fuzzy logic-based CC scheme

![Diagram](image)

**Fig. 2. Fuzzy-based congestion control model**

Fig. 2 provides a summary of the FL-CLOM design. There are four primary components:

(i) **Hierarchical Architecture.** This element is first used to create the layer-based architecture using hop count as the primary measure. The research uses the Ad hoc On-Demand Distance Vector (AODV) protocol for wireless connections to establish a many-to-one architecture from SNs to the sink node. There are two primary stages: Route Creation and Route Update.

(ii) **Energy-based Routing.** The second part uses a Fuzzy Logic System (FLS) for weight creation. Two variables being examined are hop count and residual power.

(iii) **Managing and Prediction Congestion.** This aspect is primarily employed for congestion management to assist in predicting bottlenecks. The research uses exponential smoothing, optimizing it over fuzzy logic systems tweaked by BAT, with fuzzy inputs buffering occupation and transmission rate.

(iv) **Path Selection.** After calculating the weight deduction, this last component establishes the ultimate route toward the sink node. FL-CLOM optimizes performance by employing one, two, or all three parts while considering the speed and energy usage trade-offs.

3.4 CC and prediction

Before, the primary parameters for route determination were hop count and residual power. Network congestion is a significant component in dense installations that reduces the system's efficiency by causing packet loss, poor throughput, and excessive latency. The research examined this limitation using a statistical congested forecasting approach that considers buffer occupation and employs FLS-based congested controllers. The research adjusted the FLS's member function using bio-inspired BAT for the anticipated buffer occupation and transmission rate inputs to calculate a weight attribute called Available Weight (AW).

**Congestion prediction**

The research used exponential smoothing, a robust time-series prediction methodology, in the study. Compared to short-term forecasting, its primary benefit was that it was effectively used in WSNs to assist in selecting paths to prevent congestion by taking buffer occupation into account—Equations (3) to (5) demonstrate the derivation of exponential smoothing.
\[ \bar{Z}_t(d) = \frac{s_t}{b_t} \]  
\[ S_t = \sum_{i=0}^{t-1} \alpha_i Z_{t-i} \]  
\[ \bar{Z}_{t+1} = (1 - \alpha) \bar{Z}_t + \alpha \bar{Z}_{t-1} \]  

\( \bar{Z}_t \) is the forecasted value at time \( t \), \( B_t \) is a geometric series, and \( \alpha \) is a specified constant (softening ratio) ranging from 0.02 to 0.3. Equation (6) demonstrates the method for calculating the forecasted buffer, denoted as \( B_O \) over \( \bar{Z}_t \).

\[ B_{O_{x+1}} = (1 - \alpha) B_{O_x} + \alpha B_{O_{x-1}} \]  

Adaptive membership function

BAT is a metaheuristic method inspired by nature, utilized to tackle problems by seeking optimal solutions within resource constraints, such as computing time difficulty. BAT is employed in WSNs for geolocation and radial optimization tasks. The research uses BAT to adjust the membership aspect of FLS. BAT often mimics the foraging behavior of microbats. A bat emits high-frequency pulses to locate a food supply and communicate its position to other bats. Each of the three primary steps:

Every bat emits a pulse to determine where it is and the distance of food, victims, and obstacles. The function \( f(x) \) is formulated based on the bat population's speed and transmitting frequency to optimize the answer \( f(x) \) in each iteration \( N \). Every round will choose a superior answer by modifying the pulse frequency and strength.

Each bat does not follow a set flight pattern while moving toward the food supply at a certain speed from a particular point. While flying, the wavelength \( \lambda \) and its magnitude will be modified to locate the object of interest. The bat can adjust its pulse rate within the range of \([0, 1] \), starting at a rate of 0. When near the object, the bat raises the pulse velocity. The beginning amplitude is set to 0 (highest loudness), and the bat hunts for the ideal solution while flying. Unlike the pulse pace, the sound level decreases to its lowest amplitude when the bat is near its destination.

4 Simulation outcomes

The research simulated the technique using Network Simulation (NS2) version 2.34 with a modification for WSN and Matlab. The study used Octave 4.2 to replicate FLS. The testbed used was an Ubuntu 14.04 LTS operating system. The sensor nodes were placed arbitrarily in a topographic region A, measuring 200 meters by 200 meters. After deployment, there was no movement. There were 100 sensor nodes, each with a transmission range of 50 meters.

Fig. 3. Throughput evaluation of different network traffic
Fig. 3 displays the throughput in kilobits per second (kbps) for various traffic volumes. FL-CLOM has an average throughput of 15.32 kbps, which is higher than TACC, RT-CaCC, CADC, PNPID, and REFIACC, with average throughputs of 12.46, 12.17, 12.25, 11.52, and 13.56 kbps, correspondingly. The FL-CLOM, with its fuzzy logic-based cross-layered optimization, outperforms other methods by dynamically controlling queue sizes and reducing the effects of external uncertainty. This results in higher throughput, less average latency, and improved network dependability compared to traditional approaches.

Fig. 4. End-to-end delay evaluation of different network traffic

Fig. 4 shows the end-to-end latency results in milliseconds for various traffic levels. FL-CLOM offers better performance with an end-to-end delay of 8.84 ms, surpassing TACC, RT-CaCC, CADC, PNPID, and REFIACC, which had delays of 10.33, 10.55, 9.55, 10.16, and 8.84 ms, correspondingly. The FL-CLOM reduces delays by using fuzzy logic-based cross-layered optimization, effectively adjusting to variations in queue size and alleviating congestion impacts. This leads to decreased average latency and enhanced communication efficiency compared to traditional approaches.

Fig. 5. Packet delivery ratio evaluation of different network traffic

Fig. 5 illustrates the Packet Delivery Ratio (PDR) results as a percentage for various traffic levels. FL-CLOM has better PDR performance with an average rate of 97.89%, outperforming TACC, RT-CaCC, CADC, PNPID, and REFIACC, which had average PDRs of 93.38%, 91.71%, 94.25%, 92.94%, and 96.34%, correspondingly. FL-CLOM's efficacy stems from its use of fuzzy logic-based cross-layered optimization to continuously regulate queue sizes and reduce the influence of external uncertainties, leading to increased PDR. This results in enhanced data transmission reliability compared to traditional approaches.
5 Conclusion and findings

This research suggests a cross-layer congestion management model called FL-CLOM for WSNs by including the wireless channel in a dynamic TCP model. It introduces a fuzzy-based congestion control method for WSNs. The simulation results demonstrate that the suggested method dynamically controls the buffer size in intermediate nodes, thereby preventing congestion successfully. It decreases queuing time, enhances the speed of convergence and security, and enhances the efficiency of WSN in terms of average delay, packet loss ratio, and throughput, regardless of whether the Region of Interest is 200 x 200 m². The suggested technique FL-CLOM shows improved performance based on three metrics: a mean throughput of 15.32 kbps, an overall end-to-end latency of 8.84 ms, and an overall PDR of 97.89%.

In the future, tests will be conducted to confirm the efficacy and significance of the suggested FL-CLOM system in practical WSN-based IoT systems, including smart home and farm automation. The influence of algorithm variables on network efficiency will be considered to enhance FL-CLOM to improve the stability and reliability of WSNs' cross-layer congestion management.

References


