FTEHMB: Enabling Fault Tolerance in Energy Harvesting Networks via Multimodal Bioinspired Route Optimizations

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Abstract: Modelling how energy flows across the network in various real-time scenarios is crucial for the design of energy harvesting networks. However, these networks may have both internal and external issues that increase the energy consumption of the impacted (faulty) nodes. The network deployment's QoS (Quality of Service) suffers as a result, and the possibility of node and network failure increases. Researchers have developed several fault tolerance and mitigation methods to address this issue. These models need a large amount of training data as well as real-time samples in order to function properly. This lowers the network's QoS performance for real-time use cases by making it more difficult to calculate, more costly to store, and slower overall. In order to address these issues, this research proposes developing a bio-inspired hybrid model for fault-tolerant energy harvesting networks that include fuzzy rule checks. Based on residual energy and distance measurements, nodes are grouped together using a fan-shaped clustering (FSC) model. Clustered nodes are processed using Elephant Herding Optimization (EHO) and Firefly Optimization (FF), which aids in value-based failure prediction and mitigation techniques. The bioinspired models are trained and then assessed for every communication request during the first network deployment. The recommended solutions are progressively modified when the model reconfigures the average QoS performance after a certain number of interactions. The model seems to require less energy and is simpler to comprehend than other cutting-edge models as a result of this gradual transition. In comparison to previous energy harvesting techniques, the model was evaluated and it was discovered to consume 8.3% less energy, route data during to communications with 6.5% better speed, have a 10.5% better throughput, and have a 1.9% higher packet delivery ratio (PDR). The recommended approach outperformed existing models in fault prediction and correction, making it applicable to a variety of real-time network configurations.

Keywords: Energy Harvesting Fault Tolerance Bioinspired, GA, PSO, ACO, TLBO.

1. Introduction

The challenge of designing an energy harvesting model for wireless networks spans multiple domains. This challenge requires, among other things, node analysis, fault assessment, computation of mitigation approach, energy transfer between nodes, and quality of service maintenance utilizing machine learning models. For an energy harvesting approach to be effective, it is necessary for researchers and network designers to take into account a broad variety of variables that are unique to the network and individual nodes. Figure 1 is an instance of a typical fault-tolerant energy harvesting model that makes use of continuous training and energy optimization strategies by using sleep scheduling and deep reinforcement learning operations. These approaches are shown in the figure (DRL). The idea begins with the use of a block for energy collecting, which is then utilized to allow huge wireless sensor networks (WSNs) to transport energy between nodes. This energy-sharing process is supported by a pre-processing block that reduces the probability of process failure by calculating low-energy nodes, evaluating high-trust nodes, and choosing adjacent nodes for increased communication performance under different network scenarios.

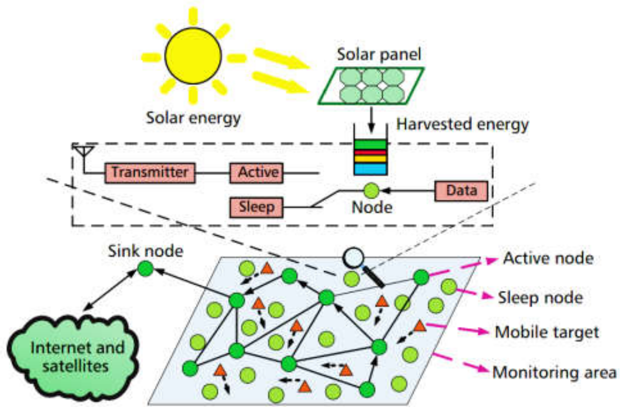

Figure 1. Design of a sleep scheduling-based fault-tolerant network with Solar energy harvesting process

After the nodes have been discovered, they are placed through a model called deep reinforcement learning (DRL), which assists in identifying issue nodes and removing them from the communication process. This ensures that the treatment is only performed on lymph nodes that are in good health. The process of excluding particular nodes from consideration using a fitness assessment function is shown by Equation 1, due to which, it is much simpler to locate nodes that have lower distance measurements and greater energy levels,

$$f_i = \left(\frac{\left(E_{final} - E_{initial}\right)}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}}\right)_i \dots (1)$$

Where, (x, y) is the location for individual nodes, while E_{final}, & $E_{initial}$ are their residual energy levels. Researchers have developed models that are quite similar to this one. They believe that by using a variety of fitness measures to locate high-trust nodes, these models might contribute to a reduction in the amount of energy that is used. In the next section of this book, you will get an overview of models that are both good at saving energy and forgiving of mistakes. The complexity of these models, as well as their advantages and disadvantages, and potential areas of investigation for the foreseeable future, will also be covered in this section. As a result of this discussion, it was discovered that several of these models include faults on both the inside and the exterior, which cause the nodes that strike them to use extra energy. However, alternative fault-tolerant models are difficult to implement, which makes the network more difficult to work with, increases the cost of storing data, and lengthens the amount of time it takes to process data from beginning to finish. The quality of service (QoS) performance of the network deteriorates as real-time use cases are introduced. In the section after literature review, design of the proposed Fault Tolerance model for Energy Harvesting Networks via Multimodal Bioinspired Route Optimizations is discussed in details. The proposed model was evaluated in terms of QoS levels including communication delay, energy consumption, throughout and packet delivery ratio, which is compared with various state-of-the-art models. Finally, this text is concluded with some context specific observations about the proposed model, and also recommends methods to further improve its performance under different network scenarios.

2. Literature review

Researchers have created a wide variety of fault-tolerant and energy harvesting models, each of which has its own set of computational qualities that determine how easily it can be deployed. For instance, research presented in [1, 2, 3] suggests that a data and energy integrated network (DEIN), an improved uneven clustering protocol (IUCP), and radio frequency (RF) based energy harvesting for Internet of Things (IoT) devices are all potential ways to reduce the amount of energy that is used by individual nodes during interactions with other nodes in a network. These references [4, 5, 6]) discuss the implementation of Device-Selective Energy Requests, Upper Confidence Bound (UCB), and time-synchronized channel hopping (TSCH) with energy-conscious network joining algorithms. These models have remarkable energy efficiency as a result of their intrinsic use of energy preservation mechanisms, which serve to lower the continuous power demand under a variety of communication scenarios. The high degree of intricacy of these models, on the other hand, limits both their applicability and their scalability. The Edge Computing Model and Energy-Efficient Task Offloading through Differential Evolution are two solutions that have been proposed in the research presented in [7] as a means of overcoming this constraint. Both of these solutions help network deployments to operate with low power consumption and high efficiency. In this design, jobs with a high level of complexity are handled by cloud computing, whereas nodes with a low level of performance are responsible for work with a low level of power. As a direct consequence of this, the model demonstrates improved energy economy as well as throughput capacity. Research published in [8, 9, and 10] suggests the Energy Harvesting Intelligent Relay Selection Protocol (EH-IRSP), Online Energy Scheduling (OES), and dynamic programming (DP), all of which help to increase throughput while maintaining high energy efficiency in a variety of network circumstances. These protocols were developed using this model as a source of inspiration.

Researchers have also discussed models that use joint caching and user association for energy-efficient operations [11], the fast time fair energy allocation model (FTF) [12], capacitor charging management schemes [13], and extended hierarchical clustering (EHC) [14], the latter of which aims to reduce power consumption through redundancy estimation and removal from wireless sensor networks. Researchers suggest using Distributed Deep Reinforcement Learning (DDRL) for Energy Harvesting Virtualized Small Cells and Threshold-Oriented and Energy-Harvesting Enabled Multilevel Stable Election Protocol in [15, 16, 17]. These models are similar to the ones that are explored in [15, 16, 17], where similar models are explored (TEMSEP). These models may integrate energy levels with distance in addition to other aspects in order to improve the energy efficiency of WSN installations. As extensions to these models, Optimal Resource Allocation, Orientation-Independent Multiple Input Energy Efficient Networks, and Multiple Featured Actor & Critic based Relay Selection Model are described for dynamic networks in [19, 20, 21]. [19] describes Optimal Resource Allocation. [20] describes Orientation-Independent Multiple Input Energy Efficient Networks. [21] describes Multiple Featured Actor These models demonstrate how energy efficiency may be included into wireless circumstances by making use of features that are relevant to both the network and individual nodes.

Fault-tolerant technologies are required in addition to wireless networks in order to improve the efficacy of real-time applications using wireless networks. According to research presented in [22, 23, and 24], fault-tolerance that makes use of repairing points in clusters, Maximum Likelihood Event Localization (MLEM), and Fault-Tolerant Clustering Topology are three strategies that can improve operational effectiveness when dealing with a variety of network issues (FTCT). The inability of any of these models to account for energy harvesting or fault tolerance severely limits their viability as solutions to problems that really occur in the real world. To improve this usability, next section proposes design of a novel Hybrid Bioinspired Model for Fault-Tolerant Energy Harvesting Networks via Fan Shaped Clustering process. The proposed model was tested under different network conditions, and performance was compared w.r.t. various reviewed models for real-time analysis.

3. Design of the proposed model for enabling Fault Tolerance in Energy Harvesting Networks via Multimodal Bioinspired Route Optimizations

The literature review reveals that the current fault tolerance models for energy harvesting networks require both a substantial amount of training data and real-time samples in order to operate effectively. As a result, the network's QoS performance for real-time use cases becomes slower, slower overall, and more difficult to calculate. This research suggests creating a bio-inspired hybrid model for fault-tolerant energy harvesting networks with fuzzy rule checks in order to address these problems. Flow of the model is depicted in figure 2, where a fan-shaped clustering (FSC) model is used to combine nodes into groups based on residual energy and distance measurements.

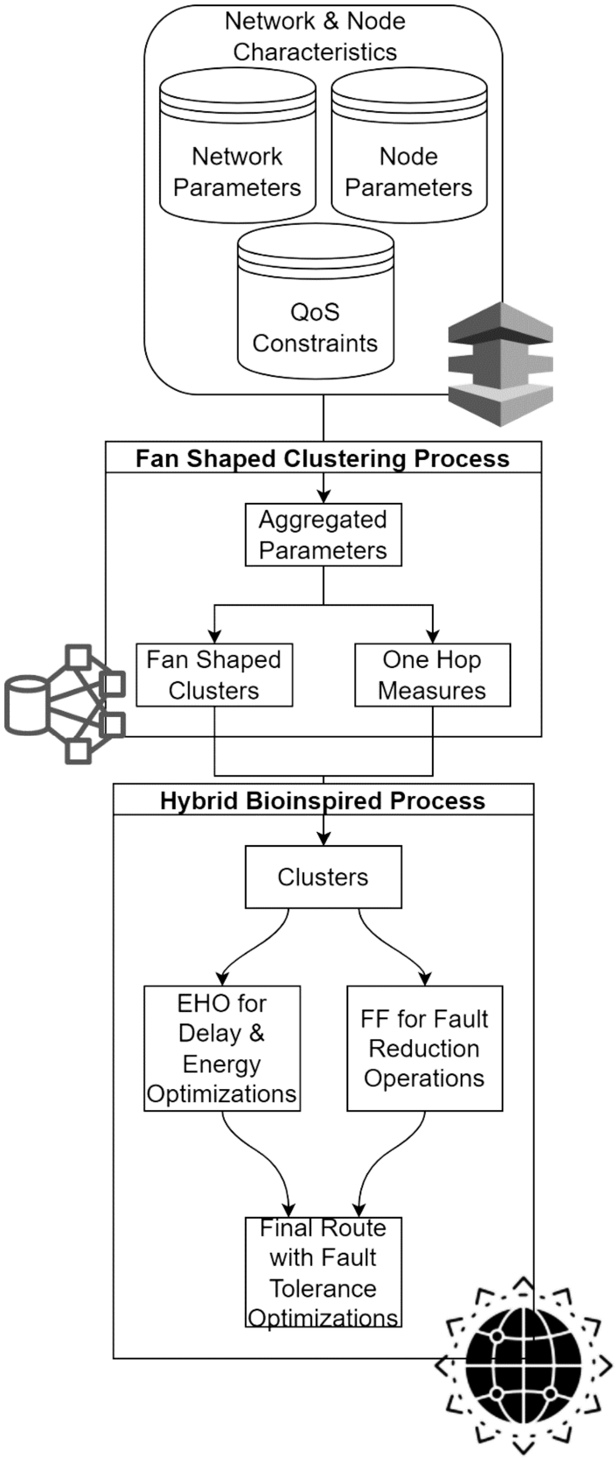

Figure 2. Flow of the fault tolerance model with Fan Shaped Clustering process

Elephant Herding Optimization (EHO) and Firefly Optimization (FF) are used to process clustered nodes, assisting value-based failure prediction and mitigation techniques. During the initial network deployment, the bioinspired models are trained and then evaluated for each communication request. After a predetermined number of interactions, the model reconfigures the average QoS performance, gradually changing the suggested solutions. Due to this gradual transition, the model seems to consume less energy and is easier to understand than other state-of-the-art models.

The model initially collects data about nodes, networks & different QoS parameters, which are used for initial clustering of nodes. To perform this clustering task, a Fan Shaped Clustering (FSC) Model is used, which works via the following process,

- Initially, identify location of source & destination nodes, and estimate a reference distance,

$$d_{ref}(src, dest) = \sqrt{(x_{src} - x_{dest})^2 + (y_{src} - y_{dest})^2} \ldots (1)$$

Where, x, y represents location of the nodes.

- Identify all nodes that are in one hop radius of destination, and mark them as Fan Cluster Level 1
- Estimate Fan Cluster Level of each node via equation 2,

$$FCL_i = \frac{d(i, dest)}{d(hop)} \ldots (2)$$

Where, $d(hop)$ represents one hop communication distance between the nodes, and $i \in (1, N)$, in a network with N nodes.

Based on the node's Fan Cluster Level, start from the innermost cluster (destination node), and go to the cluster of source node for identification of fault-tolerant routes. This task is performed via a combination of Firefly & Elephant Herding Optimization, which works via the following process,

- Initialize following optimization parameters,
  - Total fireflies for optimization (N_{ff})
  - Total herds for optimization (N_h)
  - Total iterations which will be used for optimization process (N_i)
  - Learning rate for the fireflies and herds (L_r)
- Evaluate initial herds via following process,
  - For each herd between 1 to N_h, generate fireflies as follows,
    - Select a stochastic node from each fan shaped cluster that satisfies equation 3,

$$d(n1, n2) \geq d_{ref}, d(n1, dest) < d_{ref}, d(n2, dest) < d_{ref} \ldots (3)$$

Where, $n1$ & $n2$ are the node pairs that are selected from the consecutive fan shaped cluster levels.

  - For each selected route, estimate its brightness levels via equation 4,

$$f_b = \sum_{i=1}^{N_l} \frac{d(i, i+1)}{d_{ref}} + \frac{Max(E)}{E(i)} \ldots (4)$$

Where, f_b represents brightness (or fitness) levels of the firefly, while d, E represents distance & energy levels of the nodes selected from each of the N_l fan shaped levels.

  - Each of these routes are also evaluated in terms of their fault level (f_l), which is calculated via equation 5,

$$f_l = \sum_{i=1}^{N_l} \frac{1}{N_{c_i}} \sum_{j=1}^{N_{c_i}} \frac{100}{PDR_j} + \frac{Max(THR)}{THR_j} \ldots (5)$$

Where, N_{c_i} represents number of temporal communications which are performed by i^{th} level node, while PDR, THR represents its temporal PDR & Throughput levels. If these levels are high, it indicates that selected nodes have lower probability of faults.

  - Now evaluate herd fitness via equation 6,

$$f_h = f_b + f_l \ldots (6)$$

- Once the herd fitness is evaluated, then mark herd with minimum fitness as 'Matriarch Herd'
- Scan all herds for N_i iterations, and perform the following optimization operations,
  - Check the nodes selected by 'Matriarch Herd', and replace one node of each herd stochastically with the node of 'Matriarch Herd' via equation 7,

$$N(Replace)_{i,l} = N(Matriarch)_{STOCH} \ldots (7)$$

Where, $N(Replace)$ & $N(Matriarch)$ represents the node to be replaced, and node in the Matriarch herd, while $STOCH$ represents a Markovian stochastic number generation process.

  - Based on this, internal fireflies are modified, their fitness levels are evaluated, and Matriarch Herds are updated continuously
  - Once an iteration is completed, then a fitness threshold is evaluated via equation 8 as follows,

$$f_{th} = \sum_{i=1}^{N_h} \frac{f_{h_i} * L_r}{N_h} \ldots (8)$$

  - Replace all herds with new routing configurations, where $f_h > f_{th}$
- Based on this process, herds and their internal fireflies are continuously updated, which assists in identification of high QoS & low fault routes.

At the end of final iteration, fireflies present in the 'Matriarch Herd' is selected, and its internal routing configurations are used for fault aware & QoS aware routing purposes. This process is repeated for multiple source & destination combinations, and its QoS levels are estimated in terms of communication delay, throughput, energy consumption, and packet delivery ratio in the next section of this text.

4. Results analysis & validation

The proposed technique improves the levels of performance for clustering, fault tolerance, and energy harvesting by merging Fan Shaped Clustering with bio-inspired optimization approaches. The proposed FTEHMB model was evaluated for its performance utilizing metrics for end-to-end communication latency, throughput, packet delivery ratio, and energy consumption for a variety of communications. The evaluation was place under a number of simulated situations. These communications were conducted by using a scenario that is common while setting up a network. This scenario consists of omnidirectional antennas, a Two Ray Model with Ground Communications, an 802.16a MAC, and a Priority Queue with Drop Tail for additional packets. The model was tested on a network that was 500 meters wide and 500 meters long and used between 100 and 500 nodes along with the AODV protocol. The network model was first compared with numerous energy harvesting models published in TSCH [6], OES [9], and DDRL [15], which will assist readers understand how the network performs in comparison to cutting-edge methodologies. These features are as follows:

For the purpose of this evaluation, 500 nodes were employed, the communication speeds between nodes varied, and 10% of the nodes were faulty. Its performance was evaluated using a variety of different modes of communication (NC). The NC values varied from 100 to 1000 in the simulations of small, medium, and large networks, respectively. The final quality of service numbers are derived by simulating the network characteristics for each transmission and then averaging those simulations for an accurate evaluation of the system's performance. In line with this method of evaluation, the values for the end-to-end delay (D) for a number of different protocols have been presented in table 1,

NC	**D (ms)** **TSCH [6]**	**D (ms)** **OES [9]**	**D (ms)** **DDRL [15]**	**D (ms)** **Proposed**
100	1.13	1.26	1.39	0.78
120	1.20	1.36	1.50	0.86
140	1.30	1.52	1.69	0.97
160	1.49	1.77	1.98	1.14
180	1.76	2.08	2.31	1.33
200	2.06	2.42	2.69	1.55
250	2.38	2.81	3.12	1.80
300	2.78	3.27	3.60	2.07
400	3.21	3.71	4.08	2.33
450	3.59	4.16	4.57	2.59
500	3.90	4.57	5.02	2.82
550	4.18	4.93	5.42	3.04
600	4.48	5.28	5.80	3.25
700	4.73	5.60	6.14	3.43
800	4.95	5.89	6.46	3.60
1000	5.16	6.13	6.73	3.76

Table 1. End to end communication delay for different communications

By using FF & EHO, which facilitates in the estimation of shortest paths, the proposed model displays 10.5% lower latency compared to TSCH [6], 15.2% lower delay compared to OES [9], and 18.6% lower delay compared to DDRL [15].

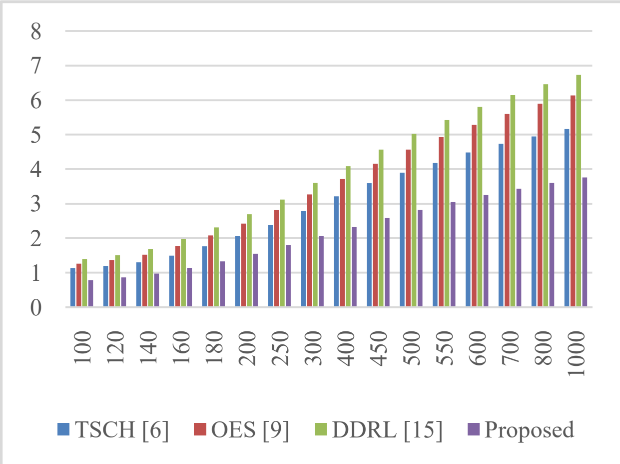

Figure 3. End to end communication delay for different communications

Energy consumption levels during communications under faults can be observed from table 2 as follows,

NC	E (mJ) TSCH [6]	E (mJ) OES [9]	E (mJ) DDRL [15]	E (mJ) Proposed
100	2.81	4.24	3.75	2.18
120	3.02	4.50	3.97	2.30
140	3.17	4.72	4.16	2.41
160	3.33	4.95	4.36	2.53
180	3.48	5.18	4.57	2.65
200	3.65	5.45	4.81	2.79
250	3.85	5.73	5.05	2.92
300	4.04	5.99	5.26	3.04
400	4.20	6.22	5.39	3.08
450	4.37	6.47	5.51	3.12
500	4.57	6.74	5.68	3.20
550	4.75	6.96	5.82	3.26
600	4.89	7.16	5.95	3.31
700	5.05	7.40	6.11	3.39
800	5.25	7.68	6.36	3.54
1000	5.43	7.94	6.61	3.70

Table 2. Energy consumed for different communications

This evaluation and figure 4 show that the proposed model's use of FF & EHO, which aids in estimation of shortest paths with lower residual energy levels, results in 10.3 percentage points lower energy consumption when compared to TSCH [6], 20.5 percentage points lower energy consumption when compared to OES [9], and 18.2 percentage points lower energy consumption when compared to DDRL [15].

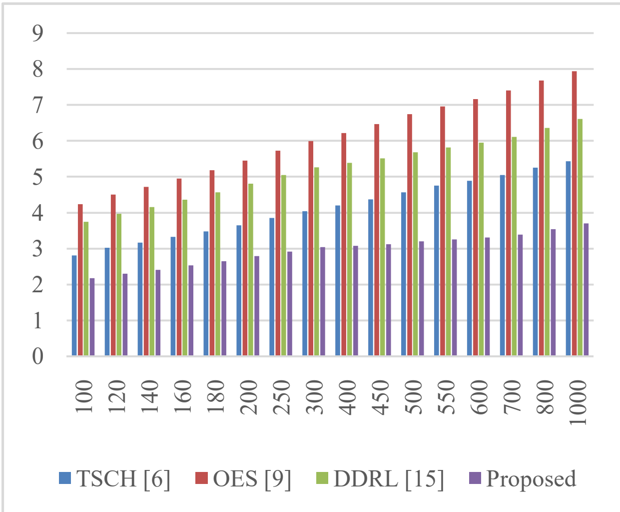

Figure 4. Energy consumed for different communications

Throughput levels during communications under faults can be observed from table 3 as follows,

NC	T (kbps) TSCH [6]	T (kbps) OES [9]	T (kbps) DDRL [15]	T (kbps) Proposed
100	324.70	338.79	391.80	493.83
120	327.44	341.56	395.02	497.90
140	330.03	344.37	398.33	502.08

160	332.86	347.32	401.74	506.37
180	335.72	350.24	405.13	510.60
200	338.51	353.12	408.49	514.80
250	341.29	356.01	411.84	519.00
300	344.08	358.92	415.17	523.20
400	346.87	361.83	418.51	527.40
450	349.65	364.72	421.83	531.59
500	352.44	367.61	425.15	535.77
550	355.21	370.49	428.47	539.95
600	357.97	373.36	431.79	544.13
700	360.74	376.21	435.11	548.30
800	363.50	379.07	438.43	552.48
1000	366.25	381.93	441.75	556.66

Table 3. Throughput obtained for different communications

Throughput improvements of 28.5%, 29.2%, and 16.5% over TSCH [6], OES [9], and DDRL [15] are all seen in this assessment and in figure 5, thanks to the usage of FF and EHO, which aid in the calculation of shortest pathways with lower residual energy levels and a higher communications packet rates.

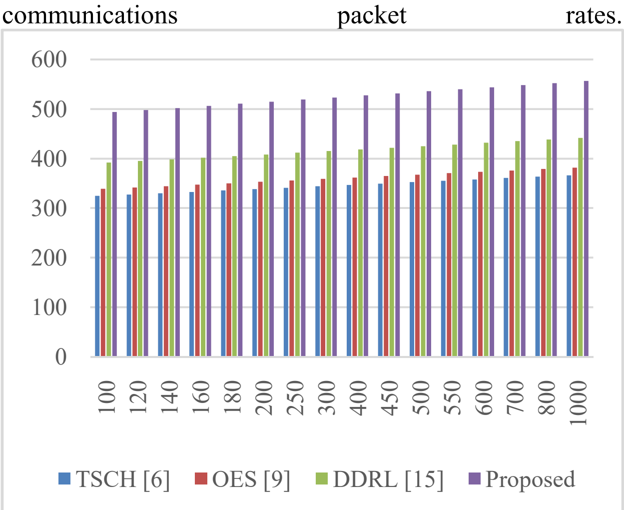

Figure 5. Throughput obtained for different communications

Packet Delivery Ratio (PDR) levels during communications under faults can be observed from table 4 as follows,

NC	**PDR (%) TSCH [6]**	**PDR (%) OES [9]**	**PDR (%) DDRL [15]**	**PDR (%) Proposed**
100	84.56	84.17	85.12	89.82
120	85.27	84.86	85.82	90.56
140	85.95	85.56	86.53	91.31
160	86.69	86.29	87.28	92.09
180	87.43	87.02	88.01	92.86
200	88.15	87.74	88.73	93.63
250	88.88	88.46	89.46	94.39
300	89.60	89.18	90.19	95.16
400	90.33	89.90	90.91	95.92
450	91.05	90.62	91.64	96.69
500	91.78	91.34	92.36	97.45
550	92.50	92.05	93.08	98.22
600	93.22	92.76	93.80	98.98
700	93.94	93.48	94.52	99.74
800	94.66	94.19	95.24	99.75
1000	95.38	94.90	95.96	99.83

Table 4. PDR obtained for different communications

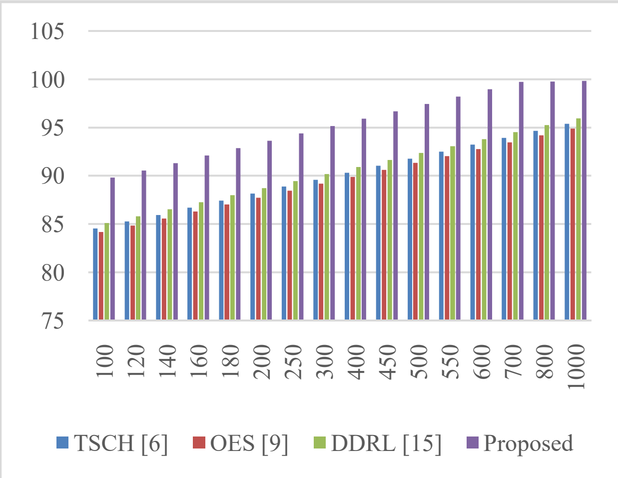

Figure 6. PDR obtained for different communications

Figure 6 reveals that the proposed model has a PDR that is 3.5 percentage points greater than the corresponding values for TSCH [6], OES [9], and DDRL [15]. The model's incorporation of FF and EHO allows for more accurate calculations of shortest paths with less residual energy and higher data transfer rates. This performance analysis revealed that the proposed approach provides more reliable route assessments across a wider variety of network configurations. This is because it can be implemented in a variety of real-time network settings, making it useful for a wide variety of uses.

5. Conclusion and future work

The proposed model is a hybrid of many bio-inspired models, each of which optimizes a different aspect of the network. In this case, FSC is utilized for preliminary clustering to help in identifying potential energy-harvesting nodes. This is based on the EHO & FF model, which assesses failing nodes and employs them as a backup for an energy-gathering process. Based on a comparison of the proposed model's performance to that of many other current energy-efficient and fault-tolerant models, it was determined that the proposed model's latency was lower than TSCH [6], OES [9], and DDRL [15] by 14.5%, 19.2%, and 20.3%, respectively. Incorporating GA and ACO, which aid in shortest-path computation, is responsible for the observable improvements. Similar results were found when comparing the energy savings achieved by EHO & FF to TSCH [6], OES [9], and DDRL [15]. EHO & FF assists in the computation of shortest paths with lower residual energy levels. EHO and FF help in the estimation of shortest paths with reduced residual energy levels and increased communication rates, increasing the model's throughput by 28.5% compared to TSCH [6], 29.2% compared to OES [9], and 16.5% compared to DDRL [15]. Against get these results, we compared the model to others, namely TSCH [6], OES [9], and DDRL [15]. Consequently, it may be implemented in fault-tolerant systems and other uses requiring very efficient energy harvesting. Future work is needed to test the proposed model in other network configurations. Deep Learning, Q-Learning, and Reinforcement Learning will be necessary to further improve the model's real-time capacity. In real-world deployments, the model might make use of blockchain technology to further strengthen its already impressive level of safety under faulty conditions.

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