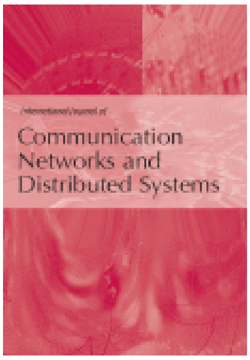

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A rapidly-exploring random tree-based intelligent congestion control through an alternate routing for WSNs

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Abstract: In wireless sensor networks (WSNs), congestion is a challenging issue, and it degrades the efficiency in terms of packet loss, energy wastage, throughput, etc. The primary cause of the congestion in WSNs is the data routing of the many-to-one pattern. It means multiple nodes can send their data to a single sink using multi-hop transmissions. To control the congestion in WSN, we use a rapidly-exploring random tree (RRT)-based mechanism to divert the data packets from the congested nodes. Initially, we use a mathematical model to determine the congested nodes in the WSNs. Further, we identify the routing path using the RRT algorithm in which the algorithm can construct a dynamic routing while avoiding the congested nodes in the routing path. We estimate the efficiency of our approach using simulation runs and compare the results using the recently published algorithm. We notice the improved performance in our method.

Keywords: wireless sensor networks; WSNs; congestion factor estimation; intelligence congestion control; rapidly-exploring random tree; routing; quality of service.

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1 Introduction

A wireless sensor network (WSN) is composed of multiple sensor nodes (SNs) which are scattered in an interested environment to accumulate data for monitoring the activities. These activities may be related to healthcare, machine, climate, etc. (Yick et al., 2008). The WSNs are widely using because of their features including cost-effectiveness, tiny size, scalability, etc. (Yang et al., 2018). The activities of an environment observed by the SNs are transmitted to the sink for further analysis. These SNs are operating using a battery and it is difficult to chance when it drain its energy completely. But, the SNs consume more energy due to the transmissions instead of accumulating from the environment. The centralised sink node need to collect the information and the many-to-one data transmissions approach leads the congestion in the WSNs (Alghazzawi et al., 2021).

The congestion is one of the most important challenges, and it degrades the performance of the WSNs. Initially, the congestion leads the data packets retransmissions, so the additional energy and buffer is needed by the data packets to successful delivery to the destination (Pandey and Kushwaha, 2020). But, this process consumes more energy, and buffer. It also increases the data packet latency. The unnecessary data transmissions also affect the data packets which preceeded by the current data packet. So, this iterative process interrupts the data gathering process by degrading the performance of the network (Al-Kashoash et al., 2019). So, it is inevitable to control the congestion in the WSNs.

There are several ways to cause the congestion in the WSNs. They are mainly categorised as buffer-based and contention-based congestion (Kafi et al., 2014; Kalaikumar and Baburaj, 2020). The buffer-based congestion occurs in the network when the buffer utilisation is not properly defined. So, the packets are stuck at a SN buffer and they cause dropping of the data packets. The second is contention-based congestion, and it causes the congestion when multiple SNs try to transmit their data to a channel simultaneously. So, the total packets send to a channel where the channel capacity is not sufficient to transmit them leads the congestion and packet drops (Qu et al., 2020). Therefore, we can imagine the problems occur with the congestion, but detecting the congestion in the network is due to various causes.

The congestion is identified based on several metrics including packet loss, buffer overflow, channel loads, throughput, packet service rate, E2E delay, etc. (Shah et al., 2017). The researcher can consider one or more of these metrics to identify either a SN or the channel involve in congestion or not. In our approach, we consider the buffer utilisation is a main source to identify the congestion in the network (Jan et al., 2018). Further, we identify the optimal routing to transmit the data while avoiding the congestion nodes in the routing path. In this way, the load on the congested nodes are reduced and the congestion in the network to be minimised. In this context, we proposed an intelligent congestion control algorithm named RRTICC, an efficient congestion detection method and alternate path by avoiding the nodes which are suffering from the congestion in the field. The novelty of RRTICC algorithm is summarised as follows:

- We estimate the congestion using the buffer occupancy and the packet generation by the SNs in the network using novel mathematical approaches. This we treated as congestion factor estimation (CFE), where it decides either a SN is suffering from the congestion or not.
- We identify the dynamic routing using an artificial intelligent algorithm called rapidly-exploring random tree (RTT). The RTT can identify the optimal routing by avoiding the congested nodes in the WSNs.
- We provide an illustration for both CFE and RRT through an example to understand the proposed RRTICC algorithm clearly.

The proposed RRTICC algorithm is compared with recently published algorithms such as CADA (Donta et al., 2020), CADC (Zhuang et al., 2018), AWFCC (Srivastava et al., 2020).

The article's remaining sections are organised as follows. In Section 2, we conduct the state-of-the-art literature study on congestion control algorithms. The system model is discussed in Section 3. The proposed RRTICC along with the complexity analysis is discussed in Section 4. The experimental results are evaluated in Section 5. Finally, the conclusion and future scope are presented in Section 6.

2 Related work

The recent advancement in congestion control protocols is studied in Donta et al. (2021b) for IoT. In contrast, these algorithms are not suitable for the WSNs because of the differences in connections and communication. A multi-path routing strategy has been proposed in Jemili et al. (2020) using a sleep-awake scheduling approach for WSNs. In this, the congestion is controlled through non-correlated paths and adjusts the overlapping intervals in the network. The performance of this work minimises the latency and maximises the throughput. In Adil (2021), the author proposed a congestion control mechanism for IoT with dynamic hop selection strategy. In this work, the author focuses on improving the lifespan of the SNs and reducing the PLR and E2E delay of packet transmissions. A rate control mechanism for congestion control in WSN is presented using k-means clustering, and ant colony optimisation (ACO) (Srivastava et al., 2020). In this, initially, the SNs are clustered using k-means clustering, and layer the ACO algorithm decides the data route. A congestion prediction and control strategy is presented in Aimtongkham et al. (2018) for WSNs. In this, the algorithm performs in three stages: initial path construction, energy-aware path derivation, and congestion prediction. This algorithm efficiently predicts and mitigates congestion and improves efficiency.

A distributed accuracy-aware congestion control mechanism is introduced in WSNs (Zhuang et al., 2018). In this approach, the algorithm minimises the overall error rate while acquiring the sensor nodes' data. A congestion control mechanism is introduced in Raman and James (2019) to detect the suitable data forwarding node for efficient transmission towards the base station. This algorithm is designed to minimise the queuing delay while performing the data exchanges among the nodes. Healthcare applications are delay-sensitive, and the congestion increases the uncertainty while transmitting the data between the nodes. A distributed priority-based routing mechanism is introduced for congestion control for health care applications in Chanak and Banerjee (2020). A data-driven congestion mitigation strategy is proposed for WSNs in Jan et al. (2019) using the data acquisition and transmission rate of SNs in the network. This work also adopts the data fusion mechanism to avoid unnecessary data transmissions between the SNs in a WSN. In Qu et al. (2020), the authors proposed a congestion mitigation protocol in between the transmission layer and medium access control (MAC) layers using fuzzy logic and sliding window mechanisms. It mainly regulates the buffer length of the congestion nodes dynamically and significantly minimises the internal and external disturbances. These approaches rapidly convergence while reducing the delay in the data transmissions.

A fuzzy logic-based queue management approach is discussed in Rezaee and Pasandideh (2018) for WSNs. A proportional integral derivative mechanism is incorporated to control the data exchange rate between the SNs. This priority-based congestion control protocol improves the network's performance in terms of data transmissions between the nodes. In Sumathi and Pandiaraja (2020), the authors presented remaining energy, buffer, and trust level-based congestion mitigation approach for WSNs. In this approach, the authors identify the alternative dynamic buffer for the nodes which are suffering from congestion in a WSN. This method efficiently identifies the alternate buffer for the congested nodes in the network while improving the network lifetime. An adaptive congestion control strategy using a congestion window is discussed in Aslam et al. (2017) for WSNs. This algorithm considers the data's sensing rate, and the channel utilisation for data transmissions is evaluated to estimate the congestion. A congestion avoidance algorithm is introduced in Yadav et al. (2021) for WSNs using Huffman coding and ACO algorithms. This algorithm considers both network traffic and available resources to transmit the data between the nodes to avoid congestion.

A multi-objective optimisation-based rate control algorithm is introduced for congestion control for WSNs in Singh et al. (2018). To tackle this problem, the authors used gravitational search algorithm (GSA) and particle swarm optimisation (PSO) to control the data rate between the sensor nodes in the network. A geographic routing algorithm is introduced for congestion control in WSNs (Tang et al., 2020). This algorithm estimates a threshold value at each sensor node based on the available buffer and energy before scheduling a packet to avoid congestion. A traffic-aware congestion control mechanism is presented in Javaid et al. (2018) for WSNs. In this approach, the congestion is detected and controls the E2E delay between the data transmissions. A congestion control approach using game theory is introduced for WSNs in Chowdhury and Giri (2018). The buffer occupancy and channel capacities are evaluated to estimate the congested SNs in the network and improve the throughput by avoiding the congestion node while routing the data. A fuzzy-logic-based dynamic traffic management algorithm is proposed for congestion control in WSNs (Shelke et al., 2019).

The delay-aware data collection from the SNs is studied in Donta et al. (2022) for WSNs. In this, the authors used a statistical approach to estimate each SN's status and Q-learning to identify the best routing that can be constructed on duty-cycled WSNs. In Letswamotse et al. (2018), the authors presented an efficient congestion control strategy using a software-defined programmability strategy to balance the data transmission in a WSN. An efficient cache management strategy is introduced in Alipio and Tiglao (2018) to avoid congestion in WSNs. This approach efficiently categorises the typologies of the WSN routing and manages the cache memories, and avoids packet loss in the network. A rate adjusted congestion control strategy is introduced in Grover et al. (2022) for WSNs to prevent packet loss in the network. This approach efficiently increases the throughput of the WSNs by avoiding unnecessary retransmissions. Machine learning-based intrusion detection strategies are studied for IoT in Jasim et al. (2022).

Adaptive load control of the SNs is presented in Chen et al. (2017) for WSNs to mitigate the congestion. This approach efficiently manages the buffer to avoid packet loss, and through this process, it improves the throughput of the WSN. A fuzzy decision-based congestion control strategy is invented by Homaei et al. (2020) for WSNs. The primary aim of this work is to control the traffic overflows in the network to avoid packet drops. A mobile sink-based congestion control strategy is proposed for WSNs in Alaei et al. (2019). The nodes are categorised in three ways and apply the routing depending on the load of the network. A multi-path routing to mitigate the congestion for WSNs is presented in Yu and Lu (2019). In this strategy, the routing is decided using the load of the WSNs.

An efficient congestion control to avoid the packet loss in WSNs is presented in Hassani and Berangi (2018). The authors used the Markov chain process to mitigate the network congestion and the other QoS degradation problems in the network. A fuzzy control-based load balancing approach for congestion control in WSNs is presented in Qu et al. (2021). This approach scales the time and load to control the buffer overflows at the SNs and avoid packet loss and energy wastage. A congestion control through bidirectional reliability strategy is adopted in Sharma et al. (2020) for the internet of drone application. This strategy is efficiently controlled and avoids congestion in the network. These strategies also balance the energy among the nodes and reduce the packet loss in the network. An ACO-based optimal routing approach is presented for congestion avoidance for WSNs in Mahajan and Kaur (2021). This intelligent routing balances the energy among the SNs and avoids packet loss at the SNs.

A traffic-aware congestion mitigation approach is presented in Abbas and Yu (2018) for multimedia WSNs. This approach mainly focuses on buffer overflows to control the congestion. It further balances the energy between the SNs, and avoids packet losses. In Hu et al. (2021), the authors presented a game theory-based data routing using ACO to mitigate the congestion in the WSNs. This algorithm uses two popular strategies: game theory and ACO algorithms to control congestion and avoid packet loss through a buffer overflow in the network. In Abd et al. (2020), SVM-based intrusion detection is presented for IoT. A bacterial foraging optimisation-based congestion mitigation strategy is proposed in Moharamkhani et al. (2021) for WSNs. In this approach, the authors perform the clustering and identify the optimal cluster heads which can balance the packet loads among the nodes by considering different properties of the SN.

From the above discussion, most algorithms focus on identifying congestion based on the buffer utility, channel control, rate-adaptive, optimal hop selection, etc. However, these algorithms are not dynamic and fail to control the congestion completely. In this context, our proposed algorithm avoids the congestion dynamically using an AI-based algorithm to determine the optimal routing between the SNs while transmitting the data packets to a sink.

3 System model and problem formulation

A WSN is represented as a directed graph and it is represented using $G(S^+, D)$. The SNs are represented as $S = \{S_1, S_2, ..., S_n\}$ are randomly placed in a region of interest. The number of SNs are represented using $n = |S|$. There is a single base station in the G is deployed randomly and it is denoted using S_0. The $S^+ = S \cup S_0$. The SNs are static once they are deployed and they have similar (homogeneous) properties. We assume all the n SNs are well connected and no isolated node found initially. D indicates the distance matrix for S^+. The distance among the SNs i and j is denoted as δ_{ij}. The communication and transmission ranges are different in the WSNs, they are denoted as r_c and r_t, respectively. Each SN in the network are initially empty buffer and fully recharged. The buffer occupancy and initial energy of a SN i is indicated using B_i and E_i^0.

Each SN i consume its energy during data acquisition from the environment (E_{id}^t), data transmissions between note i and j is (E_{ij}^t), data receive by i from its child is (E_{ir}^t) and data processing (E_{ip}^t), at particular time t. Based on these assumptions, the EC of a SN i at a time t is determined using equation (1).

$$E_{ic}^t = E_{ip}^t + E_{id}^t + E_{ij}^t + E_{ir}^t + \varepsilon \tag{1}$$

where E_{ip}^t is depends on the E_{id}^t and E_{ir}^t in terms of data type (arithmetic or non-arithmetic), and selected hardware architecture, clock cycles used, etc. The E_{ir}^t, in case of i is leaf node. E_{id}^t is considered according to equation (2).

$$E_{id}^{t}=\begin{cases}P_i\times E_s\times \mathbb{P}_i^t & \text{For event driven}\\ P_i\times E_s & \text{For continuous}\end{cases} \tag{2}$$

The energy required for a sample of sensed payload or data packet is indicated using E_s, and the probability of the occurrence of the event during a time gap t at SN i is denoted using $\mathbb{P}_i^t$. The total amount of packets collected by a SN i at time t is denoted using P_i, mathematically it is computed in the simulation as shown in equation (3).

$$P_i=\begin{cases}\sum\limits_{t=0}^{T}((P_i^t)\times \mathbb{P}_i^t) & \text{For event driven}\\ \sum\limits_{t=0}^{T}P_i^t & \text{For continuous}\end{cases} \tag{3}$$

The number of samples collected during a unit time gap t at node i is considered as P_i^t, and the total simulation time is denoted as T. The E_{ij} is the energy dissipated during the data transmission from SN i to j, and it is determined as shown in equation (4).

$$E_{ij}=\Gamma_i\times\left(\alpha_t+\alpha_{fs}\times\delta_{ij}^2\right) \tag{4}$$

where the EC for processing the data by circuits is α_t, the energy dissipation for amplification is α_{fs}, and the number of data transmissions by node i is Γ_i, and Γ_i is considered as shown in equation (5).

$$\Gamma_i=\sum_{k=0}^{P_i}\Big(\eta_k+1\Big) \tag{5}$$

where η_k represents the number of retransmissions made by the sensed data packet k. The ε in equation (1) indicates the additional EC to manage the tasks and handling the resources. The energy requires to receive β bits from a node is shown in equation (6).

$$E_{ir}(i)=\alpha_r\beta_i^t \tag{6}$$

where α_r is the EC of circuit to accumulate a bit and β_i^t indicates the number of packets received by i at t from its children. The remaining energy of a SN is determined using equation (7).

$$E_i^t=E_i^{t-1}-E_{ic}^t \tag{7}$$

Additionally, the average EC (AEC) of a WSN is considered as follows:

$$E=\frac{1}{n}\sum_{i=1}^{n}E_{ic}^t\ \forall\ t\in T \tag{8}$$

The ratio of total packets received by the base station ($\mathcal{R}$) and the ntotal packets transmitted by the SNs ($\mathcal{T}$) is considered as the packet delivery ratio (PDR) and it is denoted using (ς). The proposed RTT consider only the data packets, and not consider the control signals such as acknowledgements (ACKs). The ς of the proposed work is considered based on equation (9).

$$\varsigma = \frac{\mathcal{R}}{\mathcal{T}} \tag{9}$$

where $\mathcal{T} \geq \mathcal{R}$, and $\mathcal{T}$ is determined as shown in equation (10).

$$\mathcal{T} \cong \sum_{i=1}^{n} P_i \tag{10}$$

The packet loss ratio (PLR) is determined using equation (11).

$$\Phi_a = (1 - \varsigma) \times 100 \tag{11}$$

The total amount of data packets received by the base station during the simulation time T is denoted as throughout (σ) and it is computed as shown in equation (12).

$$\sigma = \frac{\mathcal{R}}{T} \tag{12}$$

The latency (L) of a data packet k is computed as the total time taken by a packet since it acquired from the environment to reach base station. The L includes the radio propagation delay (L_r), queuing delay (L_q), transmission delay (L_t), and signal processing delay (L_s). From these, $L_r(k) \approx L_s(k) \leq 1$, so we skip $L_r(k)$ and $L_s(k)$ because of no impact on output. The L of the packet k is determined using equation (13).

$$L_k = \begin{cases} (L_q(k) + L_t(k)) \times \eta_k & \text{For retransmitted} \\ \\ L_q(k) + L_t(k) & \text{For successful} \end{cases} \tag{13}$$

The average L of a WSN is computed as shown in equation (14).

$$L = \sum_{i=1}^{n} \left(\sum_{k=1}^{P_i} \left(L_k \right) \right) \times \frac{1}{\mathcal{R}} \tag{14}$$

The time delay for a packet k to send from source and accumulate an ACK from the sink is considered as the retransmission time (RTT), and it may be asymmetric. It is determined by the sum of L_k and the time taken to receive an ACK ($\mathcal{A}_k$) from the base station for packet k as shown in equation (15).

$$\lambda_k = L_k + \mathcal{A}_k \tag{15}$$

The average RTT is determined as shown in equation (16).

$$\lambda = \frac{\sum_{i=1}^{n} \left(\sum_{j=1}^{P_i} \left(\sum_{k=0}^{\eta_j} \lambda_k \times \frac{1}{\eta_j} \right) \times \frac{1}{P_i} \right)}{T \times n} \tag{16}$$

The σ and E are inversely proportional to each other. The E and η are directly proportional to each other, where η indicates the average number of retransmissions computed using equation (16).

$$\eta = \frac{\sum_{i=1}^{n}\left(\sum_{j=1}^{P_i}\eta_j\right)}{n \times P_i} \tag{17}$$

The maximise the value of σ when η is minimised, and L and λ are minimised when η is minimised. The maximum σ value achieved when Φ is minimised. Finally, we achieve equation (18) through η with optimal retranmission timeout (RTO).

The primary goal of the proposed RRTICC algorithm is to trade-off between minimum λ and maximum σ using a utility function (Xiao et al., 2019) as shown in equation (18).

$$Z(\sigma, \lambda) = ((1-\gamma) \times Z_\vartheta(\lambda)) - (\gamma \times Z_\vartheta(\sigma)) \tag{18}$$

where $0 \leq \gamma \leq 1$ is the relative importance of the λ and σ. The $Z_\vartheta(x)$ used in equation (18) is computed as follows:

$$Z_\vartheta(x) = \begin{cases} \log(x) & \text{if } \vartheta = 1 \\ \frac{x^{1-\vartheta}}{1-\vartheta} & \text{otherwise} \end{cases} \tag{19}$$

where ϑ is the fairness value ranging (0,∞), and x is either σ or λ. The goal of the proposed RRTICC is to optimise equation (18).

4 Proposed RRTICC algorithm

The proposed RRTICC perform mainly two phases. Initially, the algorithm estimate the congestion degree timely at each SN using existing data routing information of the WSNs the . Further, a routing path is contracted while avoiding the congested nodes in the data travelling route. In which, the RRTICC used to identify the local optimal node to send the data to a sink. These two phases iterate to monitor the congestion and data forwarding to avoid the data losses with decreased delay to reach the data packet to the base station.

4.1 Congestion factor estimation

Because of the limited communication range, the SNs can not transmit their data to a sink directly, instead they are sending through neighbour nodes. But choosing the forwarding node is very important, because choosing the wrong node leads *misdirection attack* (Kumar et al., 2019) and the data routes a longer distance to come to the base station. It further wasting the energy of the relay SNs involve in this routing path. So, identify the best forwarding node is necessary to enhance the efficiency of the WSN.

So, we consider the neighbour in which the hop count is less towards to the base station. So, the initial forwarding node of a SN S_i is considered as shown in equation (20).

$$F_i = \{j | (H_{j0} \leq H_{i0}) \forall d_{ij} \leq r_c\} \tag{20}$$

Here, H_{i0} and H_{j0} are the minimum hop distance from node i to BS and node j to BS, respectively. Here, the F_i contains more than one node, depends on the deployment.

The load of each SN is estimated based on the F_i information of each SN in a WSN. The total number of packets available at time t by a SN i is considered as shown in equation (21).

$$Load_i = P_i + \sum_{j \in Back_i} P_j \tag{21}$$

where $Back_i$ indicates the children of the node i, which is determined using equation (22).

$$Back_i = \{j | (H_{j0} \geq H_{i0}) \forall d_{ij} \leq r_c\} \tag{22}$$

The congestion load factor of a node i is calculated as

$$CLF_i = \frac{c_i}{Load_i} \tag{23}$$

where c_i is the capacity of a node i, which means i can handle c_i packets with no cause of congestion. $Back_i$ and B_i are the data generation and buffer availability at a particular time t. The SN i is treated as congestion when the C_i value is one and node i is not congested when C_i value is zero, from equation (24).

$$C_i = \begin{cases} 1 & \text{if } CLF_i \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

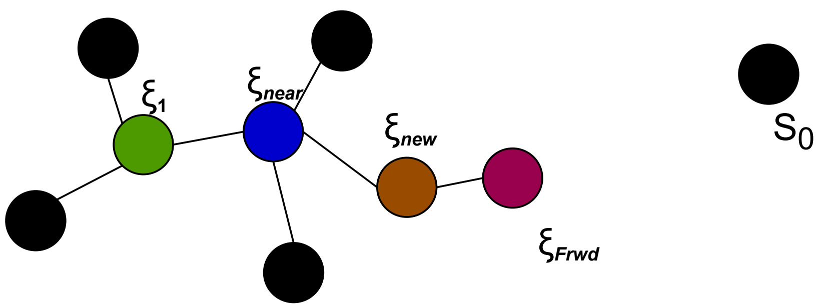
The value of $C = \{C_i\} \forall C_i = 1$ is given as an input to the RTT algorithm to construct a routing while avoid the congested nodes during the routing path generation.

The illustration of the CFE is explained through an example of 20 SNs and their data packets at time t for better understanding. From Figure 2(a), we notice the possible data transmission routes and assume that the SNs choose routing according to Figure 2(b). Assume each node can send ten packets, and each packet can hold a maximum of 70 packets at a particular time. In this scenario, The SN S_1, S_2, S_4, etc., are the leaf nodes, with only ten packets each. The S_3 can receive the data packets from S_1 and itself, so the number of packets available at S_3 is 20. The S_7 is received packets from S_3 and S_2, so the number packets available at S_7 are 40. Similar to the other SNs. The CFE can be estimated as the maximum load and available load. For instance, the CIE of Node S_7 is $\frac{70}{40} = 1.75$. So the node S_7 is not congested. Similarly we estimate the same for all the SNs and finally, the SNs S_{11}, S_{14}, and S_{15} results the CIE < 1. So, we treat them as congested.

4.2 Congestion-aware routing

This section construct a routing path from each SN to the sink node while avoid data forwarding to the congested nodes. In this context, we adopt a popular robot path planning algorithm called RRT to construct an efficient congestion-aware routing between a SN and a sink node with minimal computational time (Moon and Chung, 2014; LaValle et al., 1998) and high data accumulation efficiency. We assumed z SNs are involved in the congestion in the WSNs and we indicated them using $C = \{C_i\}\ \forall C_i = 1$, these nodes are avoided while generating a routing path between a SN S_i and the sink node S_0. The C values are changing in the network dynamically, because the congested node at the current iteration are reduced their burden due to not putting load on them. Some time the other SNs which may be lead to congestion due to heavy loads at certain point of time. So, we can conclude that the C can be changed dynamically based on changes occur in WSN environment.

Figure 1 RRT-based forwarding node selection while avoiding the congestion node (see online version for colours)



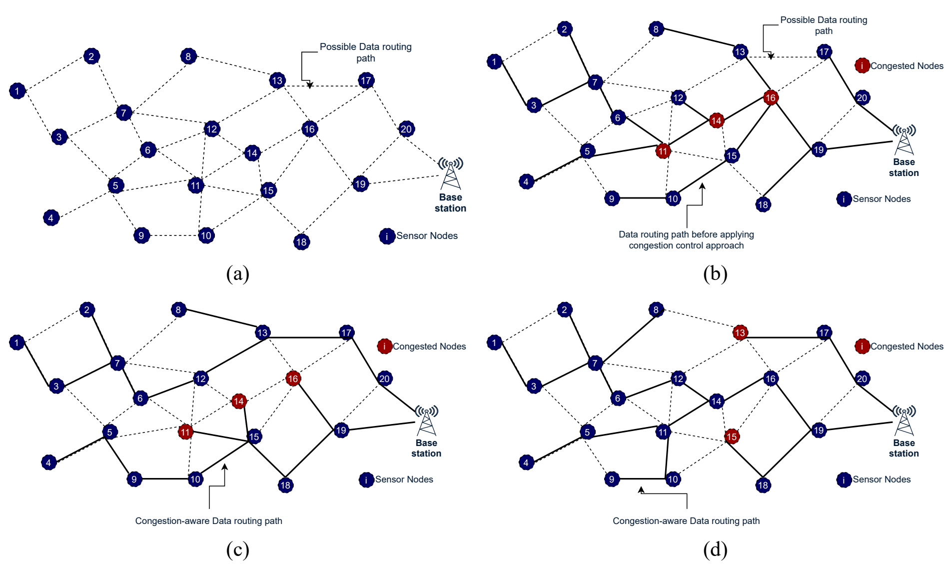
The RTT strategy can identify a routing path among SNs and sink while avoiding the congested SNs in the relay nodes set. Initially, we start with a node and assume it as a tree (called initial node, i.e., $\xi_1 \longleftarrow S_i$) and with an empty edge set $\mathbb{T}$. Then, we assume a random node ($\xi_{frwd} \in F_i$) in the WSN with a certain distance from the ξ_1 towards the S_0. We assumed a node ξ_{near} between the ξ_1 and ξ_{frwd} and it is closer to the ξ_1 with an Euclidean distance with in r_c. We generate a new state (ξ_{new}) by interacting with the given environment and it is derived with the help of an input u and (ξ_1). Here, the value of u is considered as $||u|| \leq 1$, which is the minimum distance between ξ_{near} and ξ_{frwd}. The new state ξ_{new} must be there in between ξ_{near} and ξ_{frwd}.

The ξ_{new} must be closer to ξ_{near} with an approximate distance ϵ in between them. Some scenarios, the distance from ξ_{near} and ξ_{frwd} to ξ_{new} is exactly similar. If no congested node found in between the ξ_{near} and ξ_{frwd}, then we consider ξ_{new} as a forwarding node from ξ_1, add ξ_{new} to the $\mathbb{T}$ as a routing path. In case, if no congested node found in between ξ_{near} and ξ_{frwd}, we do not consider the ξ_{new} as a forwarding a node for data routing $\mathbb{T}$, and search for another node form ξ_{frwd}. We iterate this procedure until $MaxIter$ to reach the path to base station (S_0). Once it reaches the S_0, the algorithm backtracks towards the ξ_1. Once the routing path between a node i and S_0 are constructed, we move forward with the next node and iterate the same process, until all the SNs covered at least once. The detailed congestion-aware routing algorithm is presented in Algorithm 1.

Algorithm 1 Congestion-aware routing

INPUT: S^{+}, C
OUTPUT: Routing $\mathbb{T}$
$\mathbb{T} = \phi$
for $i = 1$ to n **do**
  $\mathbb{T}_i = \phi$
  $\xi_1 = S_i$
  for $p = 1$ to $MaxIter$ **do**
    for $q = 1$ to $|F_i|$ **do**
      $\xi_{frwd} = F_i^q$;
      ξ_{near} = NEAREST_STATE(ξ_{frwd}, $\mathbb{T}$);
      μ = SELECT(ξ_{frwd}, ξ_{near})
      ξ_{new} = NEW_STATE(ξ_{near}, μ, δt)
      $\mathbb{T}.vertexAdd(\xi_{new})$
      $\mathbb{T}.edgeAdd(\xi_{new}, \xi_{near}, \mu)$
    end for
  end for
  $\mathbb{T} \longleftarrow \mathbb{T} \cup \mathbb{T}_i$
end for
return $\mathbb{T}$

Figure 2 Illustration of the congestion-aware routing between SNs and sink (see online version for colours)



The illustration of the congestion-aware routing is presented Figure 2 for better understanding. In this illustration, we consider twenty SNs and a base station. The changes in the routing paths are highlighted in Figure 2 while node is identified as a congested one.

Figure 2(a) is the initial network with twenty SNs and a base station. The possible routing and forwarding nodes of each SN are identified. For example, $F_1 = \{S_2, S_3\}$, $F_2 = \{S_7\}$, $F_3 = \{S_5, S_7\}$, ..., $F_{20} = \{S_0\}$. So, the node S_1 can send its data to either S_2 or S_3. But, to optimise the routing, they can forward their data to the nearest node or the less hop-count forwarding node towards the base station. Figure 2(b) represents the routing and the congested nodes in the first iteration. So, from this figure, we notice the nodes S_{11}, S_{14}, and S_{16} are suffered from the congestion due to heavy load on them. So, the proposed RRTICC identifies an alternate route towards the base station while avoiding the congested nodes in the route. In this context, the new route is identified in Figure 2(c). However, congestion is repeatedly occurring in WSN, and dynamic routing is needed in each round of the data transmissions. The new congestion nodes identified with the updated routing as shown in Figure 2(d) along with the dynamic congestion-aware routing. This process is repeated until an SN consumes its energy fully and becomes empty.

4.3 Complexity analysis

The time require to decide either a SN is involve in the congestion or not is required $O(n)$. The time taken to determine the path among a SN and the base station by avoiding the congested nodes is approximately $O(n \log n)$, and the detailed complexity derivation for the RRT is available in Nasir et al. (2013). So, this algorithm iterates n times to determine the routing from each SN to the sink, so it is $O(n \times n \log n)$ or $O(n^2 \log n)$. So, the total time require to control the congestion in the WSN is $\big(O(n) + O(n^2 \log n)\big) \approx O(n^2 \log n)$ because $O(n^2 \log n) > O(n)$.

5 Performance evaluation

The proposed RRTICC is simulated and tested using Python simulator through multiple runs to evaluate the performance. During simulations, we vary the number of SNs between 200 to 500 in an A of 500 m^2. We evaluate the performance of RRTICC in two scenarios such as continuous and burst. We do not assume any obstacle in the WSN environment. The SNs deployment and packet generations are followed according to Sah et al. (2021). The size of each packet in the simulation is used as 30 bytes. The continuous and burst scenarios are represented using WSN#1 and WSN#2, respectively. The r_t and r_c of these two scenarios is considered as 25 m and 35 m, respectively. The data transmissions in both WSN#1 and WSN#2 follow mesh topology. The data transmission rates vary between 80 and 250 kbps according to the changes in WSN. The EC of α_r is 29 mJ and α_t is 42 mJ. The E_i^0 is considered as 100 J. The TDMA is used in MAC layer for each SN. The proposed RRTICC algorithm with existing but related CADA (Donta et al., 2020), CADC (Zhuang et al., 2018), AWFCC (Srivastava et al., 2020) methods evaluated various performance metrics including network lifetime ($\mathcal{N}$), AEC (E), buffer utilisation (BU), throughput (τ), PDR (ς), latency (L), etc. All the simulation parameters are summarised using Table 1 for easy refer.

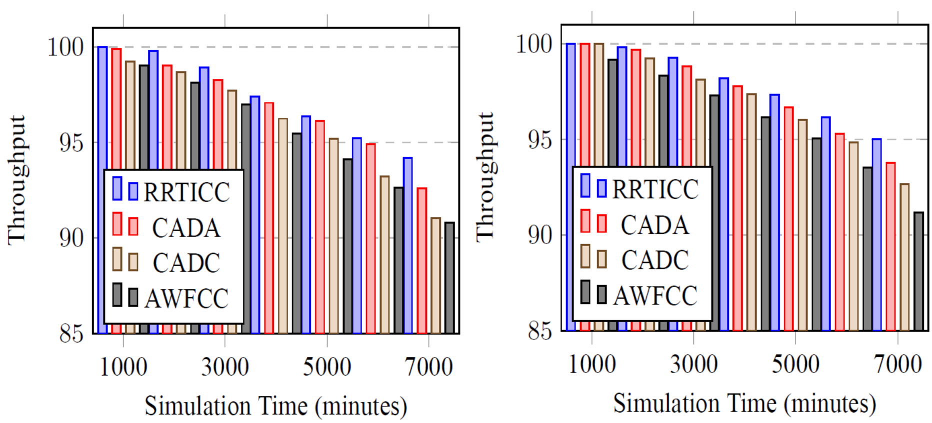
Table 1 Simulation parameters and their values

Parameter	*Value*
n	200–500
A	500 m^2
Scenarios	WSN#1 and WSN#2
r_t	25 m
r_c	35 m
α_r	29 mJ
α_t	42 mJ
E_i^0	100 J
Data transmission	80–250 kbps
MAC	TDMA
B	100 units
Packet size	30 bytes
Simulator	Python 3.X

5.1 *Throughput of a WSN*

The throughput (σ) of a WSN is treated as the amount of packets accumulated by the sink in a time unit as computed in equation (12). The σ and congestion are inversely proportional to each other. Increase the congestion automatically decreases the σ, and vice versa.

Figure 3 Throughput of WSNs, (a) WSN#1 (b) WSN#2 (see online version for colours)



(a) (b)

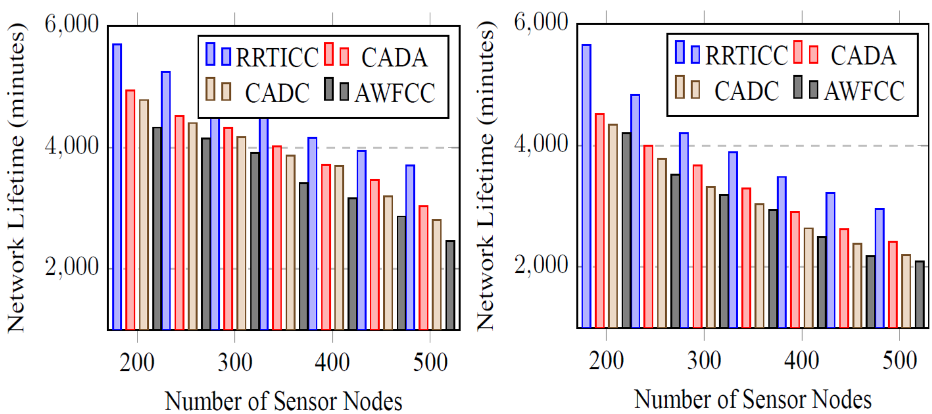
The σ of proposed RRTICC and existing CADA, CADC, and AWFCC methods in WSN#1 and WSN#2 are plotted in Figures 3(a) and 3(b), respectively. The σ of the RRTICC is better in both WSN#1 and WSN#2 approximately 93% and 95%, respectively. In WSN#1, RRTICC improves the σ over the existing CADA, CADC, and AWFCC are approximately 5–11×, 7–17× and 11–23×, respectively as shown in Figure 3(a). From Figure 3(b), we find that the growth of σ in RRTICC approximately 5–11× than CADA, 9–16× than CADC, and 13–25× than AWFCC approaches. The throughput growth in RRTICC strategy is noticed due to efficient congestion-aware routing through RRT algorithm.

5.2 Network lifetime

There are several ways to compute $\mathcal{N}$ depends on the network conditions and applications. In this work, it is calculated (in minutes) using the simulation time since the first SN battery becomes empty (Donta et al., 2019).

$$\mathcal{N} = \frac{E_i^0}{\max_{i \in S}(E_i^t)} \tag{25}$$

Figure 4 Network lifetime vs. # sensor nodes, (a) WSN#1 (b) WSN#2 (see online version for colours)



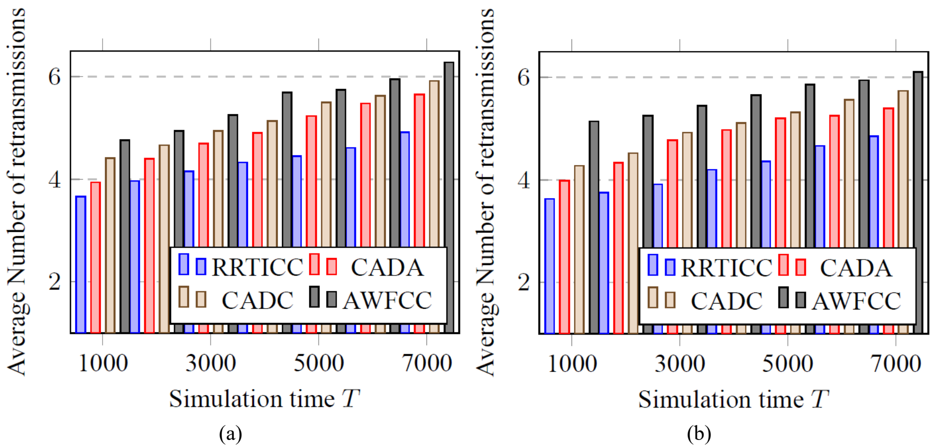
(a) (b)

We compute the $\mathcal{N}$ of the RRTICC algorithm and existing ones with 200–500 SN in each simulation for WSN#1 and WSN#2 as shown in Figures 4(a) and 4(b), respectively. From Figure 4(a), we find decreased $\mathcal{N}$ while increasing the SNs. Still, the RRTICC has longer lifespan of WSNs over the existing CADA, CADC, and AWFCC nearly 12–21$\times$, 16–27$\times$ and 19–34$\times$, respectively. Likewise, in WSN#2 the lifespan growth is noticed nearly 14–32% over CADA, 19–37% over CADC, and 23–39% compare to AWFCC algorithms. In WSN#2, the $\mathcal{N}$ of the RRTICC growth in the efficiency over the WSN#1. We notice these growths due to best routing through RRT algorithm and efficient identification of the congested nodes in the WSNs.

5.3 Average number of retransmissions

In WSNs, the retransmissions count of data packets are increased when more congestion occur. So, the congestion and retransmissions are directly proportional to each other. These retrasnmissions also increase the energy consumption due to unnecessary control signal involve in transmission. In this context, we identify the retransmissions mean (η) in a WSN to identify the quality growth of proposed RRTICC. The η in this article is computed using equation (17). Figure 5 plot the variations of η during the simulation time between 1,000 to 7,000 minutes for both continuous and burst scenarios.

Figure 5 Average number of retransmissions, (a) WSN#1 (b) WSN#2 (see online version for colours)



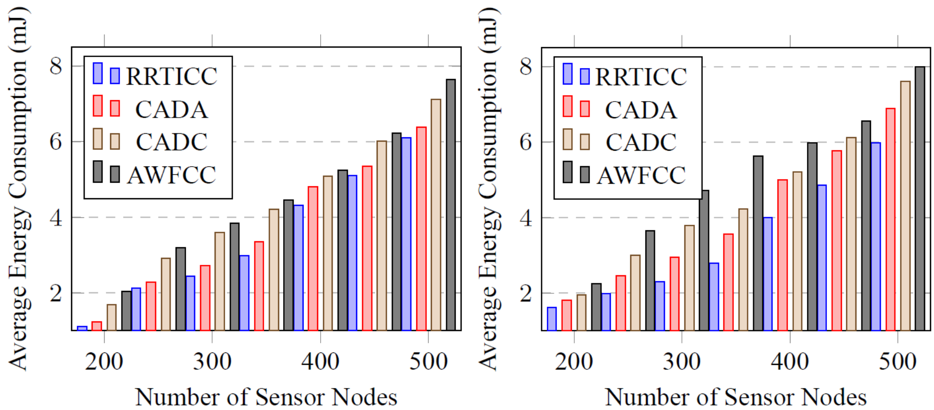
Initial state of the simulation time, there is no retransmissions due to availability of the buffers and channels. While increasing the simulation time, gradually the buffers start occupying and it leads congestion. So, we notice the retransmission in between the simulation time, i.e., between 1,000 to 7,000 units. From Figure 5(a), the η of four algorithms are varied, and the proposed RRTICC results in minimum retransmissions over the other algorithm in most of the case. From Figure 5(b), the performance of the RRTICC is better and results minimum retransmissions and the η. In WSN#1, the RRTICC achieves more than 19–31% less retransmission, whereas, in WSN#2, it improved up to 17–29% compared with existing approaches. The cause of fewer retransmissions is because of the efficient identification of congestion in the network.

5.4 Average energy consumption

The AEC of a WSN is determined by considering the mean energy used by each SN in the network, as shown in equation (8).

The E of the RRTICC and traditional recent algorithms' quality is estimated using continuous and burst environment between 200–500 SNs in Figures 6(a) and 6(b), respectively. From Figure 6(a), we notice that the RRTICC performance growth approximately 12–21%, 16–23%, 22–31% compared to CADA, CADC, and AWFCC, respectively. Likewise, in the WSN#2, the quality improvement over the traditional techniques are approximately 13–21%, 17–25%, and 21–33% compared to CADA, CADC, and AWFCC, respectively. The improvements in the proposed RRTICC is noticed due to efficient identification of the congested nodes in the network to divert the packet transmission route with minimal latency and low energy computations of the relay nodes.

Figure 6 Average energy consumption, (a) WSN#1 (b) WSN#2 (see online version for colours)



(a) (b)

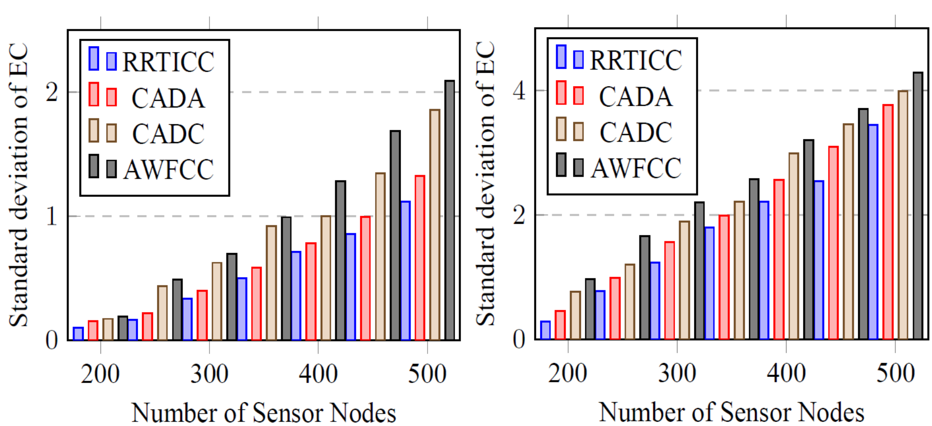
5.5 *Standard deviation of energy consumption*

The AEC may not results the shared bottleneck of the energy consumption, so standard deviation of EC is measured similar to Donta et al. (2021a) as shown in equation (26).

$$E_{SD} = \sqrt{\frac{\sum_{i=1}^{n}(E_i^t - E)^2}{n}} \tag{26}$$

where E_i^t is the available energy of node i and E is the AEC and similar to equation (8).

Figure 7 Standard deviation of EC, (a) WSN#1 (b) WSN#2 (see online version for colours)



(a) (b)

The E_{SD} of the RRTICC algorithm and CADA, CADC, and AWFCC approaches for both scenarios are evaluated and plotted using Figure 7(a) and Figure 7(b), respectively.

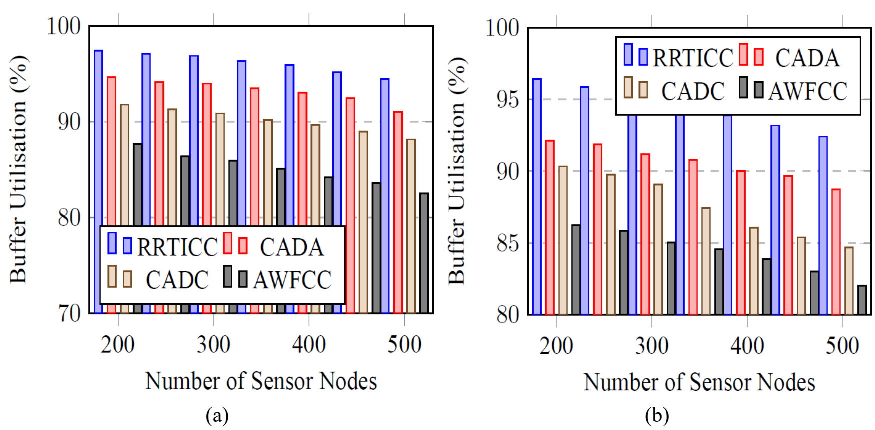
The low E_{SD} is the best equal share of energy bottleneck and vice versa. The performance growth in E_{SD} for proposed RRTICC is noticed from Figure 7(a) and it is always lower than CADA, CADC, and AWFCC approximately 4–9×, 8–15× and 12–22×, respectively. Similarly, in WSN#2, the performance of the E_{SD} is approximately 6–10× than CADA, 12–19× than CADC, and 13–23× than AWFCC algorithms are lower SD in the RRTICC. These improved performances are noticed due to efficient congestion control through RRT.

5.6 *Buffer utilisation*

It is denoted as the efficiency of the memory usage during the data exchanges. The usage of the buffer (BU) is a considerable metric and which influence to cause the congestion in the network. BU is measured as the ratio of average buffer occupancy and the initial buffer capacity as shown in equation (27).

$$BU = \frac{\sum_{i=1}^{n} \mathcal{B}_i}{\mathcal{B} \times n} \tag{27}$$

Figure 8 Buffer utilisation vs. # sensor nodes, (a) WSN#1 (b) WSN#2 (see online version for colours)



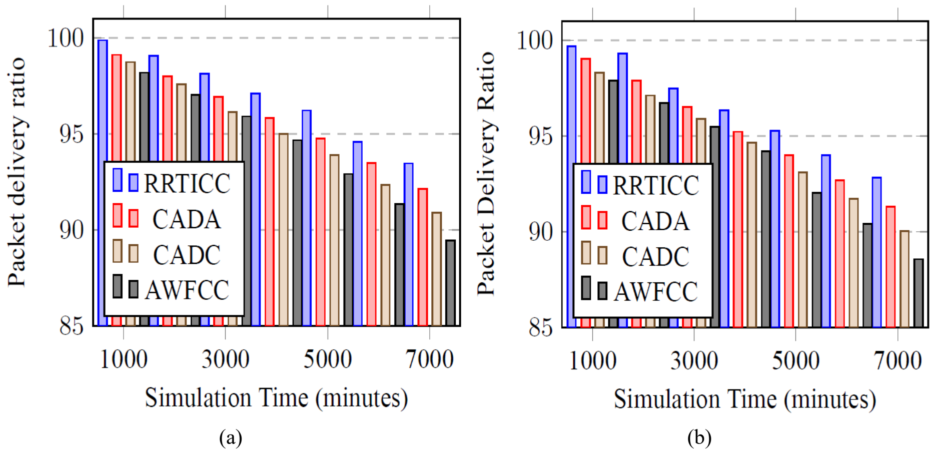
The proposed RRTICC and existing works BU is tested in both scenarios in Figure 8. In Figure 8(a), the WSN#1 is tested with 200 to 500 SNs, and we notice that the RRTICC is always use the buffer properly and efficiency is improved 4–7× better than CADA, 9–13× than CADC, and 11–19× than AWFCC mechanisms. Likewise, the WSN#2 is shown in Figure 8(b). Here, the efficiency growth of proposed RRTICC algorithm is approximately 6–11× over the CADA, 12–17× than CADC, and 15–21× over AWFCC mechanisms. The growth of the proposed RRTICC is noticed because of the efficient identification of congested nodes before scheduling the data to them.

5.7 *Packet delivery ratio*

The primary purpose of the WSN is to achieve the best PDR at the BS to provide the optimal service depends on the application. The congestion interrupts achieving the best

PDR. So, it is a necessary metric to estimate the efficiency of an algorithm. The PDR of the proposed and exiting algorithms are computed as shown in equation (9).

Figure 9 Packet delivery ratio vs. simulation time, (a) WSN#1 (b) WSN#2 (see online version for colours)



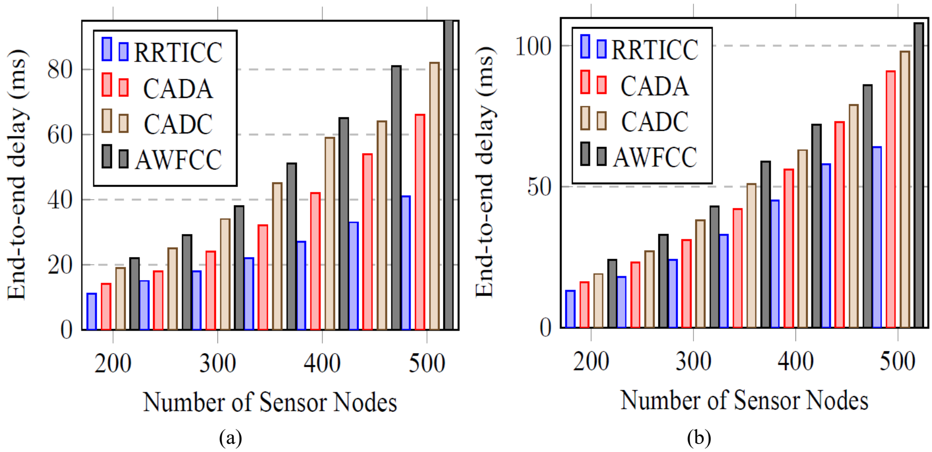
The ς comparison results of the proposed RRT and existing algorithms are presented in Figure 9. Figure 9(a) shows the comparison of PDR in WSN#1 and Figure 9(b) plot the results of WSN#2. From Figure 9(a), we observe PDR growth of the RRTICC over the existing CADA, CADC, and AWFCC approximately 11×, 16× and 19×, respectively in WSN#1. Similarly, in WSN#2 the extended performance identified as 13× better than CADA, 18× better over CADC, and 22× better over AWFCC techniques. The growth in results of the RRTICC is due to efficient identification of the congestion and the congestion aware data routing through RRT algorithm.

5.8 Latency

The latency of the proposed RRTICC is treated as the time variation among the data sensed from the environment and it is received by the S_0. It is very important to minimise the L for the delay sensitive applications. It is computed as shown in equation (13).

The L of the proposed RRTICC, CADA, CADC, and AWFCC in both the scenarios are compared in Figure 10. The L of the RRTICC is lower all the times in WSN#1 and WSN#2 over existing CADA, CADC, and AWFCC. Since, the L increase while adding more number of SNs in to the field, but the proposed RRTICC always outperforms the existing CADA, CADC, and AWFCC. These are approximately 7–21%, 9–29%, and 13–33%, respectively, in WSN#1 compare with the RRTICC. Likewise, in WSN#2 the RRTICC algorithm lower the L approximately 7× over CADA, 10× over CADC, and 14× compare to AWFCC algorithms. Efficient routing path for the data path while avoiding the congested nodes results these better results during our observation.

Figure 10 Latency vs. # sensor nodes, (a) WSN#1 (b) WSN#2 (see online version for colours)



5.9 *Congestion fairness index*

It results the "equal share of the bottleneck of congestion among the WSN", which means SNs of a particular region are more effected in the WSNs (Hoßfeld et al., 2016). The CFI is ranging from zero to one, and 1 indicates the best CFI, which means the algorithm is efficiently balancing and no particular region is more affecting due to congestion. The CFI of the proposed RRTICC is ≈0.99891 to 0.99112 depends on the SNs deployed in the network of continuous scenarios. The CFI in the burst scenario is varying between ≈0.99372 to 0.99083 depends on the number of SNs placed in the network. The CFI of the proposed RRTICC is always higher than the existing CADA, CADC, and AWFCC strategies.

5.10 *Discussion*

The proposed RRTICC algorithm can efficiently avoid the congested nodes in the routing path to avoid the unnecessary packets drop and retransmission. This advantage can also control the efficient balance of the energy in the network. IT further increases the throughput by degrading the delay of the data packets. The number of packets drop also minimised. The proposed work also balances the load in the WSNs, so the fairness index of the proposed RRTICC model is also does not put a over burden on any particular node in the network.

6 Conclusions

Congestion is a challenging problem in the WSNs, whereas it degrades the efficiency under different metrics energy wastage, packet loss, low throughput, etc. In this context, this paper proposes an intelligent congestion control approach called RTTICC. A mathematical strategy is used to identify the congested SNs in the network, and a dynamic routing path is constructed for the SNs by avoiding the congested nodes in the route. The proposed RTTICC is simulated and tested under different scenarios by considering various quality metrics, including the lifespan of WSN, energy efficiency, PDR, throughput, buffer utilisation, retransmission count, etc. The proposed RRTICC outperforms the existing CADA, CADC, and AWFCC mechanisms. The significant limitations of this algorithm are the identification of the congestion after it causes in the WSN, increased latency due to long path, and excess energy drain than regular routing. One limitation can be avoided while extending the algorithm by predicting the congestion before it occurs in the future. So, identify the suitable lightweight machine-learning algorithm for congestion prediction before appearing in the WSNs. The energy and delay of the proposed work need to be avoided, but the proposed work is still better than the existing strategies.

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