



## Smart Bandwidth Prediction, Power Management and Adaptive Network Coding for WSN

Gopalsamy Vanitha<sup>1\*</sup>Palaniswamy Amudha<sup>1</sup>Subramaniam Pillai Sivakumari<sup>1</sup>

<sup>1</sup>*Department of Computer Science Engineering, School of Engineering  
 Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore-641043, India*

\* Corresponding author's Email: vanithagphd19@gmail.com

---

**Abstract:** WSN has been widely used in many sensitive applications and it also has novel possibilities for laying the groundwork for using ubiquitous and pervasive computing, but it has also presented a number of issues and challenges, such as a dynamic network topology and a congestion problem that hinders not only network bandwidth utilisation but also performance. Proficient rate control and fair bandwidth allocation (PRC-FBA) was one of the schemes in the literature to solve issues of WSN by combining the ideas of traffic class priority and bandwidth fairness. However, because of the nature of WSN, the energy of nodes near the sink node is diminished when packets move from lowly congested nodes to highly congested nodes. This paper proposes a proficient rate control with data aggregation and fair bandwidth allocation (PRCDA-FBA) to address this problem by using an effective data aggregation approach for reducing the number of transmissions. In the proposed method, fair bandwidth allocation is simplified by an artificial intelligence-based bandwidth prediction method. Thus, PRCDA-FBA increases the network's durability. Despite having lower bandwidth utilizations, energy-critical sensor nodes require careful power management to avoid being eavesdropped upon. Along with data aggregation and fair bandwidth allocation, the effects of overhearing packets by energy-critical nodes are mitigated through network-wide route adjustments based on the energy level of nodes. Thus, in the proposed method, data aggregation is scheduled based on the availability of bandwidth, energy, queue size and packet priority. The proposed method is named as energy-aware proficient rate control with data aggregation and fair bandwidth allocation (EPRCDA-FBA). The proposed algorithms have been deployed on the Network Simulator 2.35 platform, and a comparative analysis has been performed using several metrics, including throughput, packet loss, End-to-End (E2E) delay and energy utilization. The EPRCDA-FBA method archives highest throughput which is 9.17%, 5.48%, 4.68% and 2.45% higher than congestion control strategies like discrete-time sliding mode congestion controller (DSMC), weighted priority based fair queue gradient rate control (WPFQGR), PRC-FBA and rate adjustment-based congestion control (RACC).

**Keywords:** Wireless Sensor networks, Congestion control, PRCDA-FBA, EPRCDA-FBA.

---

### 1. Introduction

WSNs are developed by connecting a large number of sensor nodes where each sensor can collect information from its neighbours and transmit it to them over a wireless network within its distribution centre. WSN is extensively used in a variety of applications, including medical practises, agricultural modelling, disaster monitoring, and so on, and it relies on a set of efficacious measures to preserve stability.

Every sensor node is equipped with all of the necessary data transmission capabilities [1]. But, due to continuous transmission congestion occurred which causes high delay, low throughput, high energy consumption, more data loss, poorer integrity and performance degradation even if such nodes employ the maximum capacity.

Over the last ten years, in the literature, many researchers focussed on developing several tailored Networking protocols [2]. An effective methods are required in WSN to handle massive amounts of frequently sensed data with limited bandwidth and

energy utilization. It's critical to get the signal from the originator node to the sink node with as little loss as possible. Congestion in the network is among the most important factors in data loss, and avoiding congestion has piqued the interest of many academics [3, 4].

In the literature, a variety of traffic delay tactics has been identified, with rate control being one of them. It has been discovered that real time (RT) traffic necessitates minimal latency and excellent consistency, and hence must be prioritised. In RT applications, WSNs can generate a wide range of data packets [5]. Due to bandwidth constraints in WSNs, such a wide range of data must be handled with different levels of priority, which helps to keep the network from becoming congested [6]. Various algorithms have been developed over the years to control congestion based on the traffic priorities of RT packets. Weighted Priority Difference of Differential Rate Control (WPDDRC) algorithm [7] has been developed which combines the DDR of a particular node with the WP of traffic class. Variations in next hops across routing paths between the transmitter and the receiver in the WPDDRC algorithm can lead to an increase in the WSN's unintended energy consumption.

For dealing with congestion and buffer overflow in WSNs, a PRC-FBA congestion control algorithm was proposed [8] in previous study. In this method, two different virtual queues are used on a single physical queue to collect incoming packets from all child nodes based on the priority. This technique prioritise different kinds of traffic and distributing bandwidth fairly. This approach first analyses the problem of bandwidth assignment in WSN using the Signal to Interference and Noise Ratio (SINR) model, which aims to find a balance between neutrality and network efficiency. Packets flow from low-congested nodes to highly-congested nodes in a WSN network, reducing the energy of nodes near sink nodes in the PRC-FBA.

To address the above problem, PRCDA-FBA is proposed in this paper that uses a well-organized aggregation mechanism to reduce the battery power across all participating nodes and leading to higher total network throughput. Aggregation mechanism just a form of adaptive network coding built on top of random linear network coding (RLNC). An adaptive network combines data for transmission to the next hop which increases channel usage and reducing packet redundancy in the network. An adaptive methodology is triggered only when congestion occurs Based on packet priority, residual energy, and latency, the parent node decides whether or not to activate networking coding, as per the

adaptive network coding approach. Long Short-term Memory (LSTM) based neural network is also used to anticipate the required bandwidth for nodes by learning from previous data, which includes packet drop rate, energy, priority of packets, latency of packets, and bandwidth use. Even though data aggregation mechanism reduce the unnecessary transmission and energy consumption, the energy management additionally required to improve the network performance further. As a result energy saving criteria also include in PRCDA-FBA and named as EPRCDA-FBA. The path selection is considered along with residual energy of nodes. The major purpose of this proposed method is ensure to meet QoS standards in terms of fast data delivery, reduced energy consumption of energy-intensive nodes and increased network durability. The excess power of the node is taken into account in this protocol's primary concern rate control approach.

Leftover paper units are made as follows: related works in section 2. PRCDA-FBA and EPRCDA-FBA are explained in section 3. Simulated findings are in section 4. Section 5 summarises the article and suggests future work.

## 2. Related works

There is a proposal for congestion control [9] that uses fuzzy heuristic and metaheuristic search to balance a variety of objectives, including travel time, energy consumption, and network density. Multiple goals are taken into account when controlling the cluster leader's queue. The reduced power usage from this technology increases the longevity of the network. However, as the simulation time increases, the delay and throughput progressively worsen. Cooperation game theory [10] is used to describe data transfer priorities. The level of congestion and the quality of service (QoS) requirements of each type of data inform the ant-based routing algorithm that is integrated with game theory to construct the path. Due to the lack of queue control, significant packet loss happens while employing this technique. To achieve this, a DSMC is developed, which successfully adjust queues at bottleneck nodes to the appropriate value [11]. In terms of latency and packet loss, this strategy is superior. However, the congestion issue will get more severe, resulting in greater delays, as the simulation time increases.

An adaptive access control is developed for more efficient traffic management and lower power usage [12]. To determine which nodes should be allowed access to the wireless channel first, second, or third, a fuzzy technique is utilised. In high-traffic settings, however, dynamic time-slot management is

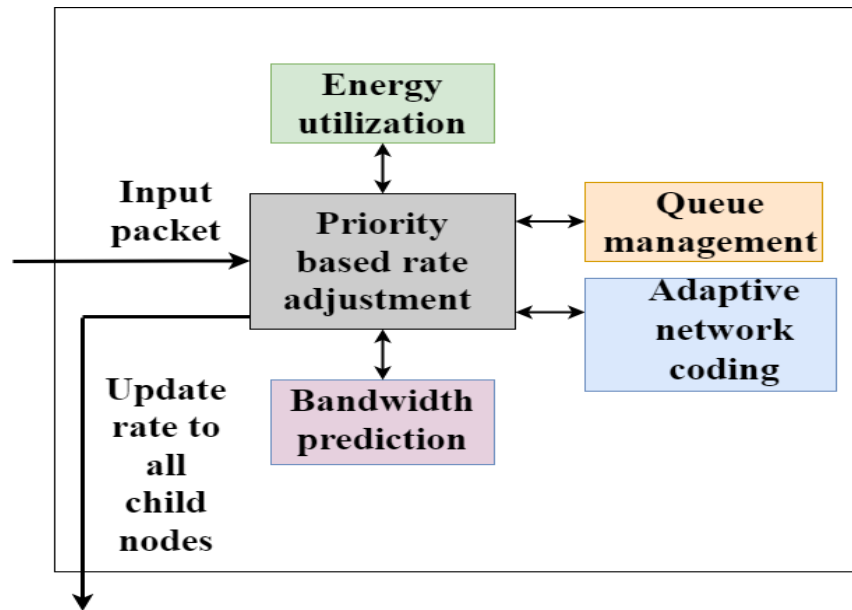


Figure. 1 The proposed method is depicted in a block diagram

challenging and will impair network throughput. To boost network functionality, an effective congestion avoidance strategy [13] is presented based on Huffman coding algorithm and ant colony optimization. This strategy is an amalgam of resource-based and traffic-based optimization strategies. Although effective initially perform well, this strategy has higher delay and low throughput as the duration of the simulation time increases.

By calculating the retransmission likelihood of packet arrival and the average energy usage, we may avoid transmission collision [14]. As energy consumption at individual nodes climbed above 50%, however, throughput began to degrade. Weighted priority based fair queue gradient rate control (WPFQGR) [15] ensures that available bandwidth is shared equitably by considering traffic class priorities, average queue sizes, and a node's connected loads. Every efficiency metric is improved upon by this technique. As the simulation period increases, however, key metrics like energy and throughput inevitably drop.

Artificial intelligence algorithms are employed for awakening scheduling of active nodes [16], while the Spatial Spider Optimization algorithm and K-means clustering enhancement are used to pick cluster heads. Provides improved delay and throughput at first, but both degrade with time. A system called RACC [17] has been developed to alleviate traffic congestion. Node buffer occupancy is monitored and used to dynamically alter the transmission rate. Additionally, a variety of modulation algorithms were used to lessen the load

on the available bandwidth. However, delays and reduced throughput become more common once a certain amount of time has passed during transmission.

### 3. Energy-aware proficient rate control with data aggregation and fair bandwidth location algorithm (PRCDA-FBA)

The model of the system is illustrated as a graph  $G(V, E)$ . Here,  $V$  represent sensor nodes and  $E$  is connections among them.  $e(a, b) \in E$  defines the communication relationship between different nodes  $a \in V$  and  $b \in V$ , and sink node is the ultimate receiving node. The connection  $e(a, b) \in E$  also symbolises the nodes  $a$  and  $b$  at the transmitter ( $T_r$ ) and reception ( $R_r$ ) ends, respectively. Connections are established between nodes in a network when the space between them is less than the maximum range of the transmission medium. The sensor node communicated the collected data to the subsequent node after returning from the application field.

The proposed method aggregates data via network coding to lessen latencies in data transmission and power consumption while increasing network throughput. The transmission frequency is the average rate at which packets are sent from a single node during a single transmission round. Reduced transmission frequency, on the other hand, increased network channel capacity, which enhanced overall network throughput. The network coding path combines data for transmission to the next hop, increasing channel usage and reducing

packet redundancy in the network [18]. When congestion occurs, an adaptive methodology is given in which the packet dropping rate is increased and the node sends packets by aggregating them using network coding.

In a dynamic environment, network coding offers a few advantages in terms of performance and throughput. In contrast, network coding necessitates extensive computational complexity on both ends of the transmission link. As a result, the necessity to devise an algorithm that provides optimal performance while minimising operating cost. A new adaptive network coding method is developed based on [19] to enable the source node to switch back and forth between archiving and transmitting actual packets into networks and going to perform RLNC of data packets and trying to deliver them into system. Fig. 1 represents the proposed congestion control mechanism.

### 3.1 Energy-aware proficient rate control

Due to the use of battery power and energy consumption, lots of energy will be loss hence power management is required to overcome this difficulty. To establish a relationship between the strength of the transmission signal and the quality of the forward connection, researchers at EPRCDA-FBA developed a receiver-based prediction model. The EPRCDA-FBA algorithm is presented to handle power regulation and extend battery life.

In the proposed EPRCDA-FBA algorithm, energy aware Proficient Rate control scheme is proposed. The major purpose is to ensure that QoS standards are met in terms of delayed data delivery, reduced energy consumption of energy-intensive nodes, and increased network lifespan. The surplus power of the node is taken into account in this protocol's priority-based rate control method. Initially, a prediction model is used to determine the proportion of node transmit energy levels that can be reduced without drastically reducing the packet delivery ratio. Then, to avoid overhearing energy-critical nodes, a priority of nodes for delivering traffic classes of packets is determined using a combination of energy.

The nodes employ this prediction model for two objectives. First, a node can use this model to determine how much power it can lower in relation to a receiver while keeping a specific level of connection quality. Second, the node can determine how much overhearing is transmitted to energy essential neighbours at a given transmit power level. Since the broadcast power level of the broadcaster greatly affects the link quality between a pair of

nodes, it is important to build a prediction model at the receiver end that links the broadcast power level at the transmitter together with the lifetime at the receiver. Traffic load of node is calculated in Eq. (1)

$$TL = \frac{\sum_{j=1}^N q(j)}{N} \quad (1)$$

The number  $N$  here represents the number of packets,  $q(j)$  represent the  $j^{\text{th}}$  packet in the queue.  $q_{max}$  is the maximum queue size. Traffic Load Intensity is calculated Eq. (2).

$$TLI_{(i)} = \frac{TL_{(i)}}{q_{max}^{(i)}} \quad (2)$$

The cost of the link is calculated based on the energy utilized for packets transmission Eq. (3).

$$LC_{i,n} = \frac{O_i}{E_{i,j}} \quad (3)$$

$E_{i,j}$  energy for transmitting  $j^{\text{th}}$  packet by  $i^{\text{th}}$  node.  $O$  Represent out coming packet from previous sensor nodes of current node. The network coding is applicable in the node whoever  $TLI$  and  $LC$  exceeds maximum limit.

Proficient rate control is followed by the previous work [8]. The primary goal of this algorithm is to deal with various kinds of non live time (NLT) packets, such as high preference NLT (HNLT), Middle preference NLT (MNLT), and Little preference NLT (LNLT). When these packets are sent out, they each have a different priority level. Therefore, the packets are identified by data rates of varying values. The live time (LT) traffic class is extremely important and receives the highest consideration.

Consider  $ptp_n^k$  and  $lp_n^k$  are packet type of preference and the location preference of packets in  $n^{\text{th}}$  queue of  $k^{\text{th}}$  intermediate sensor node.  $sp_i^{kn}$  is the source preference of  $n^{\text{th}}$  queue of  $k^{\text{th}}$  node, the packet types are  $i \in \{LT, HNLT, MNLT, LNLT\}$ .

First, the packet type of preference in  $n^{\text{th}}$  queue of  $k^{\text{th}}$  node is calculated as Eq. (4)

$$ptp_n^k = \sum_n \sum_i sp_i^{kn} \quad (4)$$

The overall preference of packets type in  $n^{\text{th}}$  queue of  $k^{\text{th}}$  node is computed as

$$Op_n^k = ptp_n^k \cdot lp_n^k + [O_{LT} - \delta(O_{HNLT} + O_{MNLT} + O_{LNLT})] \quad (5)$$

In Eq. (5),  $\delta$  is the values ( $0 \leq \delta \leq 1$ ) and  $O_{LT}, O_{HNLT}, O_{MNLT}, O_{LNLT}$  are the preference assigned to *LT* and *NLT* packet types. Likewise, the packet type preference in  $n^{th}$  queue of  $l^{th}$  next level node is computed as Eq. (6).

$$ptpt_n^l = \sum_n \sum_i sp_i^{ln} \quad (6)$$

After the preference rate has been updated, the sensor node transmits the information to the subsequent node in the hierarchy. If priorities are set properly, network congestion, buffer overflow, and dropped packets can be avoided.

### 3.2 Adaptive RLNC for data aggregation

According to the adaptive RLNC technique, the origin node determines whether to switch networking coding ON or OFF based on number of factors including packet size, the estimated disconnection time among connected hubs, and the network's data flow or packet rate. In cases where the total amount of the content being sent by the nodes is less than the maximum transmitting capacity of the link, network coding should be disabled. When the amount of information to be transmitted grows beyond a certain threshold, network coding is used. [20]. Using encoding, the packets are constructed and sent as a concatenation of the actual packets. An encoded data packet received by a node is then decoded to reveal the original data. Parameters for establishing network coding are calculated from Eq. (7) to Eq. (10)

$$Packet(sizeinbits) = 8 \times Packet(size) \quad (7)$$

$$D = Data\ rates\ in\ bps \quad (8)$$

$$ET = Estimated\ link\ expiration\ Time \quad (9)$$

$$MDT = Max\ Data\ rate\ Transmit = D \times ET \quad (10)$$

For network coding to take place, it is necessary and sufficient that nodes satisfy certain conditions in order to establish optimal pathways with potential coding nodes. Before to look at the network coding situation, let's establish some notations.  $a \in d_f$  denotes node  $a$  beside the data flow  $d_f$ , whereby the source nodes and sink node. The single-hop neighbour set of nodes  $a$  is referred as  $Ns(a)$ .  $Forward(a, d_f)$  and  $Backward(a, d_f)$  respectively represent nodes towards destination and nodes set from origin of data flow  $d_f$ . Fig. 2 represent the sample network coding from source to intermediate and destination node, As a result, the in-between

sensor node  $e$  where incoming flows meet, encrypt the obtained data and delivered by the intervening node if the network condition is met. The packet flow in the network is denoted by the letters  $O_1$  and  $O_2$ . The critical and adequate conditions under which system coding is performed should be expressed to uncover ways with possible coding chances. Unless the preceding condition is met when the flows  $d_{f1}$  and  $d_{f2}$  overlay at node  $e$  is network coding possible [20]. Due to the possibility of distinct flows interfering with each other, the issue of network coding collision has arisen.

Condition:

1: Existing node  $n_1 \in Backward(a, d_{f1})$  while  $n_1 \in N_s(m_2) \wedge m_2 \in Forward(e, d_{f2})$  or  $n_1 \in Forward(e, d_{f2})$

2: Existing node  $n_2 \in Backward(a, d_{f2})$  while  $n_2 \in N_s(m_1) \wedge m_1 \in Forward(e, d_{f1})$  or  $n_2 \in Forward(e, d_{f1})$

Here,  $n_1, n_2, m_1$  and  $m_2$  are neighbours of node  $a$  and  $e$  respectively. For a network with many flows, the one that best satisfies the coding criterion is the one along which the most possible codes can be transmitted. However, a native packet may not be decoded at the final node due to excessive coding at several contradicting nodes along the route. Flow  $d_{f3}$  does, however, connect to the network at a certain point. Node  $E_1$  pleased aggregation with the  $d_{f1}$  and  $d_{f3}$ . Node  $E_2$  perform the coding of  $d_{f2}$  and  $d_{f3}$ . Node  $E_1$  gets  $O_1 \delta O_3$  when it encodes packets  $O_1 \delta O_3$  and delivers them along route  $d_{f3}$ . Furthermore, node  $E_2$  is the coding node, which will again encode packets  $O_1 \delta O_3$  and  $O_2$ , i.e.,  $O_1 \delta O_2 \delta O_3$ , and send them to  $D_3$  and  $N_2$ , correspondingly, through the paths  $d_{f3}$  and  $d_{f2}$ . Since that overhears packets  $O_1$  and  $O_2$  from source nodes  $S1$  and  $S2$ , it may see that destination node  $D_3$  decodes packets  $O_3$  from  $O_1 \delta O_2 \delta O_3$ . If packets arrive at destination node  $D_2$ , it is unable to decode original packets  $O_2$ , but it can decode packet  $O_3$ . However, node  $E_2$  cannot be utilised as a coding node, as can be seen. Due to extensive coding along the path,  $d_{f3}$  has an impact on the coding collision problem in this situation. In order to avoid the code collision problem, extra limits should be imposed.

### 3.3 LSTM based fair bandwidth allocation

A learning based bandwidth assignment takes into account high – bandwidth traffic patterns. Training and testing done by LSTM [21] which used to handle bandwidth and traffic of various levels of burstiness. Bandwidth allocation is initially assigned

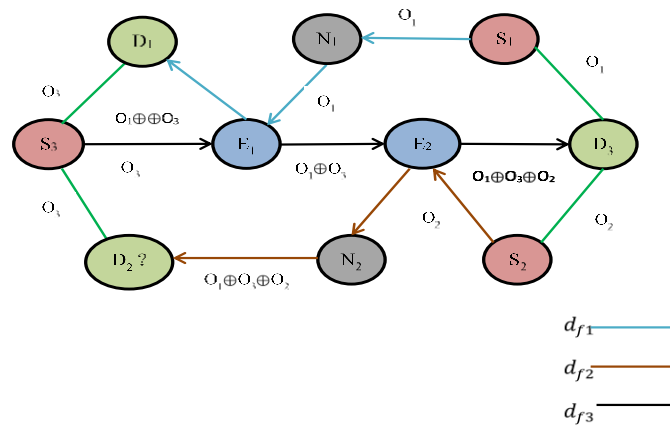


Figure. 2 An example network coding in network

based on the fair allocation scheme proposed in the previous study [8]. In this paper, the calculation of utility of bandwidth for links at every time is avoided by intelligent prediction model using LSTM. First LSTM is trained for higher and lower throughput for the parameters like packet transmit duration  $T_o$ , Packet size  $O_s$ , number of packets in the flow  $N_o$ , Bandwidth utilized  $BW_o$  and packet transmission rate  $O_R$ . The trained LSTM is used to predict required bandwidth for present packet transmission.

### 3.4 Algorithm for EPRCDA-FBA

#### Algorithm : EPRCDA-FBA

**Input:** Set of path

**Output:** Selected path

Step 1: Set the parameters:  $\beta, \delta, \mu$  are the priority values for traffic classes

Step 2: Service time (receiving packets) of sink node ( $ST_n^{sink}$ )

Step 3: Compute the mean service time of available queues in sink node

$$\overline{ST}_n^{sink}(t+1) = (1 - \alpha)\overline{ST}_n^{sink}(t) + \alpha \cdot ST_n^{sink}$$

$\alpha$  is a fixed variable ranges 0 and 1

Step 4: Calculate the rate variance  $n^{th}$  queue in the sink node using the formula

$$\Delta r^{sink} = \beta \cdot r_{out}^{sink} - r_{in}^{sink}$$

where  $r_{out}^{sink}$  is the outage rate and the receiving rate of the sink node  $r_{in}^{sink}$ .

$\beta$  is a fixed variable ranges 0 and 1.

Step 5: Compute  $k^{th}$  parent nodes using the following formula

$$\Delta r^k = \beta \cdot r_{out}^k - r_{in}^k$$

where,  $r_{out}^k$  is the outage rate of  $k^{th}$  node connected with sink. The receiving rate of the  $k^{th}$  parent node is  $r_{in}^k$

Step 6: Calculate the updated outage rate of queue in the  $k^{th}$  node

Step 7: Calculate the updated outage rate of queue in the  $l^{th}$  child node

Step 9: Continue Steps 2 to Steps 7 for updating the rate of transmission for sensor nodes

Step 10: Check for active neighbouring nodes

Step 11: If Nodes has information to share

Step 12: if ( $O_R > MDT$  or  $TLI > max_{TLI}$  or  $LC > max_{LC}$ )

{

Execute adaptive network coding

$$O_1, O_2, O_3, \dots, O_n$$

$$P(n) = O_1 \oplus O_2 \oplus O_3 \oplus O_n \dots$$

$$P(n) = \sum_{k=1}^n A_k \times O_k$$

}

Step 13: Eliminate coding collision

When flow  $d_{f1}$  and  $d_{f1}$  overlap at the node  $e$ , network coding is possible only

if

{

Existing node  $n_1 \in Backward(a, d_{f1})$

while  $n_1 \in N_s(m_2) \wedge m_2 Forward(e, d_{f2})$  or  $n_1 \in Forward(e, d_{f2})$ .

Existing node  $n_2 \in Backward(a, d_{f2})$

while  $n_2 \in N_s(m_1) \wedge m_1 Forward(e, d_{f1})$  or  $n_2 \in Forward(e, d_{f1})$

}

Step 14: intelligent fair bandwidth allocation

Node parameters :  $x_p = \{P_s, T_p, N_p, BW_p, P_R\}$

$x_{model} = Train(LSTM(x_p))$  // Training using LSTM

$$BW_{(p+1)} = Predict(LSTM, x_{model}) //$$

bandwidth prediction for next packet transmission

Step 15:

}  
Step 16: Else GOTO step 2

The link cost conditions checked in the if conditions in step 12 of algorithm is removed in EPRCDA-FBA. This paper evaluate the performance of both PRCDA-FBA and EPRCDA-FBA under various network characteristics.

#### 4. Simulation results

In this section, the PRCDA-FBA and EPRCDA-FBA technique is executed in network simulator version 2.35 (NS2.35) and its effectiveness is analysed compared to the DSMC [11], WPFQGR [15], PRC-FBA [8] and RACC [17] techniques. The analysis is conducted based on throughput, packet loss, end-to-end (e2e) delay and energy utilization. Table 1 gives the simulation parameters considered in this analysis.

##### 4.1 Throughput

It's the total amount of information transmitted from sensors to sink in a certain amount of time Eq. (11).

$$\text{Throughput} = \frac{\text{Total amount of data accepted by the target}}{\text{Time}} \quad (11)$$

Fig. 3 shows the throughput (in Mbps) for the approaches compared to the DSMC, WPFQGR, PRC-FBA, RACC, PRCDA, and EPRCDA-FBA under different simulation times in network simulator 2.35 (NS2.35) (in sec). EPRCDA-FBA is shown to have the highest throughput of all the methods studied. Throughput for EPRCDA-FBA is 9.17% higher than DSMC, 5.48% higher than WPFQGR, 4.68% higher than PRC-FBA, 2.45% higher than RACC, and 0.41% higher than PRCDA-FBA if the simulation time is 120sec. This is made possible by allocating equal bandwidth to all network nodes and assigning different traffic classes different priority levels in each virtual queue.

##### 4.2 Packet loss

It is the amount of data dropped or missed during transfer Eq. (12)

$$\text{packet loss} = \frac{\text{Amount of lost data}}{\text{amount of lost data} + \text{Amount of accepted data}} \quad (12)$$

Fig. 4 compares the packet loss (in %) across several different simulation times for the DSMC,

Table 1. Simulation parameters

Parameter	Range
Distance Covered by Nodes	300m
Data transfer rate	2Mbps
MAC layer type	IEEE802.11
Network Nodes	500
Traffic types	4
Operating frequency	5GHz
Packet size	200bytes
Routing protocol	AODV
Boundary of Simulation	1000×1000m <sup>2</sup>
Duration of Simulation	120sec
Cause of Traffic	CBR
Transmission power	285.63mW

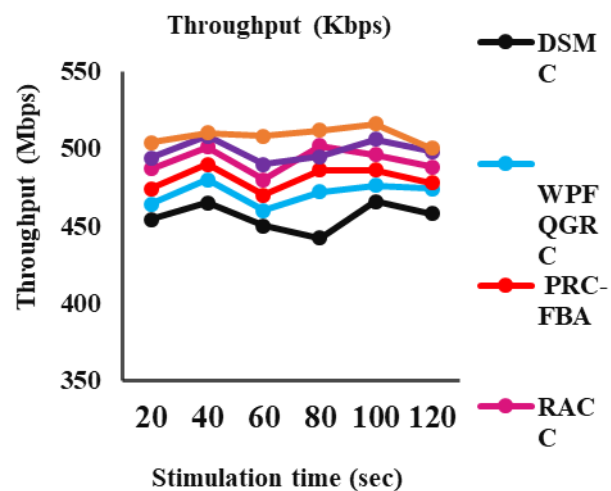


Figure. 3 Throughput vs. simulation time

WPFQGR, PRC-FBA, RACC, PRCDA, and EPRCDA-FBA methods (in sec). This finding suggests that EPRCDA-FBA achieves lower packet loss than competing methods. In a 120-second simulation, EPRCDA-FBA reduces packet loss by 57% compared to DSMC, 54% compared to WPFQGR, 49% compared to PRC-FBA, 42% compared to RACC, and 33% compared to PRC-FBA. EPRCDA-FBA uses virtual queues and fair bandwidth allocation at each node to mitigate the effects of WSN congestion, making it the most effective protocol in terms of packet loss.

##### 4.3 End-to-end delay

The amount of time it takes for information to travel from its source to its destination (sink)

$$E2E \text{ Delay} = \text{Time}_{\text{sink}} - \text{Time}_{\text{origin}} \quad (13)$$

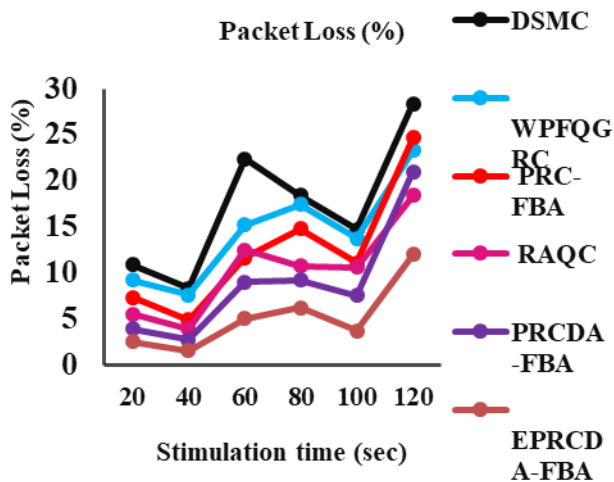


Figure. 4 Packet loss vs. simulation time

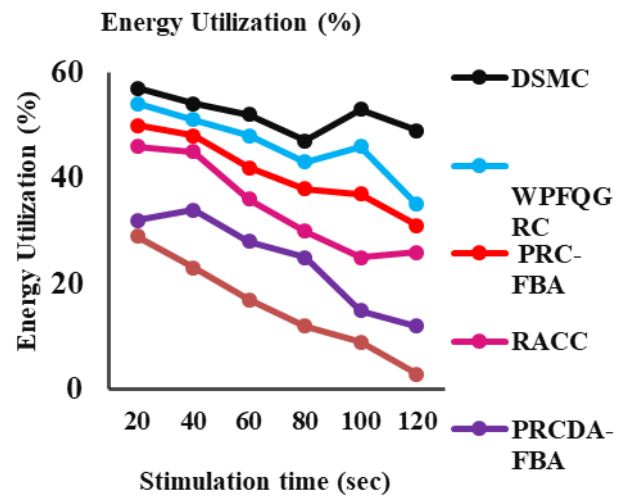


Figure. 6 Energy utilization (%) vs. simulation time

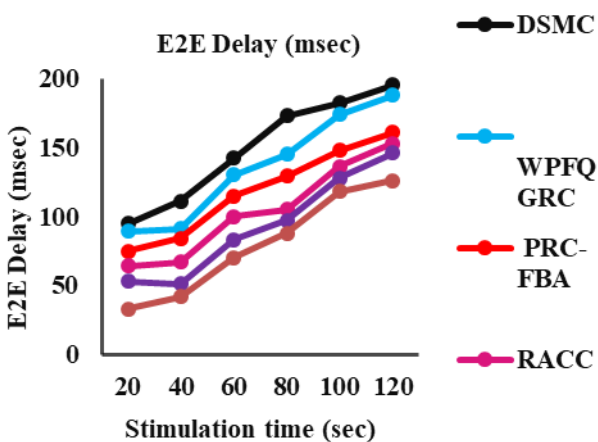


Figure. 5 E2E delay vs. simulation time

In this Eq. (13)  $Time_{sink}$  is the time at the sink while accepting the data and  $Time_{origin}$  is the time at the origin while forwarding that data.

The E2E delay (in ms) for different simulation times (in sec) is shown in Fig. 5 for the DSMC, WPFQGR, PRC-FBA, RACC, PRCDA and EPRCDA methods. When compared to the other approaches, the EPRCDA-FBA is found to have the shortest E2E delay. EPRCDA-FBA has a 35.38% lower E2E delay than DSMC, 32.97% lower than WPFQGR, 21.74% lower than PRC-FBA, 17.64% lower than RACC, and 13.69% lower than PRCDA-FBA when the simulation time is 120 seconds. The minimum E2E delay associates with the maximum throughput and the less packet loss.

#### 4.4 Energy utilization

It represents the total percentage of network energy consumption over all time steps of the simulation.

Energy utilization (in %) during simulation period is shown in Fig. 6 for DSMC, WPFQGR, PRC-FBA, RACC, PRCDA-FBA, and EPRCDA-FBA. EPRCDA-FBA is able to reduce energy consumption when compared to competing methods. EPRCDA-FBA's energy consumption is 93.88% lower than DSMC's, 91.43% lower than WPFQGR's, 90.32% than PRC-FBA's, 88.46% lower than RACC's, and 75% lower than PRCDA-FBA's. That the EPRCDA-FBA reduces energy use relative to conventional methods is thus self-evident.

### 5. Conclusion

An energy-efficient, battery-powered, and power-management-friendly approach called EPRCDA-FBA is proposed. When the data rate is greater than a predetermined threshold value, network coding is implemented. In order to ensure that everyone gets their fair share of battery life, we apply a sophisticated data aggregation, coding condition, and coding collision method. An effective predictive model has been suggested for managing the power control. In conclusion, when compared to DSMC, WPFQGR, PRC-FBA, RACC, and PRCDA-FBA, EPRCDA-FBA achieves 4.4% greater throughput, 49.2% lower delay, 25% lower packet loss, and 67% lower energy usage in simulations. In future, it is possible to expand this work by applying the same situation to wireless recharging models, in which the confluence of congestion control via EPRCDA-FBA and suitable wireless recharging solves both the lifetime improvement and congestion control issues simultaneously.

#### Conflict of interest

The authors declare no conflict of interest.



## Author contributions

Conceptualization, methodology, software, validation, Vanitha ; formal analysis, investigation, Amutha; resources, data curation, writing—original draft preparation, Vanitha ; writing—review and editing, Amudha; visualization, Vanitha; supervision Sivakumari.

## References

- [1] F. Mazunga and A. Nechibvute, “Ultra-low power techniques in energy harvesting wireless sensor networks: Recent advances and issues”, *Scientific African*, Vol. 11, pp. 1-14, 2021.
- [2] A. Rady, E. S. M. E. Rabaie, M. Shokair, and N. A. Salam, “Comprehensive survey of routing protocols for Mobile Wireless Sensor Networks”, *International Journal of Communication Systems*, Vol. 34, No. 15, p. e4942, 2021.
- [3] M. A. Jan, S. R. U. Jan, M. Alam, A. Akhunzada, and I. U. Rahman, “A comprehensive analysis of congestion control protocols in wireless sensor networks”, *Mobile Networks and Applications*, Vol. 23, No. 3, pp. 456-468, 2018.
- [4] A. Bohloulzadeh and M. Rajaei, “A survey on congestion control protocols in wireless sensor networks”, *International Journal of Wireless Information Networks*, Vol. 27, No. 3, pp. 365-384, 2020.
- [5] F. Wang, “To reduce delay, energy consumption and collision through optimization duty-cycle and size of forwarding node set in WSNs”, *IEEE Access*, Vol. 7, pp. 55983-56015, 2019.
- [6] H. Parsavand and A. Ghaffari, “Controlling congestion in wireless sensor networks through imperialist competitive algorithm”, *Wireless Pers. Commun.*, Vol. 101, No. 2, pp. 1123-1142, 2018.
- [7] S. K. Swain and P. K. Nanda, “Priority based adaptive rate control in wireless sensor networks: a difference of differential approach”, *IEEE Access*, Vol. 7, pp. 112435-112447, 2019.
- [8] G. Vanitha, P. Amudha, and S. Sivakumari, “Analysis of Algorithms to Control the Congestion by Improve Energy Efficiency in WSN”, *ECS Transactions*, Vol. 107, No. 1, p. 5191, 2022.
- [9] E. Moharamkhani, B. Zadmehr, S. Memarian, M. J. Saber, and M. Shokouhifar, “Multiobjective fuzzy knowledge-based bacterial foraging optimization for congestion control in clustered wireless sensor networks”, *International Journal of Communication Systems*, Vol. 34, No. 16, p. e4949, 2021.
- [10] Z. Hu, X. Wang and Y. Bie, “Game Theory Based Congestion Control for Routing in Wireless Sensor Networks”, *IEEE Access*, Vol. 9, pp. 103862-103874, 2021.
- [11] S. Qu, L. Zhao, Y. Chen, and W. Mao, “A discrete-time sliding mode congestion controller for wireless sensor networks”, *Optik*, Vol. 225, p. 165727, 2021.
- [12] I. Bouazzi, M. Zaidi, M. Usman, and M. Z. M. Shamim, “A new medium access control mechanism for energy optimization in WSN: traffic control and data priority scheme”, *EURASIP Journal on Wireless Communications and Networking*, Vol. 2021, No. 1, pp. 1-23.
- [13] S. L. Yadav, R. L. Ujjwal, S. Kumar, O. Kaiwartya, M. Kumar, and P. K. Kashyap, “Traffic and energy aware optimization for congestion control in next generation wireless sensor networks”, *Journal of Sensors*, Vol. 2021, 2021.
- [14] D. Singh, J. Bhanipati, A. K. Biswal, D. Samanta, S. Joshi, P. K. Shukla, and S. J. Nuagah, “Approach for collision minimization and enhancement of power allocation in WSNs”, *Journal of Sensors*, Vol. 2021, 2021.
- [15] S. K. Swain and P. K. Nanda, “Adaptive Queue Management and Traffic Class Priority Based Fairness Rate Control in Wireless Sensor Networks”, *IEEE Access*, Vol. 9, pp. 112607-112623, 2021.
- [16] V. Thalagondapati and M. P. Singh, “A self-organized priority-based MAC protocol in wireless sensor networks based on SDR-RHSO optimal relay node selection and HL-ANN wake-up scheduling”, *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-10, 2022.
- [17] A. Grover, R. M. Kumar, M. Angurala, M. Singh, A. Sheetal, and R. Maheswar, “Rate aware congestion control mechanism for wireless sensor networks”, *Alexandria Engineering Journal*, Vol. 61, No. 6, pp. 4765-4777, 2022.
- [18] M. Yoshida, A. Gallegos, and T. Noguchi, “Adaptive forwarding control using network coding for efficient multicasting in mobile ad-hoc networks”, In: *Proc. of the 8th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications*, pp. 27-33, 2018.
- [19] K. Xie, L. Wang, X. Wang, G. Xie, and J. Wen, “Low cost and high accuracy data gathering in WSNs with matrix completion”, *IEEE Trans.*

*Mobile Comput.*, Vol. 17, No. 7, pp. 1595-1608, 2018.

- [20] C. S. Babu, A. J. Rao, K. Srinivas, and S. Narayana, "Chronological Harris hawks-based deep LSTM classifier in wireless sensor network for aqua status prediction", *Ecohydrology*, Vol. 14, No. 6, p. e2302, 2021.