Machine Learning-Based Simplified Early Link Failure Detection Model for Mobile Ad-Hoc Network

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Abstract:
Mobile Ad-Hoc Network (MANET) is a self-configuring, wireless network consisting of a combination of mobile devices connected over a wireless link. Nodes in MANET are connected via multi-hop wireless links and mobility in nature that cause link failures. MANETs are mostly dynamic, with different nodes leading to common link failure problems. Link failures in MANET reduce the network performance and increase network overhead. The detection of link failures and the prediction of reliable links for data transmission always plays a vital role in several research topics of the network community. Therefore, in this paper, the proposed approach detects link failure through a Machine Learning (ML) based simplified early link failure detection model. Initially, the possibility of link failure is identified by using a simplified early link failure detection (SELFD) method, which employs Ad-hoc On-demand Distance Vector (AOMDV). The proposed approach follows both the unsupervised and supervised method of the one-Dimension Deep Auto Encoder (1D-DAE) method and logistic regression for estimating the link failure probability. Finally, the Flamingo Search Algorithm is proposed to fine-tune the hyperparameters of the proposed 1D-DAE method to detect the link failures in routing efficiently. The proposed approach is implemented in the PYTHON platform.The performance of the proposed approach is compared with existing routing methods based on packet delivery ratio, normalized routing load, average end to end delay, throughput, buffer occupancy and bit error rate.

Keywords:
Mobile Ad-Hoc Network (MANET), One Dimensional-Deep Auto Encoder (1D-DAE) method, Flamingo Search Algorithm (FSA), Link Failures, nodes.

1. Introduction

The mobile ad-hoc network (MANET) is generated periodically by wireless mobile nodes that travel at random, not including the supervision of an access point or middle location. In MANET, the source node interacts with its target via in-between nodes since the destination is beyond the source node in the range of communication [1] [2]. MANET is a collection of nodes that temporarily constructs a network of any type of topology. MANET has no base station, and every node connect to utilize a single-hop or circuitous and multi-hop routing to convey the packets [3]. These routing techniques may be refined into hybrid, proactive, and reactive routing strategies [4]. The network behaviour is enhanced via redesigning the failure nodes or connections to deliver packets along the same way as before, resulting in a reduction in typical end-to-end latency. Routing may be used to move data [5] with two principles: first identifying the path and then transferring the data across the internetwork.

In MANET, various protocols approve the assembly of routes by overflowing the RREQ (route request) packets [6] network. Due to the high control overhead, the flooding process can be affected when building connections to the required destination, destroying the MANET performance [7]. In addition, by preventing the number of mobile nodes transmitting RREQs, the network efficiency has been enhanced by selectively controlling the flooding operations. The mobility of nodes ensures a fast method of changes in a network [8]. Hence, it makes common link failures that provide overhead problems and, hereafter, interruptions made by well-known connections [9] [10]. The interrupt measures impact performance of the network, resulting in control overhead, improved delay and a reduced packet delivery ratio. These kinds of problems enhance the need for an efficient prediction approach to link failure [11].

Nevertheless, link failure is the most common challenging problem in MANET that interrupts the established connections. Moreover, due to node mobility,

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link failures occur frequently, affecting the overall network performance [12], and it enhances the demand for a successive link failure prediction approach. Nodes can move frequently and randomly since they are self-organizing and independent from each other in MANET [13] [14]. Consequently, the MANET topology varies very frequently, causing the failure of links between neighbor nodes. In addition, a link failure can occur due to the greatly reduced received signal strength [15]. Link failure indicates route errors between nodes and reduces network throughput. Therefore, detection of link failures is the main research problem in MANET.

Generally, MANET routing protocols must be automatically used to preserve paths between data sources and their matching destinations [16] [17]. Routing Protocols (RP) designed for MANET are classified into three types. (i) Proactive RP, the essential characteristic of each node must communicate with other nodes of routing information regularly to maintain the database of routing information up to date and the routes are required [18]. (ii) Reactive RP consists of a route to a destination are exists during the source requests it. (iii) Hybrid routing systems combine the traits and benefits of reactive and proactive routing methods [19]. Due to the gradual detection and response to route breakages and the superfluous exchange of periodic updates, in which hybrid and proactive RP does not ensure a better performance in terms of consuming the memory and maintaining overhead minimization in various environments with rapid framework variations [20]. Due to several hazardous conditions, node failures frequently occur in the working environment and lead to network crashes and reduced energy supply. Also, failures of a node can cause links failures among mobile nodes during the transmission of data.

The major contribution of this proposed work is listed in upcoming points

- ❖ To develop a simplified early link failure detection (SELFD) based machine learning approach for link failure detection.
- ❖ A new machine learning approach, namely One-Dimensional Deep Auto-Encoder (1D-DAE) and logistic regression, is proposed for estimating the link failure probability based on the parameters.
- ❖ Hyperparameter tuning of 1D-DAE is achieved by flamingo search algorithm (FSA).

The organization of research paper consists of introduction in section 1 and existing related works based on MANET in Section 2. The proposed simplified early link failure detection (SELFD) method are descriped in section 3. Result and Disccusion are mentioned in Section 4 and fianally the research is ended with section 5.

2. Related Work

Surabhi Patel and Heman Pathak [21] presented a scientific structure in MANET for computing the time for link failures. According to the signal strength of the received data packets, a least-square quadratic polynomial regression-based approach has been utilized for a link failure estimation. In addition, the distance among the nodes has been computed by data packets of received signal strength. To obtain the accuracy of the proposed model, a comprehensive investigation has been executed with changing network parameters. Moreover, mobility variation has been computed on predicted link failure time.

A node and link failure prediction has been presented by Sunil Kumar [22] in MANET using the Hello based path recovery (HBPR) routing protocol. The path consuming shortest way is estimated using the new effective HBPR routing protocol. The HBPR approach generates the alternate path when the link fails in the network layer during transmission. As a result, the energy consumption and the delay time has been reduced. The harmful nodes are predicted using SHPO (simplified honey pot optimization) within the network. The node security and the path stability of the network have been maintained using the SHPO approach; hence it enhances the quality of service components. Compared to other models, the approach obtained good outcomes in delay, average energy consumption, packet delivery ratio and throughput.

The prediction of link failures and the effective route detection were developed by Baidaa et al. [23] for the source routing protocol in MANET. Using the different kinds of protocols such as LFPM (link failure prediction mechanism) and ZRDM (zone-based route discovery mechanism), the on-demand source routing protocols were enhanced in this scheme. Using network simulator 3, the performance of the proposed system has been evaluated in terms of packet delivery ratio, average end-to-end delay and normalized routing load. As compared to other protocols, the proposed system achieves better performance.

Awareness link quality based effective routing has been developed by Priyanka Pandey and Raghuraj Singh [24] in MANET. In this paper, the link failure problem has been solved using the AODV based awareness of link quality (ALQ-AODV) scheme. The end path has been selected in the proposed model based on the link quality, degree of an intermediate node and the residual energy. The results of the simulation verified that the proposed method obtained optimal performance than existing protocols.

A multi-path routing has been developed by Harold Robinson et al. [25] in MANET using a PSO (particle swarm optimization)-based bandwidth and link availability prediction scheme. A mobility prediction scheme based on the link quality and available bandwidth has been presented with the help of the PSO for multi-path routing in MANET. According to the fuzzy logic scheme, the node in the prediction stage has been selected based on the mobility parameters, link quality and available bandwidth.. The presented approach provides good path optimality, end-to-end delay, and packet delivery ratio outcomes.

Table 1: Comparison of Related Works based on Link Failure Detection in MANET

Author Name	Methods Used	Objective	Merits	Demerits
Heman Pathak [21]	A scientific structure for estimating the time for link breakage.	According to the data packets of received signal strength, a least square quadratic polynomial regression method has been utilized for a link failure estimation.	Enhance the accuracy of detecting link failures.	The consequence of mobility variation has been computed on predicted link failure time.
Sunil Kumar [22]	A node and link failure prediction in MANET using the Hello based path recovery (HBPR) routing protocol.	The HBPR approach generates the alternate path during transmission if the link fails in the network layer.	The node security and the path stability of the network has been maintained by using the SHPO approach	Does not choose the path optimally.
Baidaa et al. [23]	Link failure prediction and effective route discovery for source routing protocol in MANET.	The ZRDM controlled the flooding of route requests, and the LFPM has eliminated the route breakages caused by node mobility.	Provides better performance in packet delivery ratio, average end-to-end delay and normalized routing load.	Requires more time to transmit data.
Priyanka Pandey and Raghuraj Singh [24]	Awareness link quality based effective routing in MANET.	The link failure problem has been solved using the AODV based awareness of link quality (ALQ-AODV) scheme.	Based on the signal strength parameter, maintains the neighbor nodes a once receiving hello packets.	Does not provide effective packet delivery ratio.
Harold Robinson et al. [25]	A multi-path routing in MANET using a PSO (particle swarm optimization)-	A mobility prediction scheme based on the link quality and the available bandwidth has been presented with the help of the PSO for multi-path routing in MANET.	The elected node has transmitted the data are checked for every node before the data transmission.	The accuracy of detecting a failure in a link of MANET is not precise.

Analyzing the survey of related works based on link failure detection in MANET are represented in Table 1. In MANET, all nodes act as a router, host that forwards the packets of data to the adjacent host and utilizes a high amount of energy. In addition, several causes like congestion, lack of resources, frequent attacks by malicious nodes, nodes mobility, etc., can also occur link failure. Node mobility is considered as one of the common causes for unsuccessful transmission of data packets that hampers the directional flow of a node to a destination node. Besides, it is challenging in handling link failures and maintaining routing for RP to distinguish the variation of time in the network. When the number of users has increased in MANET, it suffers network issues like network overhead, interference among the nodes, route loss, link quality, topological change, and performance degradation. Therefore, link failure detection and reliable routing protocol approaches provide a major role in MANET. In AOMDV, link failure is regarded as a significant issue that causes packet loss and network degradation. It causes transmission delay, low throughput, excess routing overhead, resource and energy wastage in path discovery, etc. To overcome these problems, a simplified early link failure detection (SELFD) based machine learning approach is proposed, which analyzes the possibility of link failure using AOMDV based beacon message dissemination.

3. Proposed Methodology

In the proposed approach, a Machine Learning (ML) based method is used to detect the link failures in a mobile ad-hoc network. Initially, the possibility of link failure is identified using a simplified early link failure detection (SELFD) method, which employs Ad-hoc On-demand Distance Vector (AOMDV). In the proposed approach, the processed data are gathered from several nodes fed into the One Dimensional-Deep Auto Encoder (1D-DAE) for feature learning. In MANET, the auto-encoder is used to detect the link failure, which is a combination of pooling units and convolutional kernels. 1D-DAE is used to extract the features from the one-dimension process for detecting failure. Therefore, users can easily access the selection process variable and also, the 1D-DAE method utilize unsupervised learning to get the representative features without information of label. Finally, Flamingo Search Algorithm (FSA) is proposed for hyperparameter tuning in 1D-DAE. Therefore, the link failures in MANET are detected earlier to minimize the average end-to-end delay. In MANET, the multi-hop wireless link is used to connect the mobile hosts in which the nodes in MANET can change the position frequently by the mobility of the network. Once the link fails during the data transmission, the entire packet will be affected by malicious attacks. Thus, the possibility of a link failure during data transmission is predicted using the AOMDV protocol.

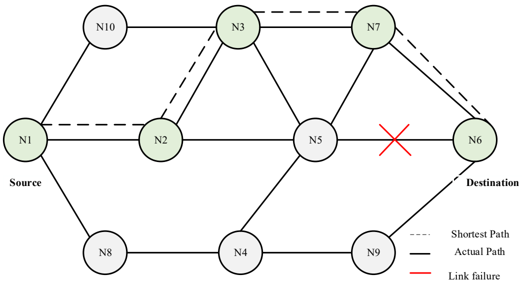

Fig 1: Link Failure Detection

The proposed method uses the AODV routing algorithm to detect the optimal path. It considers the source node to transmit the required data to the destination node. For each node among the path from source to destination, the value of request signal strength indicator (RSSI) of the last hop, source address value, distance variation, address of last hop and difference in RSSI are stored in a table. The value for RSSI is evaluated with the help of using two ray ground model.

$$RSSI = \frac{P_T G_T G_R H_T^2 H_R^2}{D_{u,v}^4} \quad (1)$$

Here $RSSI$ represents the request signal strength indicator, P_T indicates the predefined transmitted power, $G_T G_R$ represents the gain transmitting and gain receiving, $H_T^2 H_R^2$ indicates the height of transmitter and height of receiver in antennas and $D_{u,v}^4$ represents the distance among transmitting u^{th} and receiving v^{th} nodes.

Each node in MANET obtains an RSSI value for its last hope and next hope, which are used to update the difference between the last RSSI value and the new updated RSSI value. Then the threshold value for the fixed interval of time for each hop is equal to the RSSI difference value. If it exists, then the threshold value for the new link is formed. The link failure is identified if the RSSI value of the node is greater than the threshold value, then the link establishment takes place, or else link failures occur in the MANET.

In the proposed approach, the SELFD model uses both supervised and unsupervised models of the One-dimensional Deep Auto Encoder (1D-DAE). The logistic regression method is used to detect the probability of link failures by considering the parameters of RSSI, packet delay, loss rate and jitter. This 1D-DAE method is proposed to detect and diagnose the link failures in MANET. Link failures are detected by processing signals collected from different sensors to learn the feature using the 1D-DAE method. 1D-DAE combines Deep Neural Network (DNN) and Auto Encoder (AE).

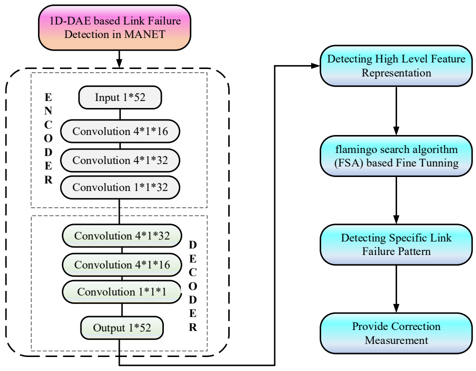

Fig 2: Flow Diagram for Proposed Method.

The flow diagram for the proposed approach is shown in Figure 2. In the proposed approach, the required feature representations are used without any use of label information in the 1D-DAE method. The spatial information of input nodes is stored in the convolution structure. Thus, the input of nodes is reconstructed by utilizing a one-dimensional method to process the data based on the latent code. The entire network of proposed approach parameters is optimized by layer-wise training. In the proposed 1D-DAE method [26], the high-level representation of unlabeled data is obtained by convolutional auto-encoders. The fine-tuning stage requires a small amount of label information to construct the classifier. In the proposed approach, two stages are used to detect the link failures in MANET: convolution auto-encoder as unsupervised learning and FSA-based tuning as supervised learning. Autoencoder is used in a convolution layer to construct the 1D-DAE method. Then in a supervised way, the network parameters are optimized layer-wise.

The hierarchical feature map is generated by the input vector of nodes optimized with the kernel in every deep autoencoder. Then, the output feature map nodes are fed into the next operation of pooling and convolution when the feature map is exposed. Tuning stage, the final feature map is used as a nodes input vector to optimize the whole network by sending it to the classification layer based on the class label information. A Deep Neural Network (DNN) is a collection of multiple hidden layers used to learn to represent the data with high-level features. DNN is used to capture the complicated structure in data and previous layer output, and the features are generated for each layer. By using DNN in the proposed model to expose the features automatically for its hierarchical structure.

Figure 2 represents the proposed 1D-DAE workflow, which holds a two-layer encoding and decoding with an activation function. In the encoder layer, the input nodes are initially transferred into a low-dimension space for the first node input to reconstruct in the layer of a decoder. The kernels are used with a lower layer of convolving features are used to generate the high-level representation for each layer to reduce the noise for the auto-encoder. In the lower layer, the patches are exposed by using a feature map to generate the optimal feature representation for the autoencoder. Using these mapping layers, the required features are exposed from the process signals to detect the link failures during data transmission. The local feature map information for input vectors is obtained using a one-dimensional kernel employed by the 1D-DAE method to provide a nonlinear transformation using the activation function formula below.

$$T_y^i = AF\left(\sum_{i \in FM_y} T_y^{i-1} * CK_{x,y}^i + BP_y^i\right) \tag{2}$$

Here the AF denotes the activation function, which is mostly considered as a sigmoid function or hyperbolic tangent function, i^{th} layer is represented as i. Then, the convolution kernel is represented as CK of $S \times 1$ which represents the size of the convolution kernel and bias parameters are denoted as BP_y^i in which a unique convolution kernel exposes each node's features. Using the sub-sampling layer, the convolution layer for the output feature map is used to the output feature dimension. The input n mapping consumes output features as n, which are measured using the down-sampling formula.

$$T_y^i = AF\left(\alpha_y^i DS\left(T_y^{i-1}\right) + BP_y^i\right) \tag{3}$$

Here the down-sampling function is denoted as $DS(\ )$, then the product and addition deviations are represented as α *and* BP. Since several $N \times 1$ input features are added using $DS(\ )$to minimize the output features as $1/n$. The operations of convolution and downsampling complete the encoding process for the input vector of the nodes. Then the decoder output features are inversed for the encoder process. In the proposed 1D-DAE method, both the encoding and decoding processes are utilized convolutionally to obtain a high-level feature representation for input data. The transformation of the tanh activation function is used to obtain input features with one-dimensional convolution kernels of the encoder process. This transformation reduces the information to get the required features. Then, the de-convolution operation is utilized for reconstructing the given input for feature representation in the decoding process, which helps to reduce the noise. Then the t neurons of the output layer are used at the top of 1D-DAE for the classification process with a feature map obtained by the previous layer of input. Then using the following equation, the output is evaluated.

$$Z = AF\big(B(v) + W(v)FM(v)\big) \tag{4}$$

Here Z represents the output, $B(v)$ represents the vector bias and $W(v)$ represents the vector weight in which the learning parameters are convolutional kernel CK. The gradient descent optimizes the bias parameters BP_y^i and bias vector $B(v)$ in the backpropagation method. Compared with a general feed-forward network, the convolutional layer of the shared weights minimizes the parameters of the network, which are used to reduce the vanishing of the gradient. The 1D-DAE loss function is calculated using the below formula.

$$LF = Avg\left|E - \overline{E}\right|^2 \tag{5}$$

where E represents the input of the encoder *and* $\overline{E}$ represents the output of the encoder. In which the gradient descend algorithm are used to reduce the reconstruction error. The proposed 1D-DAE weights are initialized randomly then the iterations are implemented for both the un-supervised and fine-tuning stage to update the weights. Table 2 represents the proposed 1D-DAE network structure and its parameters where 52 dimensions of input vectors are used in the process case. The parameters like 16denote the channel size, 4 denote the kernel size, and 2 denote the stride size for the initial convolution layer $16,\ 4 \times 1$ *and* 2×1. Table 2 represents all the key parameters used in other convolution layers. In the proposed method, the FSA based output for activation function is used for the process of classification. The number of categories used for the unique process is based on the output layer size.

In the proposed 1D-DAE method, the pooling operations do not use, so the one-dimension of input vector-only provides 52. In which the model performance is not enhanced by using the pooling layer. However, the proposed 1D-DAE model only extracts the high-level feature representation for the input vector of the nodes in an unsupervised way. Therefore, in the proposed approach, the fine-tuning for the 1D-DAE method is achieved by using the Flamingo Search Algorithm (FSA). It is an algorithm used to detect the optimal solution in the search area. By using the FSA method in the proposed 1D-DAE method, then the fine-tuning is used by label information. The deep convolutional autoencoders are used to get the feature representation of inputs in an unsupervised way. The top of the 1D-DAE method implements the fine-tuning based on a supervised way. Table 2 represents the algorithm for the proposed 1D-DAE model for parameter optimization and fine-tuning to detect the link failure in MANET optimally.

Table 2: Algorithm for Parameter Optimization in 1D-DAE model.

STAGE-1 Unsupervised Learning
Step1: Consider the hyper-parameters for convolution layer, un-sampling layer, de-convolutional layer, learning rate and down pooling layer.
Step 2: Initialize all the weights and biases in proposed 1D-DAE method.
Step 3: For Iteration number and input
Step 4: Evaluate the convolutional layer's output feature and down-sampling layer $FM(v)$
Step 5: Evaluate the output of up-sampling and de-convolutional layer
Step 6: Validate the error by using
Step 7: The gradient for de-convolutional parameters are calculated.
Step 8: Then update the de-convolutional parameters.
Step 9: The gradient for convolutional layers are calculated.
Step 10: Then update the convolutional parameters.
Step 11: End for
STAGE-2: FSA based Fine Tuning
Step 1: The weights and biases for full connection layer are initialized first.
Step 2: For iteration number , input, label information, are used to get the output features for convolutional and layer of downsampling.
Step 3: Then the classifier and connection layer are feeded.
Step 4: Get the detected label.
Step 5: Evaluate the loss by using equation (5).
Step 6: Evaluate the gradient for full connection layer.
Step 7: Then the bias in full connection layer and weights are updated.
Step 8: End for
Output: Link failure detected by using 1D-DAE model.

4 Results and Discussion

The experimental results of the proposed 1D-DAE approach are implemented in the PYTHON platform. Evaluating the performance of the proposed approach for both unsupervised and supervised models.Comparing the performance metrics of packet delivery ratio, normalized routing load, average end-to-end delay, throughput, bit error rate, and buffer occupancy with existing models [23], [27]. Initially, the proposed Packet Delivery Ratio (PDR) performance is obtained by evaluating the total number of data packets reached destination divided by a total number of data packets transmitted from the source node.

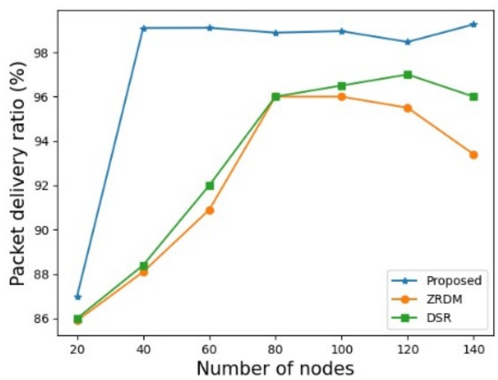

Fig 3: Packet Delivery Ratio.

Figure 3 shows the PDR performance of proposed and existing methods like Zone-based Route Discovery Mechanism (ZRDM) and Dynamic Source Routing (DSR). The obtained performance of PDR requires the ratio of the data packets received by the destination nodes, which are transmitted by the source nodes. The result of the proposed approach obtained PDR performance is improved during the 140 nodes, the performance of the proposed PDR is (99.121%) which is better when compared to the existing methods ZRDM (96 %), DSR (93.40). Then the performance of Normalized Routing Load (NRL) for the proposed approach is obtained by the fraction of whole routing control packets transmitted by every node through the number of received data packets that reached the destination nodes

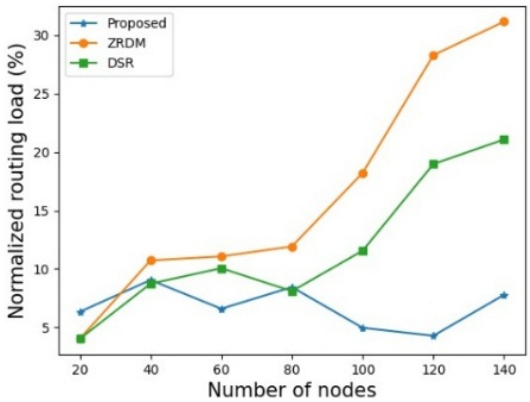

Fig 4: Normalized Routing Load (NRL).

Figure 4 represents the obtained performance of the proposed and existing methods for NRL. NRL performance is calculated by the sum of routing packets by data packets delivered at the destination nodes. The proposed method's NRL performance provides better performance than existing methods like ZRDM DSR. Existing methods generate more packets than the proposed method due to all nodes receiving the copy of packets; therefore, the number of packets becomes high when the number of nodes is greater than sixty. This result provides the proposed method provides optimal results than other approaches. Then the performance of the average end-to-end delay obtained by the proposed 1D-DAE approach is calculated between the packets generated time at the sensor to the time taken to reach the destination node.

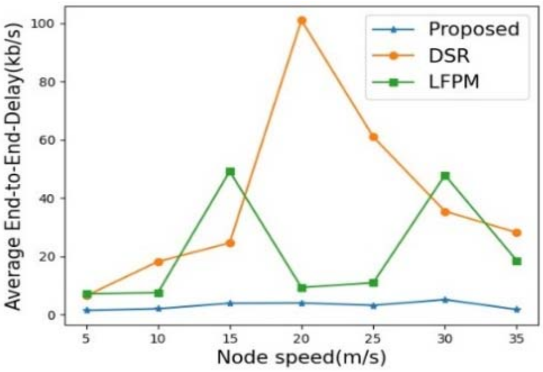

Fig 5: Average End-to-End Delay.

The performance of the average end-to-end delay for the proposed method and the existing method is represented in Figure 5. The average end-to-end delay performance for both the proposed and existing methods obtain at speed in the range of 5 m/s to 15 m/s. The average end-to-end delay is closer to the less value, representing that most received packets are delivered to the destination with less delay. The results show that the proposed method obtained a lower amount of end to end delay, which is more reliable than existing methods DSR, LFPM it obtained the maximum value of delay. Then the throughput performance of the proposed method is calculated by dividing the total number of packets delivered over the total simulation time to reach the destination node to transfer the required data.

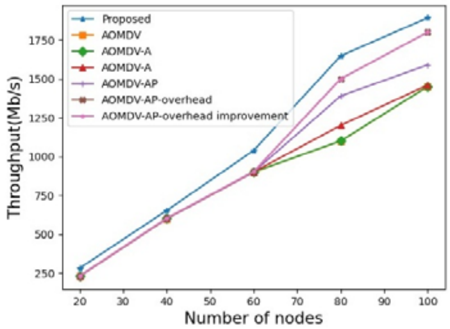

Fig 6: Throughput performance.

The throughput performance for the proposed approach and existing approaches are represented in Figure 6. It shows the comparison of proposed and existing methods like Ad-hoc On-demand Multipath Distance Vector (AOMDV), AMODV with Attack (AMOMDV-A), AMODV with Attack Prevention (AMOMDV-AP), AMODV with Attack Prevention –overhead change (AMOMDV-AP), improved AMODV-AP-Overhead improvement (AMOMDV-A) and AOMDV-SAPTV. The throughput performance of the proposed approach attains high performance (1883 Mb/s) for 100 nodes, which is better than existing methods like AMODV (1450 Mb/s), AOMDV-A (1451Mb/s), AOMDV (1460Mb/s), AOMDV-AP-overhead (1590 Mb/s) and improved-AMODV-AP-Overhead (1800 Mb/s). The performance of Bit Error Rate (BER) for the proposed approach is evaluated by measuring the transmitted sequence of bits to the received bits, which are used to count the number of errors. BER performance is calculated by the ratio of various bits received in error over the total number of bits received.

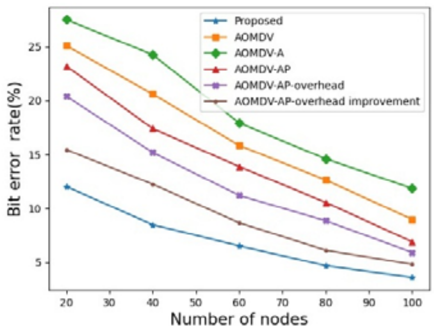

Fig 7: Bit Error Rate Performance.

Figure 7 illustrates the Bit Error Rate (BER) performance for the proposed approach and existing methods. The performance of BER in the proposed approach is very low due to the high low packet loss. For 40 nodes, the proposed approach obtained (8.49 %) of BER performance, which is more reliable than other existing methods like AMODV attains (20.60 %), AOMDV-A (24.25 %), AOMDV-AP (17.40 %), AOMDV-AP-overhead (15.19 %) and improved-AMODV-AP-Overhead (12.25 %). Finally, the transmission energy performance for proposed and existing methods are calculated between the nodes and the energy transmitted for data transmission.

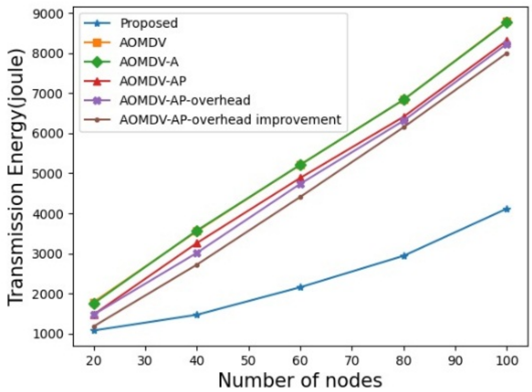

Fig 8: Transmission Energy Performance.

The transmission energy performance for the proposed approach and existing approaches are represented in Figure 8. The above graph results show that the proposed approach consumes less energy for transferring the required data, which is more reliable than other existing methods. For 60 nodes data transmission, the proposed approach requires only (2157.85 Joule). It is very less than other existing methods like AMODV attains (5212.72 Joule), AOMDV-A (5212.75 Joule), AOMDV-AP (4885.52 Joule), AOMDV-AP-overhead (4738.28 Joule) and improved-AMODV-AP-Overhead (4411.11 Joule).

Table 3: Comparison values of proposed and existing methods

Number of nodes					
Throughput	**20**	**30**	**40**	**50**	**60**
Proposed	282	653	1039	1647	1893
AOMDV	230	600	900	1100	1450
AOMDV-A	231	601	901	1101	1451
AOMDV-AP	231	601	901	1201	1460
AOMDV-AP-overhead	231	601	901	1390	1590
AOMDV-AP-overhead improvement	232	603	903	1500	1800
Number of nodes					
BER	**20**	**30**	**40**	**50**	**60**
Proposed	12.0	8.49	6.53	4.69	3.59
AOMDV	25.09	20.6	15.84	12.64	8.99
AOMDV-A	27.5	24.2	179	14.6	11.86
AOMDV-AP	23.2	17.4	13.8	10.5	6.91
AOMDV-AP-overhead	20.4	15.1	11.2	8.86	5.93
AOMDV-AP-overhead improvement	15.4	12.2	8.67	6.13	4.82
Number of nodes					
Transmission Energy	**20**	**30**	**40**	**50**	**60**
Proposed	1078	1471	2157	2942	4119
AOMDV	1785	3556	5212	6836	8787
AOMDV-A	1752	3572	5212	6836	8771
AOMDV-AP	1474	3261	4885	6411	8312
AOMDV-AP-overhead	1474	3016	4738	6313	8231
AOMDV-AP-overhead improvement	1179	2721	4411	6149	8002

Table 3 represents the comparison values of proposed and existing methods. The performance of throughput, bit error rate and transmission of energy are compared with number of nodes.

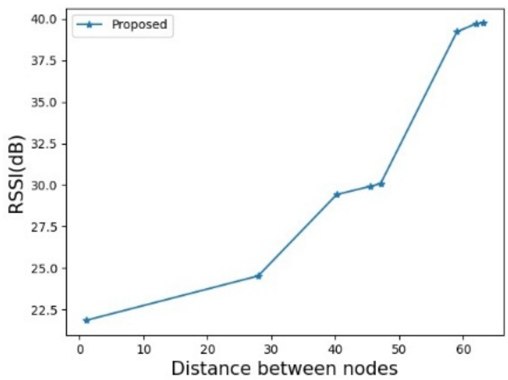

Fig 9: Received Signal Strength Indication (RSSI)

Figure 9 represent the proposed performance of RSSI by calculating the distance among nodes. Received Signal Strength Indication (RSSI) parameter is utilized to estimate the link failure probability in MANET. RSSI is used to represent the power level being received by the receiving radio and possible cable loss. The main objective of using the RSSI parameter is to measure the signal strength and distance between the nodes to determine the quality of the communication link of MANET. The following equation calculates the RSSI performance of the proposed model

$$RSSI = TP - PL(Dis\tan ce) \quad (6)$$

Where the received signal strength indication is represented as $RSSI$, then the signal transmission power is represented as TP, the path loss is denoted as PL and the distance is represented in the above equation to calculate the link failure probability in MANET.

5. Discussion

This section addresses the detection of link failures in MANET by machine learning based on the simplified early link failure detection methods [28, 29]. This paper intends to develop a simplified early link failure detection (SELFD) based machine learning approach. Initially, the SELFD model analyzes the possibility of link failure using AOMDV based beacon message propagation. In addition, the SELFD model follows both unsupervised and supervised models of One-Dimensional Deep Auto-Encoder (1D-DAE) and logistic regression for estimating the link failure probability based on parameters of packet delay, Received Signal Strength Indicator (RSSI) (two parameters taken from survey study), jitter and loss rate. In the proposed 1D-DAE model, two advantages are used for link failure detection. Initially, the DNN and 1D-DAE models are compared to ensure the best performance based on the convolutional autoencoders for learning the features optimally. Then the 1D-DAE is used for the computation speed of data for extracting the features from the process of one –dimensional failure detection.

The hyperparameter tuning of 1D-DAE is achieved by the flamingo search algorithm (FSA). The proposed approach performance is compared with other recent methods like ZRDM, DSR, AOMDV, AMOMDV-A, AMOMDV-AP, AMOMDV-AP, improved AMODV-AP-Overhead improvement (AMOMDV-A) and AOMDV-SAPTV in terms of throughput, bit error rate, transmission energy, packet delivery ratio, normalized routing load, average end-to-end delay. The existing method attains low performance due to a high delay, node failures, node mobility, etc. Several machine learning-based methods are proposed to detect the link failures in MANET, but it does not provide efficient results. The experimental results of the proposed approach show that the performance of detecting link failure in MANET provides better performance than existing works.

6. Conclusion

In MANET, the link failures during routing mostly occur due to the nodes' less energy, channel fading, nodes mobility, restricted vitality assets, dynamic snags, blurring, continuous connection disappointments, etc. Therefore, the proposed approach machine learning-based simplified early link failure detection model for MANET is proposed to detect the link failure as earlier by using the 1D-DAE method. In this work, the autoencoder is integrated with pooling units and convolutional kernels to effectively detect the link failure in MANET. 1D-DAE method extracts the features from one-dimensional for link failures detection. Therefore, users do not require any prior knowledge about the process of selection. Further, the Flamingo Search Algorithm is used for fine-tuning the hyperparameters of the proposed 1D-DAE model. The performance of the proposed approach is compared with existing methods in terms of normalized routing load, average end-to-end delay, throughput, bit error rate, packet delivery ratio and buffer occupancy.

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