

Mrcib: Design Of An Efficient Multipath Routing Model For Reducing Network Collisions Via Incremental Bioinspired Optimizations

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Abstract:

The probability of packet collisions increases exponentially w.r.t. number of communications due to which design of collision-control protocols is of primary importance for large-scale wireless networks. Existing collision control models either showcase high complexity, or have slower response, due to which their efficiency levels are limited for larger networks. Moreover, most of these models cannot be scaled due inherent computational redundancies. To overcome these issues, this text proposes design of a novel multipath routing model for reducing network collisions via incremental bioinspired optimizations. The proposed model initially deploys a Bacterial Foraging Optimizer (BFO) for segregating packets into multipath requests. This segregation is done based on temporal routing performance for different set of paths. The segregated packets are transmitted over the network via an efficient set of multiple paths which are identified by Genetic Algorithm (GA) optimizations. The selected paths are incrementally tuned by a Q-Learning based layer, that assists in reducing collisions under large number of packet requests. This is done via temporal evaluation of network parameters, and continuous model updates for high-efficiency operations. The proposed model was tested under large-scale networks with heterogeneous requests, and it was observed that the model was able to improve communication speed by 8.5%, reduce energy consumption by 6.4%, maintain high packet delivery performance and improve data rate by 3.9% when compared with existing multipath routing protocols that

support congestion control for large-scale network scenarios.

Keywords: Wireless, Congestion, Multipath, Routing, Energy, BFO, GA, Delay, Throughput, Packet, Delivery, Scenarios

1. Introduction

Individual wireless sensors with built-in communication capabilities constitute wireless sensor networks (WSNs). These sensor nodes collect environmental information, which is subsequently sent to the sink node via the ad hoc network protocol that uses Multi-Agent Deep Reinforcement Learning Congestion Control (MA RL CC) [1, 2, 3, 4] Wireless sensor networks (WSNs) are often recognized as one of the Internet of Things' most vital components. WSNs have several applications, including monitoring natural ecosystems, averting natural disasters, managing automated systems, and in the medical and health care areas. The Internet of Things has several opportunities for WSN use. The need for wireless sensor networks (WSNs) across a range of sectors is increasing, as is the requirement to execute multiple application tasks for those organizations inside the same networks. Similar to the soil monitoring system used in contemporary agriculture via Game Theory Based Congestion Control (GTCC) [5, 6], The Sink gets continual data on the physiological status of the surrounding area. Considering the limited time available, this knowledge is crucial. The temperatures must be supplied to the Sink as quickly as physically feasible, since they indicate the current environmental conditions. As the number of sensor nodes in the monitored environment increases, it becomes evident that the statistics are not very accurate, despite their use for the application. The production of non-periodic sensed data and the occurrence of the triggered event occur when the monitored value exceeds or deviates from the threshold value. For this data to be sent successfully, there can be only a little amount of lag delays [7, 8, 9]. There is a possibility that the information generated in response to a user query will have certain characteristics. In addition, the Sink must receive media data that is given with more precision, such as a freshly taken image. Due to this, contemporary WSNs are collaborative systems used to execute many applications

concurrently [10, 11, 12]. In addition, each of these apps has distinct quality of service needs and creates a distinct variety of data flow (QoS). Multiple sensor nodes provide their data to a single central processing unit, also known as a sink, which receives the majority of the data produced by WSNs. Frequently, each sensor node use the routing strategy to decide which node should serve as its parent. The structure of the network resembles a tree. When the bandwidth capacity of the topology tree is surpassed by the amount of data load, network congestion is obvious. When all of the data from the nodes is sent to the Sink, this occurs. Congestion has several effects on a network, including a reduction in throughput, an uneven distribution of data, an increase in the frequency of packet loss, and an increase in wait times. Because of unnecessary packet retransmissions, the node's resources are managed inefficiently. In addition, it will impair the network's capacity to endure for an extended term. Multiple types of data traffic attempt to transmit as many packets as possible without regard for the available capacity, resulting in congestion. Congestion may be decreased and avoided in real-time circumstances if diverse forms of data traffic work together to use network resources.

This part is followed by a comprehensive analysis of these models, which demonstrates that the high complexity or sluggish reaction times of present collision management strategies restrict their usefulness in networks with more nodes. This section is now finished. Moreover, the majority of these models are not scalable due to the computational redundancies they include. The third component of this study provides a solution in the form of a unique multipath routing model with the objective of minimizing the frequency of network collisions via bio-inspired enhancements. The performance of the model is examined in a variety of real-world settings in Section 4, which discusses model validation. Finally, some concluding remarks and proposals for enhancing the model presented for application in large-scale situations are provided to scale the model under real-time scenarios.

2. Literature Review

Various techniques and algorithms [13, 14, 15] have been developed over the last many years to alleviate WSN congestion that use Delay-based Path-specified Congestion

Control Protocol (DPCCP). When a transient surge in demand exceeds the transmission capacity of a network resource, congestion is often the outcome. Therefore, resource management and traffic control are two methods that may be used to reduce traffic volume. In the case of congestion, the first option includes rerouting data packets to the Sink through routes with lower traffic densities. It is likely that increasing the number of active nodes, routing paths, transmission distance, and capacity in wireless networks might assist alleviate congestion in these networks. As an example, work in [16, 17, 18] employs an approach for topology-aware resource adaptation as its central component. This strategy is based on the results of a model for capacity analysis that assesses the capacity of a variety of topologies. The most fundamental weakness of this strategy is that it requires expertise not just with locally accessible resources, but also with those accessible throughout the whole network [19, 20]. Working with wireless connections poses a variety of obstacles, one of which is the inability to deal with this problem simply. In contrast to the resource management approach, the traffic control strategy aims to alleviate traffic congestion by adjusting the amount of traffic at the origin or hub node. This is done to decrease the time spent sitting in traffic. When the demands on the network's resources approach or beyond the network's capacity, the traffic management will restrict the number of injected packets in order to relieve congestion. [21, 22, 23, 24] details the implementation of the end-to-end control strategy. Reactive end-to-end control is seldom used in protocols and algorithms since it is reliant on the round-trip time between the source and sink nodes. This is due to the difficulty of implementing the approach. The hop-by-hop control mechanism is now the most common method of operation due to its dispersed control style and quicker response time. The Priority-Based Congestion Control System is a hop-by-hop congestion control system created specifically for wireless sensor networks that uses Reinforcement Learning-Based Transmission Control (RLTC) [25, 26, 27, 28]. The severity of the problem is assessed, and a priority index is utilized to define how each system bottleneck should be managed. The density of a network may be estimated by examining both the inter-arrival and service times of the packets. For each and every node, a unique index has been created. A node with a higher priority index will have access

to a larger quantity of transmission capacity. When a node in HRTC [14] detects congestion, a back pressure message is sent and a report is created. By decreasing the pace at which data travels across the network, network nodes assist alleviate congestion. Despite the recent incorporation of game theory into the hop-by-hop control mechanism, early findings show that it is the most effective method for minimizing congestion. The application of game theory to traffic congestion management (GTCC) [15, 16]. Monitoring the packet transmission rate enables the discovery of congestion. The parent node will send out congestion alerts, and the children will use game theory to evaluate if they should move parents. This control protocol simplifies the process of integrating the complex routing topology into the routing algorithm. The GTCCF [29, 30] proposes utilizing game theory as the foundation for a new paradigm for managing congestion. A network is considered to be congested when child nodes broadcast an excessive quantity of data packets to their parent node at a rapid rate. To discover a solution to this bottleneck, we may imagine each child node as a player in a game in which there are no victors or losers. In the non-cooperative game, the reproduction rate of each child node is boosted to its maximum level. In the present competitive market, neither the legally prescribed minimum charge nor the quality of the service are taken into consideration. The quality of service cannot be maintained when the rate solution of the Nash equilibrium is lower than the minimal rate. Although hop-by-hop congestion management has the ability to alleviate network congestion, its design does not always account for QoS requirements and avoidance. In an effort to simultaneously enhance these two components, swarm intelligence optimization is being used. The technique described in [31, 32] is inspired by the flocking behavior of birds in order to guide data packets toward unused nodes and away from occupied nodes. When transferring data to the Sink, the recommended method prioritizes paths with lower traffic levels. Due to the unpredictability of bird flocking and the height of the landscape above, it is impossible to determine the optimal route. Ant Colony Optimization (ACO) is an additional leading optimization method. [33, 34] It is a very effective heuristic stochastic optimal strategy. The efficiency of the feedback loop is enhanced by the improvements made by the ACO. Using persistent pheromone analysis, the most effective line

of action is determined. The ACO has found widespread use in the solution of combinatorial problems, including global multi-object optimization and complex network routing, to mention just two examples. Due to their symbiotic connection, congestion management and routing issues in WSNs are ideal candidates for the ACO's distributed computing mode and low computational cost. MS-ACO refers to a system that simultaneously tackles congestion concerns and meets quality of service standards. When the MS-ACO detects congestion, it assumes a very pessimistic view of the situation and modifies the path accordingly. Despite its significant energy consumption, the bulk of this technology's applications are in next-generation networks. The ARCC's [35, 36] usage of the PCCP protocol helps to alleviate congestion. The first step in the ACO procedure is finding the most direct path from the origin to the ultimate destination. Second, the Sink's artificial ants analyze the level of congestion and use PCCP to resolve the problem. Although this approach is analogous to the ACO and PCCP, it does not account for the need of data categorization scenarios.

3. Proposed hybrid Bioinspired Model for improving Routing performance of Energy aware Wireless Sensor Networks

According to an analysis of the current congestion control models, it can be seen that these models either exhibit high complexity or have slower response times, which limits their efficacy for larger networks. Furthermore, because of built-in computational redundancies, the majority of these models cannot be scaled. This section suggests designing a novel multipath routing model to address these problems by decreasing network collisions through gradual bio-inspired optimizations. The proposed model first deploys a Bacterial Foraging Optimizer (BFO) to separate packets into multipath requests, as shown in the model's flow diagram in figure 1. This division is based on the effectiveness of temporal routing for various sets of paths. The network's efficient set of multiple paths used for the transmission of the separated packets is determined by Genetic Algorithm (GA) optimizations. A Q-Learning layer that is based on the selected paths incrementally fine-tunes them helps prevent collisions when a lot of packet requests are made. For high-efficiency operations, this is accomplished through the

temporal evaluation of network parameters and ongoing model updates.

Thus, the model initially collects network information sets, node information sets & communication parameter sets for identification of multipath routes. These routes are evaluated via a Bacterial Foraging Optimizer (BFO), that works as per the following process,

- Setup the following Bacterial Foraging constants,
 - A set of reconfigurable Bacterium (NB)
 - An iterative set of rounds for reconfiguring these Bacterium (NI)
 - Rate of social learning for the Bacterium (L_b)
 - A set of source & destination nodes (S, D)

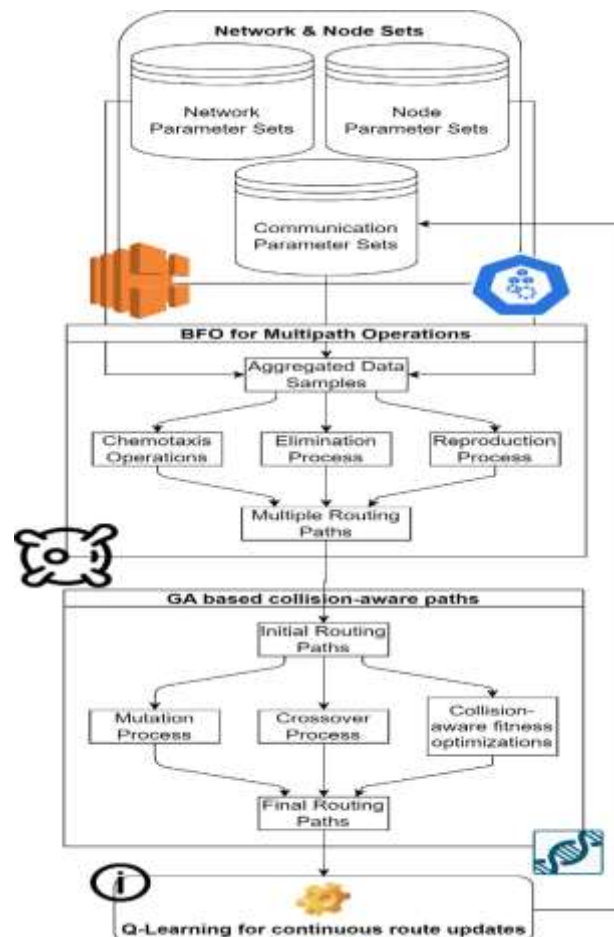


Figure 1. Design of a Dual-bioinspired Model for congestion control routing operations

- To start the optimizer, calculate a reference distance via equation 1,

$$d_{\text{ref}} = \sqrt{(x_s - x_d)^2 + (y_s - y_d)^2} \dots (1)$$

Where, x & y are the Cartesian co-ordinates of the source & destination nodes.

- Based on this distance metric, identify nodes that satisfy equation 2,

$$d(\text{src}, \text{node}) < d_{\text{ref}} \text{ \& } d(\text{node}, \text{dest}) < d_{\text{ref}} \dots (2)$$

Where, $d(i, j)$ represents distance between i & j nodes. Because of this condition, all nodes that are between source & destination can be identified, and used for multipath routing operations.

- From this set of nodes, stochastically (STOCH) select a set of nodes via equation 3, which represents a single Bacteria particle,

$$N_{\text{sel}} = L_{\text{sel}}[\text{STOCH}(1, \text{Size}(L_{\text{sel}}))] \dots (3)$$

Where, N_{set} is the selected set of nodes, while L_{set} is the list of nodes that are currently between source & destination nodes.

- This select is done only if consecutively selected nodes have lower distance from destination, than previously selected nodes.
- Once the node sets are selected, then a BFO fitness is calculated via equation 4,

$$f_b = \frac{1}{N_{\text{sel}} - 1} \sum_{i=1}^{N_{\text{sel}}-1} \left[\frac{d_{\text{ref}}}{d_{i+1,i}} + \frac{E_i}{\text{Max}(E)} + \frac{\text{THR}(i)}{\text{Max}(\text{THR})} + \frac{\text{PDR}(i)}{100} \right] * \frac{\text{FTM}_i}{\text{Max}(\text{FTM})} \dots (4)$$

Where, $d_{i,j}$ represents Euclidean distance between nodes, E_i represents residual energy of the node, THR & PDR represents their previous throughput and packet delivery ratio levels. In this equation the feedback trust metric (FTM) is initialized as 1, and updated in equation 17 via feedback operations.

- Repeat this process for all Bacterium, so that initial routing paths are generated between selected set of source & destination nodes.
- After estimation of these paths, calculate a Bacterium fitness threshold via equation 5,

$$f_{th} = \sum_{i=1}^{NB} f_{b_i} * \frac{L_b}{NB} \dots (5)$$

- Bacterium with $f > f_{th}$ are reproduced in the next iteration, while others are eliminated from the current set of iterations.
- All eliminated bacterium are regenerated via equations 3 & 4, which assists in identification new routing paths.
- Repeat this process for NI iterations, and generate NB different routing paths.

Once the iterations are completed, then all Bacterium with $f_b > f_{th}$ are selected and used for congestion control operations. To perform this task, a Genetic Algorithm (GA) based optimization process is used, which assists in identification of highly efficient routing paths even under congestions. This GA Model works as per the following process,

- Initialize the following constants for GA optimizer,
 - Total count of iterations that will be used for reconfiguration (N_i)
 - Total count of reconfigurable solutions (N_s)
 - Rate at which these solutions will mutate (L_r)
 - Set of paths provided by the BFO process (S_{BFO})
 - Total count of packets that has to be communicated between the nodes (NP)
- Based on these constants, a set of N_s solutions are initially generated using the following operations,
 - Stochastically select a set of routing paths from the S_{BFO} list, and evaluate the per-path packet count via equation 6,

$$PPC = \frac{NP}{N[S_{BFO}(Sel)]} \dots (6)$$

Where, $N[S_{BFO}(Sel)]$ represents the total number of routing paths that are selected stochastically for multipath routing operations.

- Segregate the packets among these paths via equation 7,

$$NP_i = PPC * PQ_i \dots (7)$$

Where, NP_i are the total packets that will be transmitted on the given path, and PQ is the path quality, which is estimated via equation 8,

$$PQ = \frac{1}{N_c} \sum_{i=1}^{N_c} \frac{PDR_i}{100 * N(\text{Collisions})_i} \dots (8)$$

Where, PDR represents packet delivery ratio for this path and is estimated via equation 9, and $N(\text{Collisions})$ represents total number of collisions that occurred on this path during the previous N_c communications.

$$PDR = \frac{P_{rx}}{P_{tx}} \dots (9)$$

Where, P_{tx} & P_{rx} represents the total number of packets transmitted & received by nodes during individual communications.

- Based on this segregation, simulate the routing process, and estimate solution fitness via equation 10,

$$f_s = \frac{1}{N[S_{BFO}(\text{Sel})]} \sum_{i=1}^{N[S_{BFO}(\text{Sel})]} \frac{D_i}{\text{Max}(D)} + \frac{e_i}{\text{Max}(e)} + \frac{1}{PQ_i} + \frac{\text{Max}(\text{THR})}{\text{THR}_i} \dots (10)$$

Where, D is the delay needed to perform these communications and is evaluated via equation 11, e represents the energy needed for these communications and is calculated via equation 12, THR represents the temporal throughput during these communications and is calculated via equation 13,

$$D = TS_{\text{complete}} - TS_{\text{start}} \dots (11)$$

Where, TS_{complete} & TS_{start} represents the timestamp for completing and starting the communications.

$$e = E_{\text{start}} - E_{\text{complete}} \dots (12)$$

Where, E_{start} & E_{complete} represents the initial residual energy of node before starting communications, and final energy of node after completing the communications.

$$\text{THR} = \frac{P_{\text{rx}}}{D} \dots (13)$$

- Such solutions are generated, and a fitness threshold is evaluated via equation 14,

$$f_{\text{th}} = \frac{1}{N_s} \sum_{i=1}^{N_s} f_{s_i} * L_r \dots (14)$$

- All solutions with $f > f_{\text{th}}$ are discarded in current iteration and mutated via equations 7 to 10, while other solutions are cross overed to the next set of iterations.
- This process is repeated for N_i iterations, and in each iteration a set of N_s multipath solutions are reconfigured for collision-aware routing operations.

Once all iterations are completed, then set of paths selected by the solution with minimum fitness are used for the routing process. Due to which the model is able to select routing paths with low congestion and high-fidelity performance under large-scale traffic scenarios. The selection process is further optimized via a Q-Learning based tuning process, which estimates the Q value for each of the multipaths via equation 15,

$$Q = \frac{1}{N(\text{Collisions})} \left(\frac{\text{PDR}}{100} + \frac{\text{THR}}{\text{Max}(\text{THR})} \right) \dots (15)$$

Where, PDR & THR are estimated in real-time for individual paths. This value of Q value is continuously evaluated for each communication, and a reward function is estimated via equation 16,

$$r = \frac{Q(\text{New}) - Q(\text{Previous})}{L_r} - L_r \text{Max}(Q) + Q(\text{Previous}) \dots (16)$$

If this reward factor $r \geq 1$, then it indicates the Q values are either constant or are improving, while $r < 1$ indicates that Q values are reducing, thus the path requires corrections. To perform these corrections, the BFO & GA Models are reiterated by considering current node as source node, and

re-evaluating multiple paths towards destination node from current set of nodes. Due to this reconfiguration, the number of collisions is reduced, and Quality of Service (QoS) is improved for heterogeneous communications. Paths that do not require reconfiguration are fed-back to the routing database, and are used in future for high-speed path selection & communication operations. For the nodes present in this path, a feedback trust metric is modified via equation 17,

$$FTM_i(\text{New}) = FTM_i(\text{Old}) + N[S_{\text{BFO}}(\text{Sel})] * L_r \dots (17)$$

This updated FTM is used in the previous equations in order to improve quality of path selection, thus assisting in reducing number of congestions and enhancing QoS levels. Performance of this model was evaluated on a standard simulation scenario, and compared with existing models in the next section of this text.

4. Statistical Analysis

The proposed MRCIB model initially deploys a Bacterial Foraging Optimizer (BFO) for segregating packets into multipath requests. This segregation is done based on temporal routing performance for different set of paths. The segregated packets are transmitted over the network via an efficient set of multiple paths which are identified by Genetic Algorithm (GA) optimizations. The selected paths are incrementally tuned by a Q-Learning based layer, that assists in reducing collisions under large number of packet requests. This is done via temporal evaluation of network parameters, and continuous model updates for high-efficiency operations. The proposed model was tested under large-scale networks with heterogeneous requests. To perform these tests, the following simulation settings mentioned in table 1 were used, which assisted in evaluating the network under standard network conditions via the NS2 (Network Simulator 2.34) platform, which is a standardized toolkit for evaluating network performance levels.

Parametric Network Settings	Value for the settings
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Propagation model used during communications	Dual rays with wireless communications
Protocol used for MAC Layer	802.16a
Type of Queue	Drop Tail Queue with Packet Priorities
Total network nodes	1000
Underlying protocol used for routing operations	TORA (Temporally Ordered Routing Algorithm)
Network Dimensions	2km x 2km
Energy consumed by nodes during idle mode	0.05 mW
Energy consumed by nodes during reception mode	1.5 mW
Energy consumed by nodes during transmission mode	3 mW
Energy consumed by nodes during sleep mode	0.001 mW
Energy consumed by nodes during transitioning between modes	0.2 mW
Delay needed by nodes for transitioning between modes	0.01 s
Initial energy levels	0.2 W

Table 1. Simulation configuration of the network for estimating model performance levels

As per these configurations, the model evaluated for different number of communications (NC), and its QoS metrics including communication delay (D), energy needed during communication (E), throughput obtained during communication (T), and packet delivery ratio (PDR) during these communications was evaluated and compared with GTCC [5], DP CCP [14], and RLTC [27] under similar simulation conditions. For each of these communications, traffic congestion was varied between 1% to 20%, and average

communication delay obtained after these communications was estimated, and tabulated in table 2 as follows,

NC	D (ms) GTCC [5]	D (ms) DP CCP [14]	D (ms) RLTC [27]	D (ms) MRC IB
250	1.08	1.35	1.43	0.69
500	1.14	1.43	1.52	0.73
750	1.20	1.53	1.64	0.79
1000	1.29	1.71	1.85	0.91
1250	1.48	2.01	2.19	1.08
1500	1.78	2.43	2.64	1.29
1750	2.17	2.91	3.13	1.53
2000	2.56	3.38	3.61	1.76
2250	2.93	3.83	4.08	1.98
2500	3.29	4.28	4.56	2.22
3125	3.66	4.80	5.11	2.47
3500	4.00	5.29	5.63	2.70
3750	4.29	5.72	6.09	2.89
4375	4.59	6.15	6.54	3.09
4750	4.86	6.52	6.93	3.28
5000	5.18	6.93	7.36	3.49

Table 2. Delay needed for communication during 1% to 20% congestions

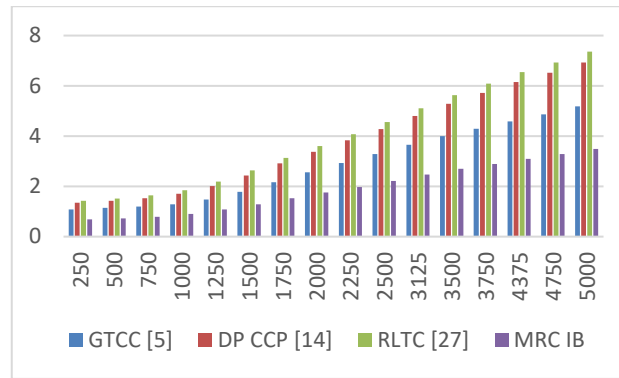


Figure 2. Delay needed for communication during 1% to 20% congestions

As per these evaluations and their visualization in figure 2, it was observed that the proposed model was able to improve the communication speed by 9.4% when compared with GTCC [5], 14.5% when compared with DP CCP [14], and 19.2% when compared with RLTC [27] even under congestions. The reason for this improvement in speed is use of delay & distance metrics during evaluation of routing paths via the BFO & GA processes. Due to which the model is useful for high-speed application scenarios. Similarly, the energy needed for communication can be observed from table 3 as follows,

NC	E (mJ) GTCC [5]	E (mJ) DP CCP [14]	E (mJ) RLTC [27]	E (mJ) MRC IB
250	2.66	4.53	3.88	1.92
500	2.86	4.83	4.13	2.03
750	3.02	5.09	4.35	2.14
1000	3.18	5.34	4.56	2.24
1250	3.33	5.58	4.76	2.34
1500	3.47	5.82	4.97	2.45
1750	3.62	6.11	5.22	2.58

2000	3.79	6.43	5.50	2.72
2250	3.98	6.78	5.79	2.86
2500	4.19	7.11	6.06	2.98
3125	4.39	7.40	6.29	3.09
3500	4.57	7.67	6.51	3.20
3750	4.75	7.94	6.74	3.31
4375	4.92	8.22	6.98	3.43
4750	5.09	8.50	7.22	3.55
5000	5.25	8.79	7.45	3.66

Table 3. Energy needed for communication during 1% to 20% congestions

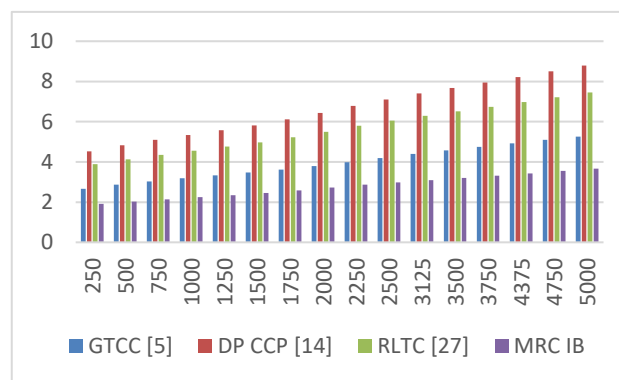


Figure 3. Energy needed for communication during 1% to 20% congestions

As per these evaluations and their visualization in figure 3, it was observed that the proposed model was able to reduce the energy needed for communication by 8.5% when compared with GTCC [5], 16.4% when compared with DP CCP [14], and 12.5% when compared with RLTC [27] even under congestions. The reason for this reduction in energy is use of residual energy levels while multipath estimations via BFO & consideration of consumed energy levels in the GA process.

Due to which the model is useful for high-lifetime application scenarios. Similarly, the throughput obtained during communication can be observed from table 4 as follows,

NC	T (kbps) GTCC [5]	T (kbps) DP CCP [14]	T (kbps) RLTC [27]	T (kbps) MRC IB
250	315.3	371.4	416.1	495.9
500	317.9	374.5	419.6	500.0
750	320.5	377.6	423.1	504.3
1000	323.3	380.9	426.8	508.6
1250	326.1	384.1	430.4	512.9
1500	328.8	387.3	434.0	517.1
1750	331.5	390.5	437.6	521.4
2000	334.2	393.6	441.1	525.6
2250	337.0	396.8	444.7	529.8
2500	339.7	400.1	448.3	534.1
3125	342.4	403.3	451.8	538.3
3500	345.1	406.4	455.3	542.5
3750	347.8	409.6	458.9	546.7
4375	350.5	412.7	462.4	550.9
4750	353.2	415.9	466.0	555.1
5000	355.9	419.1	470.5	559.4

Table 4. Average throughput levels for communication during 1% to 20% congestions

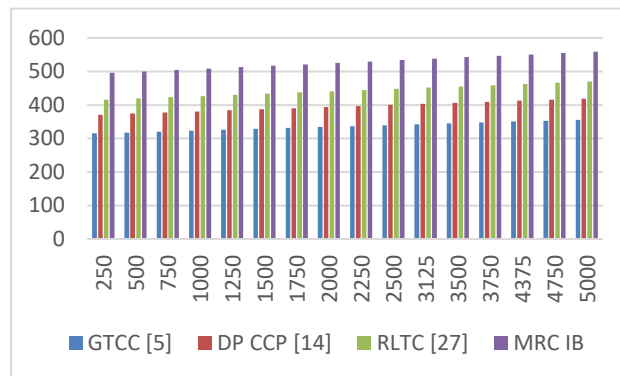


Figure 4. Average throughput levels for communication during 1% to 20% congestions

As per these evaluations and their visualization in figure 4, it was observed that the proposed model was able to improve the communication throughput by 19.3% when compared with GTCC [5], 14.2% when compared with DP CCP [14], and 10.4% when compared with RLTC [27] even under congestions. The reason for this improvement in throughput is use of temporal data rate while multipath estimations via BFO & consideration of current throughput in the Q-Learning process. Due to which the model is useful for high-data-rate application scenarios. Similarly, the PDR obtained during communication can be observed from table 5 as follows,

NC	PDR (%) GTCC [5]	PDR (%) DP CCP [14]	PDR (%) RLTC [27]	PDR (%) MRC IB
250	80.66	80.29	81.20	88.50
500	81.34	80.96	81.88	88.76
750	82.01	81.64	82.57	89.51
1000	82.71	82.34	83.28	90.28
1250	83.43	83.04	83.98	91.04
1500	84.12	83.73	84.68	91.79

1750	84.82	84.42	85.37	92.55
2000	85.51	85.11	86.07	93.30
2250	86.21	85.80	86.76	94.05
2500	86.90	86.49	87.46	94.81
3125	87.60	87.18	88.16	95.56
3500	88.29	87.86	88.85	96.32
3750	88.99	88.55	89.54	97.07
4375	89.68	89.23	90.23	97.82
4750	90.37	89.92	90.92	98.57
5000	91.06	90.60	91.62	99.32

Table 5. Average PDR levels for communication during 1% to 20% congestions

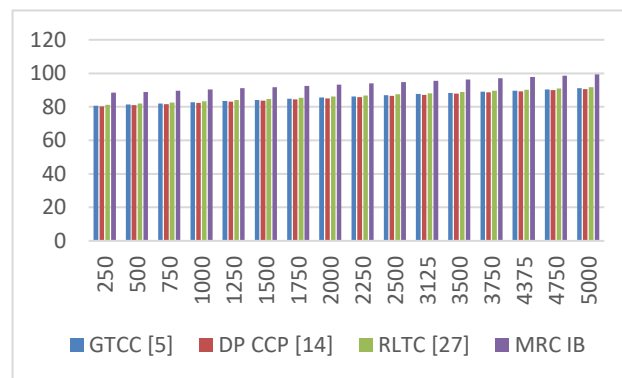


Figure 5. Average PDR levels for communication during 1% to 20% congestions

As per these evaluations and their visualization in figure 5, it was observed that the proposed model was able to improve the communication PDR by 8.3% when compared with GTCC [5], 9.2% when compared with DP CCP [14], and 6.4% when compared with RLTC [27] even under congestions. The reason for this improvement in PDR is use of packet delivery

performance while multipath estimations via BFO & consideration of current PDR levels in the Q-Learning process. Due to which the model is useful for high-consistency application scenarios. As per these evaluations, it can be observed that the proposed model is highly useful for a wide variety of real-time routing scenarios even under different rate of congestions.

5. Conclusion and future scope

A Bacterial Foraging Optimizer (BFO) is initially used by the proposed MRCIB model to separate packets into multipath requests. This division is based on the effectiveness of temporal routing for various sets of paths. The network's efficient set of multiple paths used for the transmission of the separated packets is determined by Genetic Algorithm (GA) optimizations. A Q-Learning layer that is based on the selected paths incrementally fine-tunes them helps prevent collisions when a lot of packet requests are made. For high-efficiency operations, this is accomplished through the temporal evaluation of network parameters and ongoing model updates. The suggested model was evaluated in large networks with diverse requests. When the proposed model was validated in terms of communication delay, it was found that it was able to increase communication speed even in congested areas by 9.4% when compared to GTCC [5], 14.5% when compared to DP CCP [14], and 19.2% when compared to RLTC [27]. This increase in speed is attributable to the use of delay and distance metrics during the BFO and GA processes' evaluation of routing paths. The model is useful in scenarios involving high-speed application because of this. While it was noted that the proposed model was able to reduce the energy needed for communication by 8.5% when compared with GTCC [5], 16.4% when compared with DP CCP [14], and 12.5% when compared with RLTC [27] even under congestions, in terms of energy consumption levels. The use of residual energy levels during multipath estimations via BFO and consideration of consumed energy levels in the GA process are the causes of this energy reduction. The model is advantageous for high-lifetime application scenarios as a result.

When the proposed model was compared to GTCC [5], DP CCP [14], and RLTC [27] in terms of data rate, it was found that it was able to increase communication throughput even

in the presence of congestion by 19.3%, 14.2%, and 10.4%, respectively. The use of temporal data rate during multipath estimations via BFO and consideration of current throughput in the Q-Learning process are the causes of this increase in throughput. The model is useful in high-data-rate application scenarios as a result. While it was noted that the proposed model was able to improve the communication PDR by 8.3% when compared with GTCC [5], 9.2% when compared with DP CCP [14], and 6.4% when compared with RLTC [27] even under congestions in terms of packet delivery performance. The use of packet delivery performance during multipath estimations via BFO and consideration of current PDR levels in the Q-Learning process are responsible for this improvement in PDR. The model is helpful for high-consistency application scenarios as a result. These evaluations show that the proposed model, even with different rates of congestion, is very helpful for a wide range of real-time routing scenarios.

In future, the efficiency of proposed model must be validated under different network scenarios, and can be improved via use of transformer models for pre-emption of network congestions. This performance can also be improved via use of deep-learning based techniques, which will assist in enhancing QoS performance via finer selection of paths even under large-scale congestions.

6. References

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