

Soft Computing-Based Congestion Control Schemes in Wireless Sensor Networks: Research Issues and Challenges

Shoorangiz Shams Shamsabad Farahani

Department of Electrical Engineering, Islamshahr Branch, Islamic Azad University, Islamshahr, Iran.

Email: shams@iiu.ac.ir

Received: September 2020

Revised: December 2020

Accepted: January 2021

ABSTRACT:

Wireless Sensor Networks (WSNs) are a special class of wireless ad-hoc networks where their performance is affected by different factors. Congestion is of paramount importance in WSNs. It badly affects channel quality, loss rate, link utilization, throughput, network life time, traffic flow, the number of retransmissions, energy, and delay. In this paper, congestion control schemes are classified as classic or soft computing-based schemes. The soft computing-based congestion control schemes are classified as fuzzy logic-based, game theory-based, swarm intelligence-based, learning automata-based, and neural network-based congestion control schemes. Thereafter, a comprehensive review of different soft computing-based congestion control schemes in wireless sensor networks is presented. Furthermore, these schemes are compared using different performance metrics. Finally, specific directives are used to design and develop novel soft computing-based congestion control schemes in wireless sensor networks.

KEYWORDS: Congestion Control, Fuzzy Logic, Game Theory, Learning Automata, Neural Network, Soft Computing, Swarm Intelligence, Wireless Sensor Networks (WSNs).

1. INTRODUCTION

A WSN is a collection of sensor nodes which is distributed in a network to estimate the monitored system state. WSNs gather the required information by smart environments as home, buildings, industrial sites, and utilities. In WSNs, there exist one or more sinks and many sensors which are deployed on a physical area. The unique characteristics in WSNs can be listed as resource limitations, special traffic characteristics and the multi-hop tree topology utilization [1].

Congestion is an important problem in WSNs. It occurs in case the input load exceeds the available capacity ending in node buffer overflow, or wireless channel is shared by multiple nodes ending in collision, or in case the link bandwidth reduction occurs due to fading channels [2]. Three types of congestion in WSNs are shown in Fig. 1.

Congestion renders loss rate rise, channel quality degradation, unfair traffic flow, increased delay and wasted energy. It also ends in retransmission increase, and throughput and network life time decrease. So, it is necessary to mitigate congestion in WSNs.

In soft computing techniques, the effectiveness of wireless sensor networks is enhanced in different aspects as design, deployment, network challenges and

power consumption. These techniques are used in different applications in wireless sensor networks.

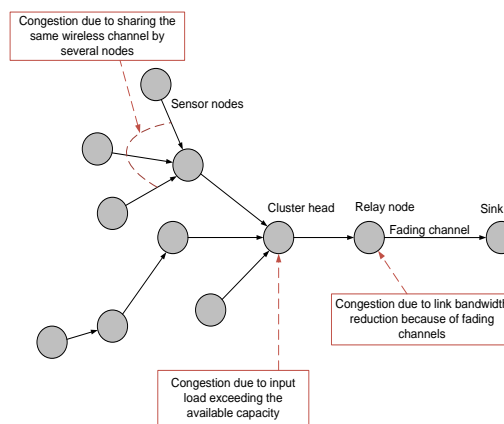


Fig. 1. Congestion appearance in WSNs [2].

Some significant survey studies regarding congestion control are presented in [3]-[10], however, presenting a novel classification on WSNs, introducing new ideas on soft computing-based congestion control schemes, using classifications, comparing the schemes, recommending future directions and discussion are rare.

In this paper, congestion control schemes are classified as classic or soft computing-based schemes. Thereafter, soft computing-based congestion control schemes in WSNs are classified and reviewed. Furthermore, these schemes are compared using different performance metrics. Finally, specific directives are used to design and develop novel soft computing-based congestion control schemes in wireless sensor networks.

The organization of this paper is as follows: Section 2 presents an overview of congestion mitigation in wireless sensor networks, followed by the soft computing-based congestion control protocols in section 3 and comparison of these schemes in section 4. Finally, the paper is concluded and the future directions are presented.

2. CONGESTION MITIGATION

Congestion mitigation schemes take reactive actions in case that the congestion occurs in WSNs and aims to control it. MAC, network, and transport layer operations are used in the aforementioned schemes. Congestion mitigation algorithms are classified according to the way congestion is detected, the way other nodes are notified for this incident, and the way congestion is faced [10]. Fig.2 shows the congestion mitigation in WSNs.

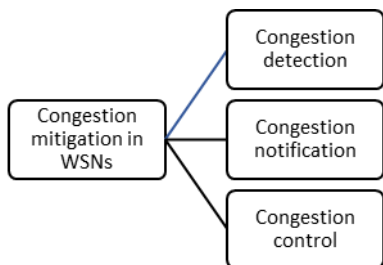


Fig. 2. Congestion mitigation in WSNs [10].

2.1. Congestion Detection

In WSNs, congestion detection is accomplished by one or more nodes towards the sink. There exist different metrics to detect congestion, i.e., packet loss, queue size, queue size and channel load, packet service time, packet service time and queue size, channel busyness ratio and throughput measurement, delay, scheduling time, reliability parameters and application fidelity [11]-[12].

2.2. Congestion Notification

Congestion notification is assessed after it is detected. In order to notify congestion, congestion information is transmitted in different ways. It can be notified either implicitly or explicitly across the WSN. In implicit method, by overhearing the sent data packets, congestion information is transmitted in the packet header. However, in explicit method, congested

nodes broadcast separate control packets to notify their congestion status. For congestion notification, implicit congestion notification is suggested to prevent extra load in the congested network [10].

2.3. Congestion Control

In this paper, congestion control algorithms are listed under two categories, i.e. classic or soft computing-based schemes. The classic congestion control schemes are listed under 12 categories, i.e. traffic control, resource control, traffic and resource control, fairness-based, priority-aware, E-2-E or H-by-H, energy efficient, reliability-based, queue-assisted, centralized or distributed, generic or cross layer and content-aware congestion control schemes. However, soft computing-based congestion control schemes are listed as fuzzy logic-based, game theory-based, swarm intelligence-based, learning automata-based, and neural network-based congestion control schemes. Fig. 3 shows the congestion control classification on WSNs.

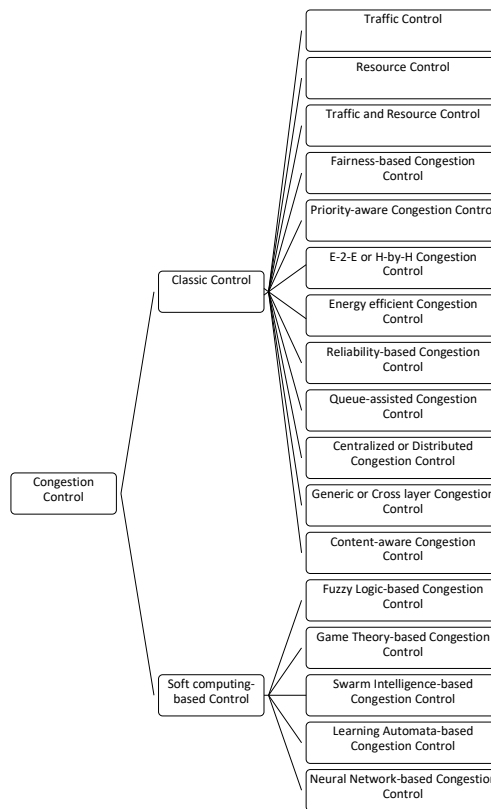


Fig. 3. Congestion control in WSNs.

3. SOFT COMPUTING-BASED CONGESTION CONTROL SCHEMES IN WSNs

In this section, soft computing-based congestion control schemes are listed as fuzzy logic-based, game theory-based, swarm intelligence-based, learning

automata-based, and neural network-based congestion control schemes.

3.1. Fuzzy Logic-based Congestion Control Schemes in WSNs

Network traffic in different layers is constantly monitored by network operators. Several techniques are presented to overcome network congestion. One such method is fuzzy logic which is actively utilized in wireless sensor networks for different applications [13]. Fuzzy logic is close to natural language comparing with the traditional logical systems which can capture the approximate real-world nature. The Fuzzy Inference System (FIS) includes the Fuzzification, the Rule Base, the Inference Mechanism and the Defuzzification interface module [13]. Fuzzy logic-based congestion control can be considered as one of the latest approaches to control congestion. Some well-known fuzzy logic-based congestion control schemes are summarized as follows [14]-[28], [43], [57]:

3.1.1. Fuzzy Rate Control in WSNs (FRC)

In [14], a hop-by-hop (HbyH) fuzzy rate control scheme is presented. In this protocol, the node queue size is continuously monitored. Thereafter, the admissible upstream node rate is calculated using a fuzzy inference system where the sensor nodes constraints are considered. In FRC, congestion detection is accomplished based on queue size and implicit congestion notification is used. The protocol is energy-efficient and fair. Also, it is simple and can adapt to network conditions. The results show that FRC renders superior performance in comparison with IEEE 802.11 on the basis of utilization, delay and throughput.

3.1.2. Congestion Control Based on Node Trustworthiness Using Fuzzy Logic (CCTF)

In [15], congestion control using fuzzy logic is accomplished based on node trustworthiness. In CCTF, the behavior of neighbors is investigated by the nodes. In this protocol, the malfunctioning nodes are isolated and valueless packets are blocked which ends in overhead ratio reduction. In this scheme, the buffer capacity is increased which renders congestion reduction. In CCTF, the traffic ratio overhead resulted from corrupted node packets are removed. The results show that CCTF ends in delivery ratio increase.

3.1.3. Fuzzy Logic-based Congestion Estimation Scheme (FLCE)

FLCE [16] presents a model for fuzzy logic-based congestion estimation in a QoS architecture. The architecture includes QoS management and control module which is implemented at the sink and node

level. In FLCE, traffic is classified based on different application classes by a queuing model in the node buffer. In this scheme, fuzzy logic is used for congestion estimation. The protocol is energy-efficient; however, it is not fair. The results show that in FLCE, the packet generation rate is increased and packet loss is minimized.

3.1.4. Hierarchical Tree-Based Congestion Control Using Fuzzy Logic (HTCCFL)

In HTCCFL [17], the topology control algorithm is utilized to construct a hierarchical tree in hierarchical tree construction phase. In this protocol, congestion detection is accomplished using a fuzzy logic technique. Moreover, a priority-based rate adjustment scheme is used to control congestion. In this protocol, energy efficiency and packet delivery ratio are improved, however, excessive jitter is obtained.

3.1.5. Fuzzy Priority-based Congestion Control (FPCC)

In [18], congestion is indicated by a technique which is similar to Random Early Detection (RED) Active Queue Management (AQM). In the fuzzy system used in FPCC, the node congestion level is estimated using the maximum drop probability of RED algorithm and the minimum and maximum thresholds. The parent node sending rate is adjusted with a fuzzy logical controller. The results show that FPCC renders superior performance in comparison with PHTCCP and PCCP on the basis of end to end (E2E) delay, loss ratio, and energy.

3.1.6. Optimized Fuzzy Logic-based Congestion Control Scheme with Exponential Smoothing Prediction (OFES)

In [19], a path determination architecture is presented for wireless sensor networks considering the congestion issue. The architecture comprises initial path construction in a hierarchical structure, path derivation with energy-aware assisted routing, and congestion prediction using exponential smoothing. In this scheme, the buffer occupancy is predicted by adopting exponential smoothing. Also, proper weights are determined to determine paths by applying FLS, and finally, the membership functions are tuned by FLS optimization using bat algorithm. The protocol is energy-efficient; however, it is not fair. The results show that the protocol renders superior performance in comparison with HTAP, DAIPaS, and CCEbH on the basis of energy efficiency, throughput, network lifetime, and loss ratio.

3.1.7. AQM Based Fuzzy Congestion Control (AFCC)

In [20], an AQM is presented to determine packet loss probability which integrates RED and Fuzzy Proportional Integral Derivative (FuzzyPID) schemes. FuzzyPID controls the desired buffer queue and adjusts the node sending rate. In [20], congestion detection is accomplished based on buffer occupancy and node rate and implicit congestion notification is used. The protocol is energy-efficient; however, it is not fair. The results show that AFCC renders superior performance in comparison with PCCP, CCF and OCMP on the basis of E2E delay and loss rate.

3.1.8. Fuzzy Sliding Mode Congestion Control (FSMC)

In [21], a congestion control model is presented between MAC and the transmission layer. Afterwards, fuzzy control and sliding mode control are combined. The resultant controller adaptively regulates the buffer queue size in the congested nodes and reduces the uncertain disturbance impact. The results show that FSMC renders superior performance on the basis of convergence, throughput, loss ratio, and delay.

3.1.9. Congestion Control Scheme Based on Fuzzy Logic (CCSFL)

In [22], a fuzzy logic-based congestion control is presented which considers buffer occupancy and congestion index to detect congestion. In CCSFL, the buffer occupancy changes are considered as the congestion index. In this protocol, implicit congestion notification is used. Moreover, fuzzy logic is used to calculate the congestion degree in CCSFL and rate adjustment is accomplished using the congestion degree. CCSFL is able to adapt to network status which prevents packet loss. The results demonstrate that CCSFL renders superior performance in comparison with SenTCP on the basis of delay, packet loss and throughput.

3.1.10. Network Status Aware Congestion Control (NSACC)

In [23], the congestion severity is predicted and the sending rate is regulated based on the congestion level. There exist two modules in NSACC algorithm, namely, the congestion identification and the rate regulation module. The congestion level severity is estimated using the fuzzy logic inputs as the buffer occupancy, priority, packet arrival rate and fuzzy rule-base. Afterwards, congestion is mitigated by regulating the sending rate which is accomplished by the rate regulation module. The results show that NSACC algorithm renders superior performance in comparison with PCCP on the basis of packet loss, retransmission number and throughput.

3.1.11. Fuzzy Control-based Congestion Detection and Control (IFCCDC)

In IFCCDC [24], congestion detection is accomplished based on the ratio between packet inter arrival time and service time which is defined as the congestion degree. In IFCCDC, congestion is implicitly notified and rate adjustment technique is used for congestion control where fuzzy logic is applied to implement the congestion controller. The results show that IFCCDC renders superior performance in comparison with CODA in terms of packet delivery ratio.

3.1.12. CONTROL of Sensor Queues (CONSEQ)

In CONSEQ [25], a lightweight distributed congestion control scheme integrated with load balancing is presented for WSNs. Congestion detection is accomplished based on the queue length and channel conditions. In this protocol, each node observes its one-hop neighbors to detect congestion. Moreover, fuzzy control is used for dynamic rate adjustment to control congestion. The results show that CONSEQ renders superior performance in comparison with PCCP on the basis of E2E delivery ratio, energy consumption and E2E delay.

3.1.13. Fuzzy Congestion Controller in WSNs (FCC)

In [26], congestion is controlled using ad hoc fuzzy rules base and membership functions. In FCC, congestion detection is accomplished based on queue length and channel load which are considered as FCC input. However, the FCC output is obtained from Fuzzy Rule Base and Fuzzy Inference Engine. In this protocol, congestion is implicitly notified and rate adjustment technique is used for congestion control. The results confirm the superior performance of FCC on the basis of energy efficiency, E2E delay, throughput and packet loss.

3.1.14. Fuzzy-based Adaptive Congestion Control (FBACC)

In FBACC [27], fuzzy logic is used for congestion estimation which adapts to the traffic rate changes with minimum packet loss. In this protocol, congestion detection is accomplished based on the traffic rate, buffer occupancy and participants. Also, implicit congestion notification is used. The protocol is energy-efficient; however, it is not fair. The results show that FBACC renders superior performance in comparison with ESRT, FLCE, CCSFL on the basis of energy efficiency, E2E delay and packet loss.

3.1.15. FLC With Exponential Weight Priority-Based Rate Control (FEWPBRC)

In [28], the sink output transmission rate is estimated by Fuzzy Logical Controller (FLC) where the FLC is associated with the Exponential Weight (EW) algorithm to select the proper weight parameter. Afterwards, the transmission rate is assigned according to the priority of child nodes. The results show that FEWPBRC renders superior performance in comparison with PBRC in terms of transmission rate, transmission delay and loss probability. Moreover, in FEWPBRC the system QoS requirements are met since it can efficiently control different types of the transmission data.

3.2. Game Theory-based Congestion Control Schemes in WSNs

Game theory is becoming more important in WSNs specifically for congestion control. Game theory is based on the player's behavior. It can be either cooperative or non-cooperative where in the former, players cooperate and form group decisions, however, in the latter, players act independently. Moreover, Game theory offers benefits to networking with respect to different layers [29]. Some well-known Game theory-based congestion control schemes are summarized as follows [30]-[34]:

3.2.1. Evolutionary Game Theoretical Resource Control (EGRC)

In [31], an evolutionary game theoretical resource control scheme is presented for wireless sensor networks. In EGRC, a non-cooperative game is developed to alleviate congestion in WSNs by controlling the radio transmission power and using the available resources. In EGRC, the transmission power is adjusted in accordance to the node congestion level and the energy capacity. The results confirm that in EGRC, throughput and energy saving are improved and packet drop is decreased.

3.2.2. Game Theory-based Congestion Control (GTCC)

In GTCC [32], the congestion problem is addressed among parent and child nodes in RPL-enabled networks with low power and resource constraint devices. In this protocol, congestion detection is accomplished using net packet flow rate. Afterwards, nodes in the congestion area perform parent-change procedure to find better parents using the game theory technique. The results confirm that in comparison with ContikiRPL implementation, GTCC ends in throughput enhancement and packet loss reduction.

3.2.3. Stochastic Differential Game Approach for Optimal Data Transmission

In [33], health care based wireless sensor networks are studied. In this scheme, four kinds of transmission costs are considered, namely, the pure transmission cost, the transmission cost, the penalized cost for data unreliability and the congestion cost. Also, game theory is used to minimize the transmission cost. In [33], three kinds of game models, namely, cooperative, partial cooperative and non-cooperative models are constructed to minimize the transmission cost. Also, the optimal transmission strategies under different game modes are gained for health care based wireless sensor networks. The techniques are compared and the validity of methods is verified.

3.2.4. A Game Theoretic Approach to Control Congestion

In [30], Diminishing Weight Schedulers (DWS) is presented as a class of service disciplines where the congestion avoiding users are rewarded and the misbehaving ones are punished. Also, a sample service discipline from the DWS scheduler class is presented. In this scheme, the max-min fair rates constitute a unique Nash and Stackelberg Equilibrium. The results confirm that in a WSN with DWS scheduling, the max-min fair rate can be properly estimated irrespective of the round-trip times. Moreover, the excessive congestion problem is rectified.

3.2.5. Evolutionary Game Approach to Control Congestion (EGCC)

In [34], evolutionary games are applied to non-cooperative networks with individual non-cooperative sensors. In EGCC, the congestion control evolution is investigated and it is shown that the wireless channel affects the congestion control evolution and the Evolutionary Stable Strategies (ESS). In EGCC, a framework is provided to investigate the protocol in a competition between aggressive and peaceful behaviors. Also, a framework is provided to control the evolutionary dynamics by choosing a gain parameter which governs the replicator dynamics.

3.3. Swarm Intelligence-based Congestion Control Schemes in WSNs

Social groups in nature contribute to a common goal by collectively carrying out their tasks. Wireless sensor networks have common characteristics in comparison with social groups, i.e. nodes perform their tasks collectively as constituents of social groups. Swarm intelligence is suggested to mitigate congestion by mimicking the collective behavior of swarms where swarms are low-intelligence interacting agents which are organized in small societies [35]. Some well-known swarm intelligence-based congestion control schemes are summarized as follows [36-43]:

3.3.1. Bio Inspired Swarm Intelligence-based Algorithm to Control Congestion

In [36], a bio inspired swarm intelligence scheme is utilized to mitigate congestion and enhance energy efficiency by forming clusters. In this scheme, Biography Based Krill Herd (BBKH) algorithm is used to improve network performance. BBKH algorithm is inspired by a bio-based swarm intelligence algorithm where the objective function is the highest swarm density and the distance from food. Also, few control variables are required to adjust BBKH. The results confirm that the algorithm renders superior performance on the basis of network lifetime increase.

3.3.2. Hybrid Multi-Objective Optimization for Congestion Control

In [37], Particle Swarm optimization (PSO) and Gravitational Search Algorithm (GSA) are combined to form a hybrid multi-objective optimization (PSOGSA) which is used to control congestion. PSOGSA is used to optimize and regulate the data arrival rate from child node to parent node where the node energy is considered in the corresponding fitness function. In case the arrival rate is regulated based on the priority, the transmission is enabled. Moreover, rate adjustment to the optimal value is utilized for congestion mitigation. The results confirm the superior performance of algorithm comparing with Cuckoo Search (CS) and Adaptive Cuckoo Search (ACS) algorithms.

3.3.3. Bird Flocking-based Congestion Control (BFCC)

In [38], the bird flocking behavior is the key point to design a congestion control scheme in WSNs. In BFCC, a swarm intelligence paradigm is applied which is inspired by the bird flock's behavior. In this protocol, flocks are formed by the packets (birds) which flow towards the sink and at the same time congested areas are avoided. It is quite simple to implement the scheme at node level since minimum information exchange is required. The results confirm the scalability of BFCC and that it is robust against the failing nodes.

3.3.4. Epsilon Constraint-Based Adaptive Cuckoo Search Algorithm for Rate Optimized (EACSRO)

In [39], the congestion occurrence is detected by the node incoming packets. Afterwards, the virtual queue length is used to determine the congestion level. The Epsilon parameter is used to formulate the fitness function to gain the optimal value. Thereafter, the fitness is exploited and the step size is adaptively adjusted. The best solution is gained in case the data transmission is accomplished without congestion. The

results confirm the effectiveness of EACSRO on the basis of sending rate and throughput.

3.3.5. Computational Intelligence-based Congestion Control and QoS Enhancement

In [40], different metaheuristic and computational intelligence schemes are used for congestion mitigation and QoS enhancement. In this regard, throughput, residual energy, the number of retransmissions and the distance between nodes are used to formulate the objective function which is optimized by nature inspired computational intelligence techniques. The results confirm the superior performance of water wave algorithm in comparison with Firefly Algorithm, Improved Bat Algorithm, Ant Colony Optimization (ACO), PSO, and CODA on the basis of throughput and drop ratio.

3.3.6. Bio-Inspired Protocol for Congestion Control

In [41], a hybrid congestion control protocol for large-scale WSNs is presented. In this protocol, congestion avoidance is accomplished by a competitive Lotka-Volterra model and fairness is maintained among sensor nodes. Moreover, PSO is used to enhance C-LV by minimizing the E2E delay. The results confirm the effectiveness of the scheme for QoS enhancement. This protocol is fair; however, it is not energy efficient.

3.3.7. Improved Bat Algorithm Energy Efficient Congestion Control (IBAECC)

In [42], an improved bat algorithm is implemented on the basis of bat echolocation. In IBAECC, sonar echoes are used by bats to detect and avoid obstacles. The sonar echoes are then reflected from the obstacle and transformed to frequency. The optimum solution is obtained by applying the aforementioned algorithm on the fitness function. The results confirm the superior performance of IBAECC comparing with ACO, PSO and CODA in terms of throughput and network lifetime.

3.3.8. Cuckoo Fuzzy-PID Controller (CFPID)

In [43], queue size is controlled using PID controller and the effective sensor data collection is realized by applying the PID algorithm on cluster head nodes. Moreover, the problems concerning PID controller, i.e., the limited adaptive ability, slow parameter optimization, and poor optimization precision are rectified using a fuzzy control scheme. CFPID optimizes the quantization factor of fuzzy PID controller and the PID parameter. The results confirm that CFPID outperforms IBLUE and PID on the basis of real-time loss rate and instantaneous queue length.

3.4. Learning Automata-based Congestion Control Schemes in WSNs

Learning Automata (LA) is a self-operating mechanism which responds to a sequence of instructions to achieve a specific goal. The automaton adapts to the environmental dynamics or responds to a pre-determined rule set. The automata learn the best action from a set of possible actions offered by the operating environment [44]. Learning automata-based congestion control can be considered as one of the latest approaches to control congestion. Some well-known Learning automata-based congestion control schemes are summarized as follows [45]-[51]:

3.4.1. Learning based Congestion Control Protocol (LCCP)

In LCCP [46], a learning-based rate adjustment and AQM are used to mitigate congestion. Since different physiological signals are discriminated and assigned different priorities, better QoS is provided for transmitting important signs in LCCP. In LCCP, the source rate is adjusted by the learning automata-based transport protocol which is located in the sink which ends in congestion mitigation. The results show that LCCP outperforms LACAS on the basis of delay, throughput, and drop ratio.

3.4.2. Intelligent Closed-Loop Learning Automaton-Based Congestion Control (ICLACC)

In [47], a learning automation-based congestion control scheme is presented for Wireless Body Area Networks (WBANs). In this scheme, each packet is assigned as the appropriate queue based on the conditional probabilities. In [47], an exponential arrival and service time is considered in each queue. In this scheme, each packet is directed to a suitable queue for QoS enhancement and meets the application real-time constraints by congestion mitigation. The results confirm the effectiveness of ICLACC on the basis of throughput and the drop ratio.

3.4.3. Learning Automata-Based Congestion control Scheme (LACC)

In [45], congestion control is assessed using LA. In this scheme, a learning-automata based algorithm is presented where each node has an automaton which selects an action and adjusts the corresponding rate according to the environment responses. Also, the algorithm enhancement is gained as it learns from the past.

3.4.4. Prioritization-based Congestion Control

In [48], a service prioritization and congestion control scheme is presented for real time monitoring of vital signs of patients using wireless biomedical

sensor networks. It includes bandwidth allocation and learning automata based AQM in intermediate nodes. In this scheme, different priorities are given to patients based on the corresponding physiological conditions. In this scheme, less packet loss and higher throughput are gained by selecting a proper source rate. Also, the optimal packet service rate is chosen in the intermediate nodes which renders E2E delay reduction.

3.4.5. Learning Automata-based Congestion Avoidance Scheme (LACAS)

In LACAS [49], a learning automata-based congestion is addressed in healthcare WSNs. In this protocol, the flow rate is controlled to minimize congestion occurrence. Using the past experience, LACAS can adaptively learn and intelligently choose better data rates in future. In LACAS, congestion detection is accomplished based on the queue size and implicit congestion notification is used. In this protocol, a proactive approach is taken by the intermediate nodes to control the packet flow rate. The results confirm that LACAS renders superior performance comparing with other schemes available in the literature.

3.4.6. Learning Automata-based Protocol for Solving Congestion Problem

In [50], an action is selected by an automaton, and the rate is adjusted based on the environment responses. Learning from the past can be considered as an important feature of this scheme. In this protocol, a proactive approach is taken by the intermediate nodes to control the packet flow rate and enhance the network performance on the basis of energy consumption and life time. In this scheme, the intermediate nodes do not feedback the source nodes to slow down the network performance.

3.4.7. Optimized Congestion Management Protocol (OCMP)

OCMP [51] consists of a congestion control scheme and an AQM technique where the latter is used to avoid congestion and provide QoS. Based on the source traffic priority, separate virtual queues are used on a single physical queue. In case the incoming packet is accepted, congestion control is accomplished. In OCMP, congestion is detected by a three-state machine and virtual queue status. Moreover, the child's sending rate is adjusted by an optimization function. The scheme outperforms PCCP, CCF and backpressure algorithms on the basis of fairness, packet loss, E2E delay and energy consumption.

3.5. Neural Network-based Congestion Control Schemes in WSNs

Neural networks (NNs) are able to approximate an arbitrary nonlinear function [52]. NNs are studied in traffic control or prediction of networks due to their flexible learning capabilities [53]. NNs can model the network behavior to predict the occurrence of network congestion and manage the traffic. Some well-known neural network-based congestion control schemes are summarized as follows [54]-[59]:

3.5.1. Particle Swarm–Neural PID Congestion Control (PNPID)

In [54], first the queue management of WSN nodes is accomplished by the PID control. Then, the online weight adjustment is gained to adjust the PID parameters. Finally, the online optimization is achieved using PSO to neural PID (PNPID) algorithm which is applied to initial PID parameter values and neuron learning rates. PNPID algorithm renders superior performance on the basis of packet loss rate and throughput which confirms network QoS enhancement.

3.5.2. NARX Neural Network-based Rate Adjustment for Congestion Avoidance and Control (NNRA-CAC)

In [55], Neural network-based Rate Adjustment (NNRA) uses the LM-based NARX neural network to avoid and control congestion. The optimized share rate for congestion control is provided by the optimization algorithm. In this protocol, data transmission is accomplished according to the priorities of parent and child nodes. Moreover, dropping the packets that arrive the parent nodes ends in congestion avoidance. Packet drop at the parent nodes depends on the importance of data. The results show the superior performance of NNRA-CAC comparing with SS, ORA, CS, ACS, and EACS on the basis of packet loss, throughput, queue length, delay, and the congestion level.

3.5.3. Neural Network-Based Congestion Control (NNCC)

In [56], a congestion scheme with sensitivity to delay and the corresponding changes is presented. In this scheme, congestion is detected using neural networks. It prevents network service failures and detects the congestion source. In NNCC, time distance between source and sink and the remaining energy are considered in the transmitted message. The results confirm the superior performance of NNCC in terms of E2E delay, E2E reliability, and network lifelong.

3.5.4. Congestion Control Based on $L_{1/2}$ Regularization

In [57], the congestion problem near the central node is solved. In this scheme, the collected data is compressed to balance the network load. Then, the dimension of the compressed sensing observation matrix is adjusted by the fuzzy neural network. In this protocol, the PID queue management parameters are optimized by the fuzzy control to maintain the node queue size near the desired value. Moreover, the compressed transmission data is reconstructed using a $L_{1/2}$ regularization half-threshold iterative algorithm which has small data loss and high reconstruction precision. The results confirm that the scheme renders superior performance on the basis of delay, drop ratio and throughput.

3.5.5. Radial Basis Neural Network Congestion Controller (RBNNCC)

In [58], the possibility of using the shortest path routing in WSNs is explored where the perfect path for data transmission within an exact time is obtained using an ideal routing technique. In RBNNCC, congestion is estimated by a multilayer perceptron neural networks with sigmoid activation function and Radial Basis Neural Network Congestion Controller at the sink. The results confirm the effectiveness of the scheme in terms of data lost, the execution time, memory utilization and the traffic received at the sink.

3.5.6. Modified Neural Network Wavelet Congestion Control (MNNWCC)

In [59], the wavelet activation function is used to activate the neural network and control the WSN traffic. In MNNWCC, congestion is detected using the congestion level indications, then the traffic rate is estimated for congestion avoidance, and finally QoS enhancement is obtained in terms of network energy, packet loss ratio, buffer utilization, and throughput. The results confirm the effectiveness of MNNWCC for QoS enhancement.

4. COMPARISON OF SOFT COMPUTING-BASED CONGESTION CONTROL SCHEMES IN WSNs

In this section, first, the above-mentioned soft computing-based congestion control schemes are compared with each other. Tables 1, 2, 3, 4 and 5 summarize the fuzzy logic-based, game theory-based, swarm intelligence-based, learning automata-based, and neural network-based congestion control schemes, respectively. In the aforementioned Tables, congestion detection, notification and mitigation of several soft computing-based congestion control protocols are outlined. Also, the evaluation type and the comparison with protocols are outlined and the fairness and the energy conservation are presented. Afterwards, in

Table 6, the aforementioned protocols are compared using different parameter evaluation metrics.

Table 1. Comparison of Fuzzy logic- based congestion control schemes.

Protocol	Congestion detection	Congestion notification	Congestion control	Energy efficiency	Generic /crosslayer	Loss recovery	Fairness	Compared with	Evaluation type
CCSFL [22]	Buffer occupancy, congestion index	Implicit	Fuzzy logic- based congestion control	No	Generic	No	No	SenTCP	OPNET
FRC [14]	Queue size	Implicit	Fuzzy logic- based congestion control	Yes	Generic	No	No	IEEE 802.11	Simulation
FBACC [27]	Traffic rate, participants, buffer occupancy	Implicit	Fuzzy logic- based congestion control	Yes	Generic	No	No	ESRT, FLCE, CCSFL	MATLAB Simulink
AFCC [20]	Buffer capacity, node rate	Implicit	Fuzzy logic- based congestion control	Yes	Generic	No	No	CCF, PCCP, OCMP	OPNET simulator and MATLAB
HTCCFL [17]	Fuzzy based congestion detection	Implicit	Priority Based Rate Adjustment	Yes	Generic	No	No	PHTCCP	Network Simulator (NS2)
FPCC [18]	Average queue size	Implicit	Rate adjustment	Yes	Generic	No	Yes	PCCP, PHTCCP	OPNET simulator and MATLAB
IFCCDC [24]	Congestion degree	Implicit	Rate adjustment	No	Generic	No	No	CODA	Simulation
FCC [26]	Channel load, queue length	Implicit	Rate adjustment	Yes	Generic	No	No	-	OPNET
CONSEQ [25]	Queue lengths and channel conditions	Implicit	Dynamic rate adaptation via fuzzy control	Yes	Cross layer	No	No	PCCP	OMNeT++ network simulator

Table 2. Comparison of Game theory- based congestion control schemes.

Protocol	Congestion detection	Congestion notification	Congestion control	Energy efficiency	Generic/ crosslayer	Loss recovery	Fairness	Compared with	Evaluation type
EGRC [31]	Queue size	Implicit	Game theory- based congestion control	Yes	Generic	No	Yes	TADR	OPNET simulator
GTCC [32]	Net packet flow rate	Implicit	Alternative path selection	No	Generic	No	No	CRPL- OFO, CRPL- OF-ETX	Cooja simulator
[33]	Queue size	Implicit	Game theory- based congestion control	No	Generic	No	No	-	MATLAB simulation

Table 3. Comparison of Swarm intelligence- based congestion control schemes.

Protocol	Congestion detection	Congestion notification	Congestion control	Energy efficiency	Generic/cross layer	Loss recovery	Fairness	Compared with	Evaluation type
[37]	Node congestion level	Implicit	Rate adjustment	Yes	Generic	No	No	Cuckoo Search (CS), Adaptive Cuckoo Search (ACS)	Simulation
Bio-Inspired scheme for Congestion Control [41]	Queue size	Implicit	Rate adjustment	No	Generic	No	Yes	-	Implementation using NS3 network simulator

Protocol	Congestion detection	Congestion notification	Congestion control	Energy efficiency	Generic/cross layer	Loss recovery	Fairness	Compared with	Evaluation type
EACSRO [39]	Virtual queue size	Implicit	Rate adjustment	No	Generic	No	No	-	Simulation
BFCC [38]	Buffer occupancy	Implicit	Rate adjustment	Yes	Generic	No	No	NCC, CAwR, AODV, AntHocNet, AntSensNet	ns-2 simulator
CFPID [43]	Buffer occupancy	Implicit	Rate adjustment	No	Generic	No	No	IBLUE, PID	MATLAB

Table 4. Comparison of Learning automata- based congestion control schemes.

Protocol	Congestion detection	Congestion notification	Congestion control	Energy efficiency	Generic/cross layer	Loss recovery	Fairness	Compared with	Evaluation type
LACAS [49]	Queue size	Implicit	Learning automata adjust flow rate	Yes	Generic	No	Yes	-	Simulation
LCCP [46]	Queue length and packet loss rate	Implicit	Learning automata-based congestion control	Yes	Generic	No	Yes	LACAS	OPNET simulator
ICLACC [47]	Queue size	Implicit	Learning automata-based congestion control	No	Generic	No	No	-	OMNeT++ simulation
[48]	Automata-based congestion detection	Implicit	Learning automata-based congestion control	No	Generic	No	Yes	-	Simulation
OCMP [51]	Automata-based congestion detection	Implicit	optimized Rate Adjustment	Yes	Generic	No	Yes	CCF, PCCP	OPNET simulator

Table 5. Comparison of Neural network- based congestion control schemes.

Protocol	Congestion detection	Congestion notification	Congestion control	Energy efficiency	Generic/crosslayer	Loss recovery	Fairness	Compared with	Evaluation type
PNPID [54]	Queue size	Implicit	Rate adjustment	No	Generic	No	No	PI, PID, NPID, PNPID	Simulation NS2
NNRA-CAC [55]	Queue size	Implicit	LM-based NARX neural network congestion control	No	Generic	No	No	SS, ORA, CS, ACS, and EACS	MATLAB simulation
[57]	Queue size	Implicit	Rate adjustment	No	Generic	No	No	PID	MATLAB simulation

Different metrics [51] are used to evaluate the performance of the soft computing-based congestion control schemes. The features and evaluation metrics are the source rate, throughput, goodput, network efficiency or life time, energy efficiency, packet loss ratio, fairness, memory requirements, end-to-end delay, instantaneous queue size, control packet overhead, fidelity index and penalty where the schemes are compared regarding the aforementioned features in Table 6.

Table 6. Comparison of soft computing-based congestion control schemes in WSNs based on different performance metrics.

Protocol	Performance metrics	Protocol	Performance metrics
CCSFL [22]	Throughput, delay, packet loss rate	Bio-Inspired scheme for Congestion Control [41]	E2E delay, packet delivery ratio, throughput
FRC [14]	Utilization, throughput,	EACSRO [39]	Throughput, sending rate

	delay		
FBACC [27]	Packet loss, E2E delay, energy	BFCC [38]	Energy tax, packet loss, delay, packet delivery ratio
AFCC [20]	Data loss rate, E2E delay	CFPID [43]	Instantaneous queue length, packet loss rate
HTCCFL [17]	Delay, Energy consumption, Packet drop, Packet delivery ratio	LACAS [49]	Energy consumption, throughput
FPCC [18]	Packet loss, E2E delay, energy	LCCP [46]	Throughput, delay, packet drop ratio, energy efficiency
IFCCDC [24]	Packet Delivery Ratio, delay	ICLACC [47]	Drop ratio, throughput
FCC [26]	Energy efficiency, E2E delay, Throughput, Packet loss	[48]	Packet loss ratio, Source rate, Delivery ratio, Throughput, Queue Length, Delay
CONSEQ [25]	E2E packet delivery ratio, E2E delay, energy efficiency	OCMP [51]	Packet loss, energy efficiency, E2E delay, fairness
EGRC [31]	Packet drop ratio, throughput, energy efficiency	PNPID [54]	Throughput, packet loss rate
GTCC [32]	Packet loss rate, throughput, average hop count	NNRA-CAC [55]	Throughput, delay, packet loss, queue size, congestion level

[33]	Transmission Time	[57]	Throughput, packet loss rate, delay
[37]	Energy efficiency, E2E delay, packet loss, queue length, sending rate, throughput, congestion level		

5. CONCLUSION

Congestion mitigation schemes are classified based on the way congestion is detected, notified to nodes, and faced. Congestion can be detected using different metrics. Congestion notification is accomplished either explicitly or implicitly. In this paper, congestion control algorithms are classified as classic or soft computing-based schemes. Thereafter, a comprehensive review of different soft computing-based congestion control schemes in wireless sensor networks is presented. Furthermore, these schemes are compared using different performance metrics. In this paper, the classic congestion control schemes are listed under 12 categories, i.e. traffic control, resource control, traffic and resource control, fairness-based, priority-aware, E-2-E or H-by-H, energy efficient, reliability-based, queue-assisted, centralized or distributed, generic or cross layer, and content-aware congestion control schemes. However, soft computing-based congestion control schemes are listed as fuzzy logic-based, game theory-based, swarm intelligence-based, learning automata-based, and neural network-based congestion control schemes. Hop-by-hop congestion control schemes are also suggested, since E2E schemes end in error rate and latency increase and reduced responsiveness.

6. FUTURE DIRECTIONS

Future directions for soft computing-based congestion control schemes in WSNs should consider the following items:

- Soft computing-based congestion control schemes shall be robust against internal perturbations and external stimuli.
- Soft computing-based congestion control schemes shall be scalable to be able to adapt to the number of sensor nodes.
- Soft computing-based congestion control schemes shall be self-adaptable to respond to sudden environmental changes and node removal or addition.

- Soft computing-based congestion control schemes shall consider deployment aspects.
- Soft computing-based congestion control schemes shall consider the possibility of using mobile agent techniques for performance enhancement.
- Soft computing-based congestion control schemes shall consider both wireless channel contention losses and queue occupancy or buffer drops to infer congestion. This is due to the fact that queue occupancy alone is not an indication of congestion and wireless channel contention losses quickly increase with channel load and end in buffer drop increase.
- Soft computing-based congestion control schemes shall consider new WSN generations. New WSN generations as Under Water Sensor Networks (UWSNs), Body Area Sensor Networks (BASN) and Wireless Multimedia Sensor Networks (WMSNs) bring about new issues in the design of congestion control schemes which shall be considered as a future work.
- Soft computing-based congestion control schemes shall consider energy efficiency.
- Soft computing-based congestion control schemes shall consider QoS provisioning in WSNs.
- Soft computing-based congestion control schemes shall optimize network performance since network performance is of paramount importance and the trade-off among different factors to control congestion and optimize network performance is required.
- Soft computing-based congestion control schemes shall consider the security issue.
- Soft computing-based congestion control schemes shall be cross-layer to be able to interact with different layers.
- Soft computing-based congestion control schemes shall be autonomous and decentralized to provide fast congestion relief.
- Soft computing-based congestion control schemes shall be easily implementable due to the existing energy and memory constraints of sensors in wireless sensor networks.
- Soft computing-based congestion control schemes shall consider the experimental methods to demonstrate their effectiveness in real life scenarios.

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