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Research Article

Reliability estimation for drone communication by using an MLP-based model

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ABSTRACT

Unmanned aerial vehicles (UAVs) or drones have been widely employed in both military and civilian tasks due to their reliability and low cost. UAVs ad hoc networks also acknowledged as flying ad-hoc networks (FANETs), are multi-UAV systems arranged in an ad hoc manner. In order to maintain consistent and effective communication, reliability is a prime concern in FANETs. This paper presents an analytical framework to estimate the reliability of drones' communication in FANETs. The proposed system takes into account the reliability of communications in FANETs, including channel fading. The suggested analytical investigation is used to generate a dataset, then an artificial neural network (ANN) based multi-layer perceptron (MLP) model is used to estimate the reliability of drones' communication. Moreover, to define the best MLP model with hidden layers, the correlation coefficient (R^2), mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE) are obtained. Moreover, numerical results are presented which verify analytical studies.

1. Introduction

Recent technical advancements in fields like robotics, telecommunications, and computer networks have led to the emergence of unmanned aerial vehicles (UAVs) as an alternate method of offering a variety of applications in both military and civilian domains. UAVs or drones will have a significant breakthrough in the upcoming 6G [1]. Flying ad hoc networks (FANETs) enable drone-to-drone (D2D) and drone-to-infrastructure (D2I) communication. FANETs have received numerous attention in recent years for a variety of services. UAVs must be able to interact effectively with one another and with existing networking infrastructures in order to fully benefit from their provided services. Therefore, the important concern in FANET is increasing the reliability of message dissemination [2-7]. In order to fulfill the criteria and achieve life-saving objectives, a drone must be able to transmit packets reliably in FANETs.

Deep learning (DL) has drawn a lot of interest and is frequently utilized in various disciplines to enhance the effectiveness of earlier techniques [8]. DL-based approaches can avoid the time-consuming task of identifying features and gathering private information since it automatically extracts and picks features from raw data. In terms of resource requirements, while training a DL-Based method requires a significant amount of computational power, the majority of trained DL classifiers are small and computationally efficient. In short, DL-based approaches are appropriate for usage since they can achieve improved performance with simply raw traffic inputs and low resource needs [9].

The authors' method improves the localization mission by utilizing a decision-making approach based on a temperature-based probabilistic model developed to anticipate the distance to the forest fire in [10]. A control system for moving UAVs within a designated coverage region is provided in [11]. The motion control system, which is reliant on the distance between the drones and their signal strength, enables the drones to successfully connect and subsequently transmit data at fast speeds [12–14]. A dependable and effective cooperative MAC protocol was put up by [15] to increase communication dependability. For extremely reliable multi-hop message distribution under a variety of channel situations, [16] presented a cooperative communication strategy. In [17], a method for generating stable cluster structures was proposed for emergency message dissemination. A route finding method based on ant colony optimization is

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described in [18]. A reliability parameter was also created in order to choose trustworthy links and eliminate bad connections from a route. To improve reliability, [19] proposed a routing system based on QoS and particle swarm optimization (PSO). A dependable UAV routing system was introduced in [20]. This protocol allowed dependable vehicles to communicate by halting the flow of pointless packets. [21] outlines a technique for using ANN models to find misbehavior. This technique combined feedforward and backpropagation algorithms to classify misbehavior. The neural networks (NN) and the simulated annealing clustering approach were used to choose the cluster's head in the clustering-based reliable routing system [22]. The optimum routes were assigned and traffic was managed in VANETs using the convolutional neural network (CNN) model [23]. [24] describes a resource allocation system based on deep reinforcement learning. [25] determined the optimal contention window (CW) size using PSO, differential evolution, and the artificial bee colony approach. The major goal of [26] is to outline the wireless and security challenges that arise in relation to UAV-based delivery systems, real-time multimedia streaming, and intelligent transportation systems. Such problems are addressed using ANN-based solution strategies.

With the use of machine learning, analytical models may be automated nearly fully without the need for human participation. In order to automate the evaluation of the dependability of drone communications, this article uses ANN, one of the most efficient machine learning techniques. Biological neural networks, such as those in the human brain, are imitated by ANNs, which are mathematical tools. The networks execute non-linear input-to-output mapping in the absence of comprehensive information. The neuron, sometimes referred to as a node, is the smallest information processing unit and the basis of network activity. Usually, one neuron is not enough to solve an issue. As a result, a layer is often composed of a collection of neurons. To create neural networks with various topologies, ANN neurons can be connected in a number of different ways. A neural network often functions as a "black box" that may be taught to predict the values of certain output variables given adequate input data. The most influential ANN designs are feedforward multi-layer neural networks. The fundamental neurons that make up the input layer, the hidden layer(s), and the output layer are often included in these networks. The input signal travels forward via the network layers at a time. Multi-layer perceptron (MLP) is the name of the network that was employed in this study [27–29].

Being able to benefit from offered services requires reliable packet delivery, which is one of the communication challenges in FANETs. In this paper, the reliability of drones' communication is estimated using an artificial neural network (ANN) based multi-layer perceptron (MLP) model. The following are the article's primary contributions:

- A Markov model based analytical study is presented for FANET considering Nakagami-m fading.
- An algorithm is provided to calculate the reliability of drones' communication.
- Using the proposed analytical analysis, a dataset is generated and an ANN based MLP model is designed for the reliability estimation of drone communications.
- In order to support theoretical studies, numerical results are provided. Correlation coefficient (R^2), mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE) are obtained for different models and the best MLP model is defined.

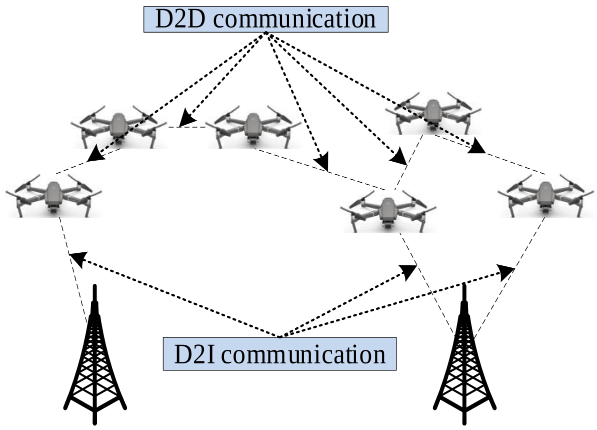

Figure 1. Structure of a basic FANETs

2. Reliability Estimation of Drone Communication

A basic structure of FANETs is shown in Figure 1. We consider a network of N drones in which drones are deployed at random. Let $b(t)$ represent the drone's stochastic backoff time counter for the given time t. The backoff value in this Markov chain [2] is obtained uniformly from $[0, CW_0 - 1]$ at the beginning. The backoff is lowered by 1 if it is detected to be idle. When the channel detects idleness once again, it is resumed after pausing if the channel gets busy. The packet will then be transmitted if the backoff value falls to zero. If any of the remaining drones transmit at the same time slot then the collision will occur. A packet will be retransmitted until the retransmission limit. Even if there is no collision, packet transmission can be unsuccessful due to channel fading. If the transmitting drone is reliable, the channel is idle, the transmission does not fail due to channel fading, there is no contention, and there is no collision from the hidden drones, then the transmission will be successful.

If the packet is reliably sent by the transmitting drones and the communication hardware of the receiving drone is reliable, then communications between drones are reliable. The packet sent by the originating drone may be

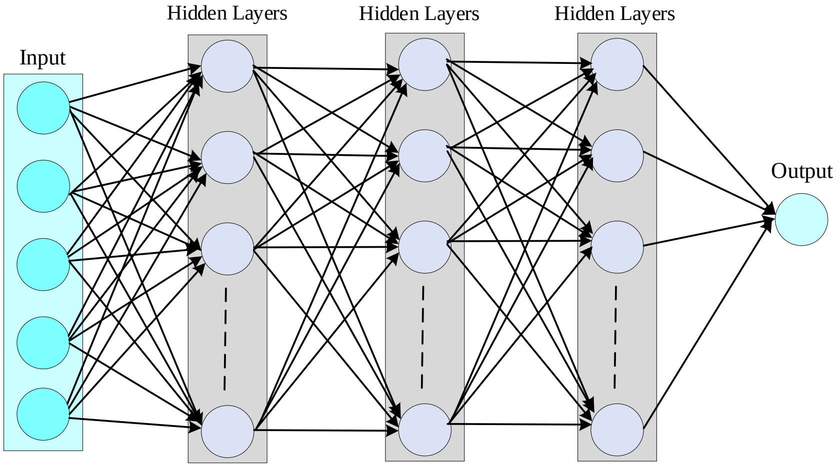

Figure 2. MLP's schematic diagram

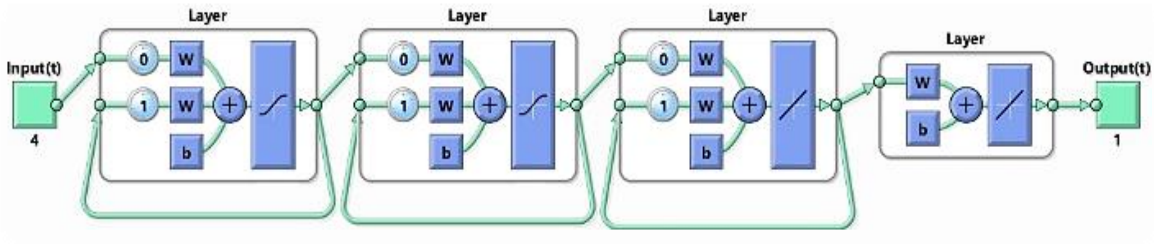

Figure 3. Structure of MLP with 3 hidden layers

retransmitted by the drones between the source and destination. Therefore, the hardware reliability of the receiving drone, the success of the transmission, and the number of transmitters are the factors that define reliable communications. Hence, the reliability of communications (*RoC*) is written as [15]

$$RoC = R(t) \times \left(1 - \prod_{i=1}^{n} (1 - RoT_i(t))\right). \quad (1)$$

where *R* is UAV's communication-related hardware reliability. RoT_i(t) is the reliability of transmission for the i_{th} drone, and *n* is the redundant transmission value. *RoT* can be calculated as [15]

$$RoT(t) = R(t) \times (1 - P_b) \times (1 - P_c)(1 - P_l). \quad (2)$$

P_t is the probability of transmission and can be expressed as [2]

$$P_t = \frac{2}{1 + CW + m_r CW / 2}. \quad (3)$$

Here, m_r is the maximum retransmission limit.
Probability of channel busy (P_b) can be given as

$$P_b = 1 - (1 - P_t)^N. \quad (3)$$

P_c is the probability of collision and can be given as

$$P_c = 1 - (1 - P_t)^{N-1}. \quad (4)$$

P_l represents signal loss probability due to channel fading. P_l on Nakagami-m channel fading can be expressed as

$$P_l = \frac{m^m}{\Gamma(m)} \times \int_0^{\frac{d}{TR}\alpha} z^{m-1} e^{-mz} dz. \quad (6)$$

where *d*, *m*, *TR* and α denote the distance between two nodes, Nakagami-m fading parameter, transmission range, and path loss exponent, respectively. $\Gamma(.)$ is also standard Gamma function.

3. Multi-Layer Perceptron

The multilayer perceptron (MLP) is built on statistical learning theories that are applicable to making a relationship among input variables and are suitable for solving nonlinear problems [31-32]. In other words, the MLP can connect input and output variables without

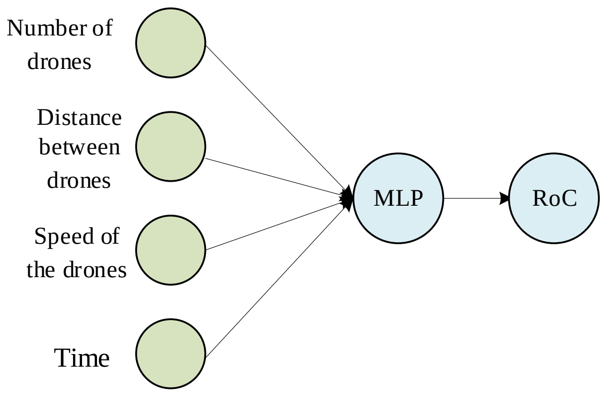

Figure 4. The proposed MLP structure.

Table 1. A dataset of the current study

	Number of drones	Distance between nodes	Speed of drones	Time	Reliability of Communication
1	5	5	10	5	0,3691
2	10	5	10	5	0,3376
3	15	10	20	10	0,1544
4	20	10	50	10	0,3530
5	25	20	30	20	0,0484
6	30	20	20	50	0,0118
7	35	30	40	30	0,0240
8	40	30	10	30	0,0055
9	45	40	50	50	0,0113
10	50	50	30	10	0,0245
11	60	60	40	40	0,0058
12	70	70	50	30	0,0069
13	80	80	70	20	0,0106
14	90	90	80	10	0,0180
15	100	100	90	10	0,0152
16	30	50	30	5	0,0709
17	40	60	40	15	0,022
18	20	20	70	50	0,0494
19	50	5	25	30	0,0689
20	10	15	50	40	0,0703
21	40	10	50	25	0,0988
22	70	25	10	45	0,0026
23	60	45	20	60	0,0026
24	25	60	45	35	0,0138
25	65	70	80	75	0,0048

Input: *N, d, v, t*
Output: Reliability of communication
1. for j=1 to *n (number of redundant transmissions)*
2. for j=1 to *N (number of UAVs)*
3. calculate P_b *(probability of channel busy)*
4. END
5. calculate *R(t) (reliability of UAV's communication-related hardware)*
6. calculate P_l *(probability of signal loss)*
7. calculate *RoT (reliability of transmission)*
8. calculate *RoC (reliability of communication)*
9. END

Figure 5. The proposed structure's pseudo algorithm

requiring complex mathematical and computational methods. MLP is made up of three layers: input, hidden, and output, as displayed in Figure 2. The reliability of communications is included in the output layer. Neurons in the hidden layers are considered for reliable communication based on the trial and error method. Figure 3 shows the MLP structure, which has three hidden layers.

Figure 4 depicts the proposed MLP structure. The neural network's inputs are made up of four parameters: number of drones (*N*), velocity of the drones (*v*), distance between drones (*d*), and time (*t*).

The main objective of this work is to estimate the reliability of drones' communication as a target parameter using an MLP algorithm. Various analyses were performed to assess the effectiveness of MLP in the estimation of reliability for drone communication. The obtained results demonstrated that MLP had a high level of ability and accuracy in predicting the intended parameters. The RMSE and MSE for each step of the process were also calculated to demonstrate the performance and applicability of this artificial intelligence approach. Based on the outcomes of this work, it is possible to conclude that MLP could be used as a useful

Table 2. Parameter values used in numerical analysis

Parameters	Values
CW	64
m_r	5
TR	500 m
Activation functions	ReLU + Linear
Hidden layers	1-5
Loss function	MAE
Number of epochs	50
Batch size	50
Dropout	0.4

tool in a variety of industrial processes. Table 1 contains a list of 25 different datasets.

A dataset of drone communication analyses is compiled from various sources. The database was separated into training (50%) and test (50%) sets for the development of the MLP-based models. While the training set is utilized to build models, test sets were used to evaluate and validate the models' generalization capability. Each model's performance is evaluated using statistical quantities such as coefficient of correlation (R^2), RMSE, and MAPE, as defined below;

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(P_j - C_j)^2} \tag{7}$$

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(P_j - C_j\right)^2 \tag{8}$$

$$MAPE = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{P_j - C_j}{C_j}\right| \tag{9}$$

$$R^2 = \frac{N\left(\sum_{j=1}^{N}P_jC_j\right) - \left(\sum_{j=1}^{N}P_j\right)\left(\sum_{j=1}^{N}C_j\right)}{\sqrt{\left(N\sum_{j=1}^{N}\left(P_j\right)^2 - \left(C_j\right)^2\right)\left(N\sum_{j=1}^{N}\left(C_j\right)^2 - \left(P_j\right)^2\right)}} \tag{10}$$

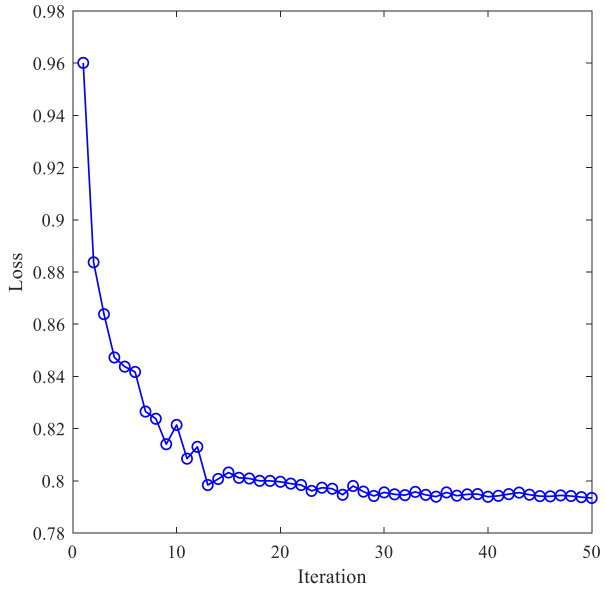

Figure 6. Loss of the MLP during training

where C is the calculated value, and P is the estimated value.

4. Numerical Results

In this section, the effect of MLP on communication reliability in FANETs is assessed. MATLAB is used to generate numerical results. Table 2 lists the parameter values used in numerical analysis.

We can learn about MLP models by observing how they perform during training. Figure 6 depicts the epoch-by-epoch loss of training data. Loss of the MLP during training is decreasing with the increase in the number of iterations.

Table 3 compares all correlation equations under various scenarios. The MLP with one and five hidden layers performs better than the MLP with three hidden layers, as seen in Table 3. Because there are three neurons in a system with one hidden layer whereas there is only one in a system with three hidden layers, the findings from one hidden layer are better than those from three hidden layers. Five hidden layers provide the highest prediction ability, as evidenced by their high correlation coefficient (0.9939), low RMSE (0.0409), MSE (0.0017), and MAPE (0.0096).

Table 3. Comparisons of correlation equations in each different scenario

Number of hidden layers	Number of neurons	R-Squared	RMSE	MSE	MAPE
1	3	0.9907	0.0481	0.0023	0.0098
3	1	0.9643	0.0537	0.0029	0.0101
5	4	0.9939	0.0409	0.0017	0.0096

Data collection is a critical issue and an active research topic in machine learning. As far as we are aware, there is no dataset available for estimating the reliability of drone communications. The analytical reliability estimate is then used to construct a dataset. After determining the reliability of drone communications for different values of the four criteria taken into account, a dataset is created to train the specified MLP. There are 25 sets in the dataset, and the predicted reliability and the four inputs each have different values.

Due to its higher correlation coefficient and lower RMSE and MAPE compared to the other instances, the MLP with five hidden layers and four neurons in the hidden layer is found to be the best network. Additionally, the correlation coefficient rises and the error rate falls as the number of neurons increases.

5. Conclusion

Reliable packet delivery is one of the communication challenges in FANETs that must be accomplished before drone services can be used. In this study, we use an MLP-based model to estimate drone communication reliability. A dataset is created. An analytical approach based on Markov model is presented to obtain reliability related parameters. Analytical studies are verified by numerical results. The correlation coefficient, RMSE, MSE, and MAPE are obtained for different models. The MLP with five hidden layers and four neurons is demonstrated to be the best network when compared to the other models owing to its better correlation coefficient and lower MSE, RMSE, and MAPE values.

Declaration

Regarding the research, writing, and/or publishing of this paper, the authors reported that they had no potential conflicts of interest. The authors further said that no specific authorization or approval from an ethical committee was needed because this article was entirely original and created in conformity with international publication and research ethics.

Author Contributions

A. F. M. S. Shah developed the methodology, supervised and proofread the manuscript. M. A. Karabulut performed the analysis. The authors wrote the manuscript together.

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