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APPLICATION OF SOFT COMPUTING

Toward in-flight Wi-Fi: a neuro-fuzzy based routing approach for Civil Aeronautical Ad hoc Network

T. Gurumekala[1] **· S. Indira Gandhi**[1]

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Abstract

In-Flight Wi-Fi connectivity (IFC) paves way for supporting the Internet of Things over the clouds by connecting things inside a moving aircraft to the ground. Aeronautical Ad hoc Networks (AANET) is a new breed of Mobile Ad hoc networks envisioned to experience IFC over remote or oceanic regions. Due to the challenging characteristics of AANET such as limited bandwidth, intermittent connectivity, dynamic topologies, the greater velocity of aircraft, and variable geographical network sizes, it is very hard to design a realistic mobility model and network routing with remarkable Quality of Service (QoS) and requires immediate research solution. As the complexity of provisioning QoS network services significantly relies on the routing layer, this work aims at providing intelligent, reliable, and efficient data delivery with ensured QoS. In the aim of attaining a solution for QoS routing, this paper presents twofold design strategies. Firstly, the mobility of moving aircraft is modeled with International Civil Aviation Organization separations standards to avoid collisions among moving aircrafts, second is, a novel hybrid approach combining deep learning and fuzzy logic is proposed to deal with highly dynamic nature and growing air traffic. The neighbor discovery phase of existing routing protocols incurs more packet overhead and delay because of the traditional beaconing method, which is overcome in this work by using Automatic Dependent Surveillance-Broadcast as it is kept on broadcasting the neighbor's information in the cockpit display of every aircraft. To avoid the overwhelming of nodes, this work uses queuing delay of the neighbors to identify the node's ability for packet transmission fairly distributes the load among aircrafts. The simulation results show that the proposed work provides notable improvements in packet delivery ratio, end-to-end delay, and traffic overhead compared to the existing routing protocols in sparse and dense network scenarios.

Keywords Neuro-fuzzy inference systems · Aeronautical Ad hoc Networks · Internet of Things · Quality of Service · Deep neural networks · Automatic dependent service – broadcast

1 Introduction

The drastic growth in communication technologies has emanated a thirst in air passengers to experience the seamless internet connection as in ground to share their valuable information online rather than offline for their personal as well as commercial purposes utilizing Gmail, Facebook, and onboard video conferencing. Consequently, In-Flight Wi-Fi Connectivity (IFC) was introduced by the airline industries in civil aviation to support the economic growth of various domains by means of keeping people always connected even at and above 35,000 ft. As per the reports of Honeywell (Honeywell 2016), the statistics show that around 75% of air passengers are willing to switch airliners for seeking reliable and faster internet access, and more than 20% of air passengers already switched their airline to have a better internet experience. Moreover, the IFC helps to realize the Internet of Things (IoT) in civil aviation by interconnecting a massive number of computing devices inside the moving flights with the internet and keep them always connected (Chettri et al. 2020; Zhang

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✉ T. Gurumekala
gurumekala.ssk@gmail.com

S. Indira Gandhi
indira@mitindia.edu

1 Department of Electronics Engineering, MIT-Campus, Anna University, Chennai, India

et al. 2019; Gupta and Aggarwal 2017; Whitmore et al. 2015). However, challenges persist in providing internet connectivity in moving aircrafts with higher data rates, less delay, and low cost (Ercetin et al. 2005). In addition, the air traffic keeps on increasing drastically, which results in resource scarcity in the AANET environment (Pasztor 2016). Figure 1 shows the current air traffic over the region of Europe as an example. Currently, airline industries are working toward incorporating IoT on moving airplanes with the help of internet access and cellular connectivity (Lutz et al. 2005; Ky et al. 2006). Internet access is provided to moving aircrafts by relying on either satellite-based or cellular-based systems. Cellular-based systems offer a direct link between moving flights and the ground station by using the existing cellular-based infrastructure. Due to the shorter coverage range, lack of ground infrastructure, and line-of-sight problem, cellular-based systems are unable to cover remote or oceanic regions (Xu et al. 2019). Satellite-based systems (Peter Brooker 2008; Medina et al. 2011; Vey et al. 2014) make a way for flights to stay connected with the ground while flying over these regions in the role of a relay. This system can cover wider regions with higher speed, at the expense of long delay and high cost. In real-time, Gogo Inc. is the leading in-flight Wi-Fi service provider which provides both cellular-based (ATG, ATG-4), and satellite-based (ku-band, Ka-band) (GoGo 2016).

Sakhaee and Jamalipour (2005) introduced the concept of AANET among moving airplanes as a supporting communication system (air-to-air) when flights traverse over the remote or oceanic regions. A typical architecture of an aeronautical ad hoc network is depicted in Fig. 2.

AANETs is a member of MANETs as it inherits some of the characteristics such as self-configuring, self-organizing, self-healing, frequent topology changes, and mobility patterns. Nevertheless, the unique natures of AANET, namely geographic size of the network, high velocity of nodes, limited bandwidth, and high node densities are the factors complicating the process of routing and forwarding in AANET not as of MANET. Specifically, the nodes in AANETs fly at the speed of 700 km/hr to 900 km/hr, which leads to frequent topology changes while the nodes in MANETs move in human walking speed around 5–20 m/s. Hence, speed is the crucial factor in dealing with great effort for improving routing performance above 30,000 ft. As the nature of AANET is highly different from MANET, different design strategies for respective layers are necessary to make the complete paradigm successful. Among those, designing QoS-aware routing is a challenging phenomenon as it is the key to transmitting and receiving data and determinant of end-user satisfaction. To design an accurate QoS routing system in any kind of network, it is mandatory to investigate different dimensions of the network characteristics such as nature of the

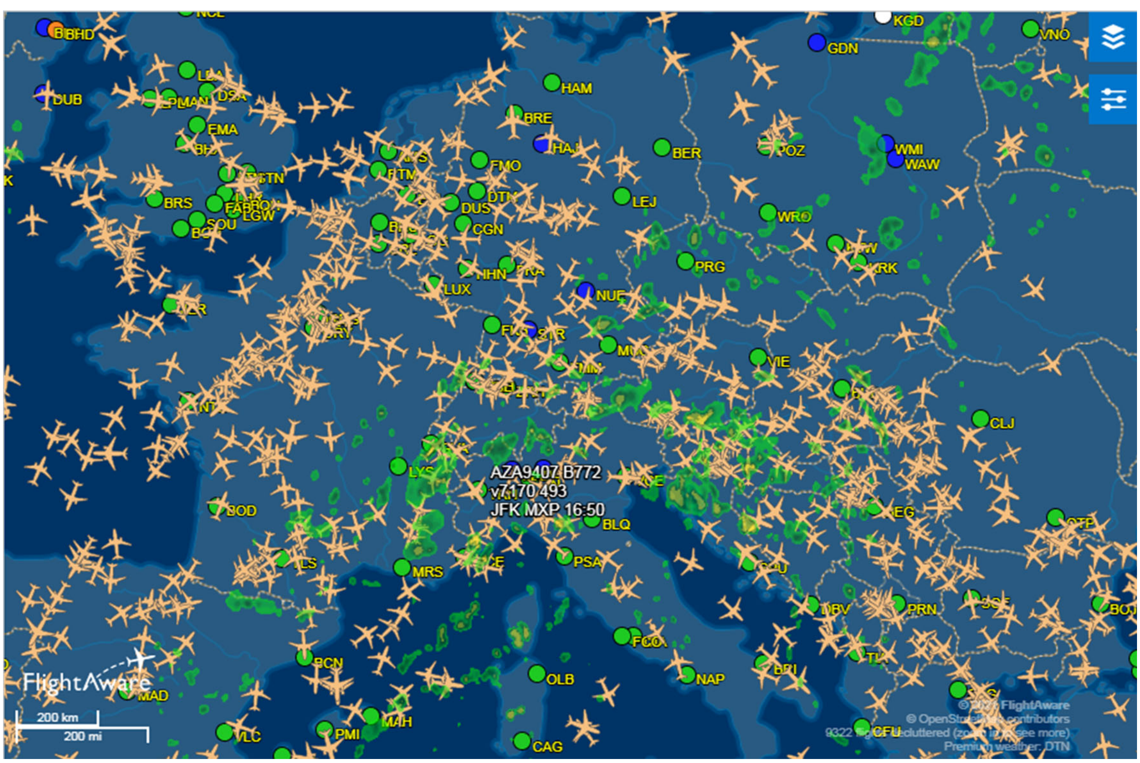

Fig. 1 Air traffic over Europe

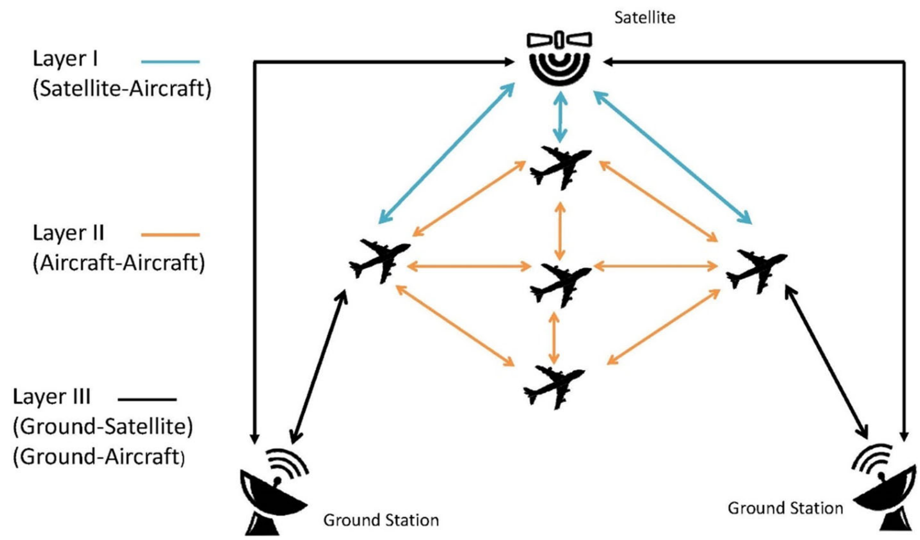

Fig. 2 Typical Aeronautical Ad hoc Network

communication medium, degree of adaptability of the routing strategies, limited resources, and capacity of the node (Jahn et al. 2003). In the case of AANET, the higher mobility of the aircrafts and the restricted amount of resources such as bandwidth, link availability, frequent topology changes require significant effort in ensuring the QoS to the end-users. The existing routing approaches for AANET failed to consider the QoS of the routing as an imperative factor and adaptive strategies according to the dynamic and complex environments. For example, Luo and Wang (2017) used the traditional beaconing method for distributing and collecting neighbor information, which results in inefficient use of the scarce resources in the perspective of QoS routing. There is a trade-off between accuracy and frequent update. Unlike any other network, AANET has a native property called automatic dependent surveillance-broadcast (ADS-B) for maintaining high accuracy with little overhead. Moreover, QoS routing inherently loads balancing in nature which is absent in the existing approaches. By investigating the nature of AANET and the research gap in QoS routing, this work aims to accompany the strength of the artificial intelligence-based learning method and the reasoning ability of fuzzy logic.,

Due to the growth of a huge volume of communication and computation in various emerging IoT applications (Thompson et al. 2019), DL-driven algorithms started to incorporate in wireless communication and network design by many industries and researchers. For example, Li et al. (2019) applies a DL algorithm, namely Q-learning for solving traffic explosion problems in hierarchical wireless networks. For improving the accuracy of indoor position by integrating ML and DL algorithms, namely deep neural networks with K-nearest neighbor algorithm (Abebe Belay Adege et al. 2018). According to the prediction of *EUROCONTROL*, in Europe alone, there will be 14.4 million flights in the year 2035, which is 1.8% average annual growth compared to the flights in 2012. The AI can be introduced to aircrafts by applying suitable machine learning algorithms and soft computing techniques. In a crowded environment, the aircrafts can be made as an intelligent router to forward the data through an effective routing path in the absence of an internet connection based on the fuzzy rules trained neural network models. Many Neuro-fuzzy systems are existing, namely, ANFIS, FuNe, Fuzzy RuleNet, GARIC, or NEFCLASS, and NEFCON (Berenji et al. 1992; Halgamuge et al. 1994; Nauck et al. 1996; Tschichold-Gürman 1996).

Due to the high adaptive nature of the situation, Adaptive Neuro-Fuzzy Inference System (ANFIS) is widely used in various areas (Yadav and Balakrishnan 2014). ANFIS techniques were originally framed and presented in the year 1993 by Jang, which deals with complex nonlinear systems. ANFIS is a data learning approach that uses the knowledge reasoning ability of Fuzzy Logic to transform the given inputs to the expected output through the multi-layered feed-forward neural network processing elements. ANFIS integrates the ability of two concepts, namely Fuzzy Logic and Neural networks. The ANFIS functions by applying the neural network learning methods to tune the linguistic variables of the fuzzy logic. To enhance the QoS in routing packets, the knowledge reasoning of fuzzy logic in a nonlinear system by setting IF–THEN rules and refining those rules with a multi-layered feed-forward neural network is adapted in this work. The remaining section of this work is organized as follows. In Sect. 2, the existing routing methods and the application of deep learning techniques wireless domain is thoroughly studied. Section 3 illustrates the modified mobility model, and Sect. 4 explains the proposed ANFIS based routing protocol in detail. Section 5 deals with results and discussion, where results attained for the proposed work and comparison with the existing protocols is explained. Finally, Sect. 6 concludes this work.

1.1 Problem statement

The ever-increasing air traffic growth and the unique nature of AANET urge researchers to incorporate AI to ensure QoS in routing strategies as the high-speed node movement results in frequent topology changes. The existing works are not sufficiently cover the network requirements of civil aviation and fail to handle such a highly dense and complex network environment, as the existing routing approaches are completely unsuitable (Neji et al. 2013; Zhang et al. 2019). The reason is, firstly, they are unable to fit civil aviation applications as the network requirements have differed. Secondly, they failed to model the real movements of aircrafts. Thirdly, the existing AANET protocols considered single routing metrics for route selection and failed to utilize AI for improving the overall network performance. Fourthly, they fail to deal with the density of data traffic as the traditional way has been applied in neighbor discovery. Finally, the adaptive nature of routing strategies needs to be developed to deal with the scalability of the network. This work proposes a neuro-fuzzy based technique called ANFIS to produce greatly accurate results in highly dynamic and complex AANET by combining the merits of adaptive control mechanism, neural network, and fuzzy logic and modeled the real movements of aircrafts and avoids the collisions by following the separation standards of ICAO.

1.2 Authors contribution

- This work models the realistic mobility of the aircrafts with ICAO standards to avoid collisions among moving aircrafts.
- Beaconless way of neighbor discovery has been followed with the help of Automatic dependent surveillance-broadcast (ADS-B), which leads to bringing accurate information at low cost. As a consequence, routing delay and packet overhead are remarkably reduced.
- The learning capability of neural networks and the interpretation capability of fuzzy logic have been utilized for finding the next hop in the routing process.
- To support the load-balancing aspect of QoS routing, the queuing capacity of nodes is considered to reduce the end-to-end delay and to improve the packet delivery ratio.

2 Related works

The AANET routing protocols for AANET are classified based on their origination as modified and Domain-Specific routing protocols.

2.1 Modified MANET protocols

At the initial stages, the existing routing protocols for MANET such as AODV, DSR, GPSR, ZRP, and OLSR extended for AANET by considering its distinguished features. Iordanakis et al. (2006) proposed an Ad hoc routing protocol for aeronautical mobile ad hoc networks (ARPAM) extended from AODV to find the shortest route between source and destination by taking distance and number of hops between them into account in a proactive way and utilized Ka-band satellite link. This protocol turns its mode to reactive to avoid routing overhead in the case of error reporting alone. The Geographic Load Sharing Routing (GLSR) approach extends Greedy Perimeter Stateless Routing (GPSR) protocol for wireless networks, where the packets are forwarded to geographically closest neighbor of destination (Karp and Kung 2000; Medina et al. 2008). They have attempted to reduce packet loss by calculating the relative distance between source and neighbor toward destination. Gu et al. (2012) proposed DMDR, which is reactive and derived from the DSR routing protocol. They have concentrated on overwhelming conditions of aircraft, and tried to eliminate it by observing the expected queuing delay of next-hop and Doppler shift of the nodes aims at load sharing and based on the Doppler shift (relative velocity of nodes) and expected queuing delay of the nodes in moderate and high-density AANET. PLAR (Zhong et al. 2016) routing suggested extending the link availability duration by using the aircraft densities along with the topology construction methods. This protocol extended OLSR (Optimized Link State Routing) to enhance the link availability time to achieve a lower probability of link breakages when aircrafts have higher velocities with too many assumptions of the dynamic environment. Zhong et al. (2016) proposed hierarchical space routing protocol (HSRP) to provide efficient and reliable communication in AANET with the use of node movement features. This protocol has been designed based on the zone routing protocol (ZRP) for the mobile ad hoc networks that works based on the zones of the node. ZRP is a hybrid routing that combines both proactive (IARP) and on-demand routing protocols (IERP), where IARP is a kind of proactive link-state protocol that keeps track of the routing information for nodes that are available inside the zone.

2.2 Domain-specific routing protocols

The routing protocols (Sakhaee et al. 2006a; Seung et al. 2010; Wang et al. 2013; Vey et al. 2017; Luo et al. 2017) are AANET domain-specific. Sakhaee et al. (2006b) proposed Multipath Doppler routing protocol (MUDOR) to find stable routes between source and destination by using Doppler shift of the nodes. Furthermore, in their subsequent work, the QoS issues have been considered along with extending the link lifetime through various theoretical analyses. AeroRP (Jabbar et al. 2009) is a domain-specific geolocation-assisted routing protocol designed for dynamic airborne ad hoc networks. This work used Active snooping for the neighbor discovery phase, where the packets in the medium are overheard to extract the location information store in it. The TTI (Time to intercept) is the primary metric used for selecting the next hop for packet transfer by taking the location of the destination, and the predicted location of the neighbors along with the velocity of the nodes. However, the broadcast nature leads to network congestion and network delay in packet delivery. Seung et al. (2010) proposed Geographical Routing for A position-based routing approach to cope up with the highly dynamic nature of the network topology by extending the Greedy Perimeter Stateless Routing (GPSR) designed for MANET. The position of the moving aircrafts is periodically updated from a ground station, which incurred a higher delay in packet delivery. In addition, the delay in getting position information from the ground leads to inaccuracies in next-hop selection. Shangguag Wang et al. (2013) proposed a geographical routing approach by employing a velocity-based metric for next-hop selection to deal with the fast-moving nature of commercial aircraft and the frequent topology changes. They have used ADS-B system to enhance the performance of routing in terms of routing overhead by replacing the traditional broadcasting methods for neighbor discovery. Vey et al. (2017) proposed a node density and trajectory path-based routing approach named Node Density-Trajectory based Routing (NoDe-TBR) for Aeronautical Ad-hoc Networks. It works by splitting the regions into sub-regions as per the Voronoi diagram and computes the geographical path between source and destination by Fast-Forwarding method. Luo et al. (2017) mainly focuses on the civil aviation requirements and attempted to achieve good performances in terms the link durations, load balancing, and end-to-end delay. The neighbor discovery has been done by flooding the advertisement messages periodically. The routing tables are updated based on the reply messages from the neighbor. To avoid the congestion due to flooding of advertisement messages, they followed an optimization method with broadcast ID and IP address of the source node.

2.3 Artificial intelligence and routing in wireless networks

Artificial Intelligence (AI) is being applied in the wireless communication and networking area for the past several years for various aspects such as decision-making, interference mitigation, congestion avoidance, and network management. In recent years, networking researchers have been working to look into the power and importance of deep learning by exploiting their learning abilities in complex and dynamic environments in the wireless and mobile networking domain (Ge et al. 2019). AI concepts are capable of making a device intelligent by integrating Machine Learning (ML) and Deep Learning algorithms (DL). ML and DL are the subset of AI that enables the system to learn from the environment and produces better decisions by applying the learned model. DL is the extension of ML, which can predict the environment on its own without human interactions (Yahya et al. 2021; Safdari Shadloo 2021; Yahya and Aghel 2021).

Buzzi et al. (2016) analyzed the need to employ deep learning techniques for future wireless networks paradigm. As the world goes into the digital revolution, the massive number of connected devices to the internet urges innovative technologies (Kato et al. 2019) for densifying the infrastructures, antenna design, and energy-efficient network management systems to attain 1000-fold performances improvement in upcoming generation wireless networks compared with the existing wireless paradigm. Mohammadi et al. (2018) surveyed paradigm of applying DL on IoT devices was reviewed and numerous approaches to attain it were presented. In addition, they surveyed DL-based fog and cloud infrastructures to support IoT applications and identified the key requirements, technical challenges, and future research direction in integrating DL for IoT applications. MAO et al. (2018) concluded that the DL is more profitable in making wireless network management as intelligent in a complex wireless network with a large number of nodes in terms of searching the routing path and traffic load balancing. They have stated that, due to its similarity with human brain activity in learning from the dynamics, the multi-layered DL techniques such as RNN, CNN learn from high-dimensional raw data to come up with appropriate network behavior based on the analysis of various network parameters such as packet loss rate, delay, and signal-to-noise ratio.

Decisions on routing path selection must be efficient to ensure the required level of Quality of Service. DL started to be utilized in the network routing field to improve the efficiency of routing rules (Komeilibirjandi et al. 2020). To make energy-efficient routing, Assaf et al. (2016) used Multi-Layer Perceptron in WSNs, in the aspect of facilitating pollution monitoring. They used neural networks for providing efficiency threshold value and dynamically changes nodes that consume minimum energy than resulted threshold, thus improving energy efficiency. Qingchen Zhang et al. (2017) proposed a 3-layered deep neural network for node degree based on the provided information of the routing nodes. The classification results have been obtained for a temporary route that is further used for virtual route generation by using the Viterbi algorithm. Valentin Radu et al. (2016) employ Deep Belief Network (DBN) for choosing the next forwarding nodes and constructed a software-defined router. They achieved up to 95% of accuracy by utilizing the OSPF (Open Shortest Path First) as the optimal routing strategy. In their further attempt, tensors have been used to represent weights, biases, and the hidden layers of DBNs, by which they attained still more improved performance in routing.

3 Network model

This section describes the modeling of AANET. The network consists of 'N' number of moving aircrafts, each with half-duplex transceivers on a shared channel. An aircraft node is identified by its unique number $i \in \{N_1,\ldots, N_n\}$. A communication link between node i and j is represented as L_{ij}. Each aircraft is equipped with 1090 ES ADS-B In/Out systems which broadcast its position, velocity, and identity information to nearby aircrafts every half-seconds. Aircrafts are moving in various levels, namely (l_1, l_2,…,l_n) both in the same and opposite directions. This work considers the neighbor nodes flying in the same direction, as the aircrafts flying in opposite directions are not reliable due to the great impact of the Doppler shift (Gu et al. 2012). As per the standards of ICAO, the airspace is separated into multiple height levels below and above 29,000 ft. The separation between two neighboring levels is 600 m below 29,00ft and 300 m above 29,000 ft. All aircrafts flying in the same direction on the cruise stage are distributed in different levels as per the guidelines of ICAO. Figure 3 shows the distribution of flying aircrafts at different levels. The separation between two neighboring levels is denoted by 'h,' and 'k' denotes the total number of height levels. Two aircrafts can communicate with each other only if the distance between them is smaller than their communication range 'R', which is the same for all in this work.

The entire network imitates the Gauss-Markov model (Maakar et al. 2018) with ICAO separation standards with three dimensions. This model nearly depicts the real movement of aircrafts such as accelerate, decelerate, or

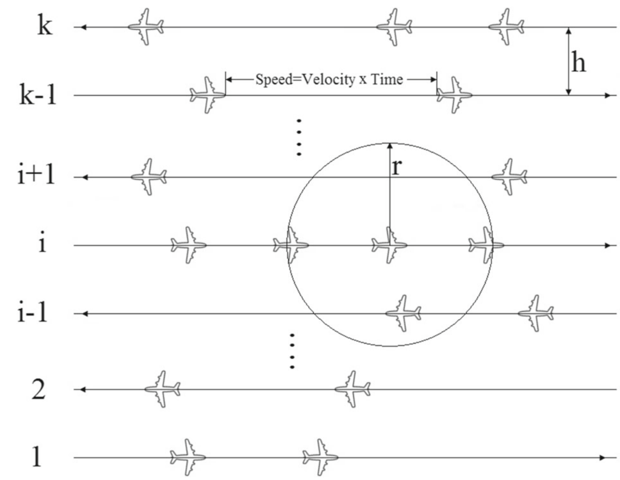

Fig. 3 Mobility model of an AANET

turn phase progressively. This model keeps track of the current movement of a node to compute the next position through Gaussian equations using average speed, direction, and Gaussian random noise. At a fixed level of intervals 'n', the current speed 's', direction 'd' and position of the aircraft (x, y, z) are updated using Eqs. (1), (2), (3), (4) and (5).

$$x_n = \alpha x_{n-1} + (1-\alpha)\bar{x} + \sqrt{(1-\alpha)^2} x_{x_{n-1}} \tag{1}$$

$$y_n = \alpha y_{n-1} + (1-\alpha)\bar{y} + \sqrt{(1-\alpha)^2} y_{x_{n-1}} \tag{2}$$

$$z_n = \alpha z_{n-1} + (1-\alpha)\bar{z} + \sqrt{(1-\alpha)^2} z_{x_{n-1}} \tag{3}$$

$$speed_n = \alpha speed_{n-1} + (1-\alpha)\bar{s} + \sqrt{(1-\alpha)^2 s_{x_{n-1}}} \tag{4}$$

$$dir_n = \alpha dir_{n-1} + (1-\alpha)\bar{d} + \sqrt{(1-\alpha)^2 d_{x_{n-1}}} \tag{5}$$

where α- tuning parameter, $\bar{s}$- mean speed, $\bar{d}$- mean direction, $s_{x_{n-1}}$ and $d_{x_{n-1}}$ are variables of Gaussian distribution used for adding randomness to the model. The variable α takes a value from 0 to 1. When $\alpha = 0$, the model becomes memoryless, and $\alpha = 1$, the movement of aircrafts is more predictable and imitates the cruise phase.

4 Proposed ANFIS based routing approach

The main aim of the proposed work is to enhance the QoS level of routing in highly dynamic multi-hop AANET by utilizing the deep learning concept. The problem of attaining QoS enhancement in routing is twofold; one is the metrics used for decision-making and the second is the decision-making approach on the next-hop selection. The poor design of these two steps leads to performance degradation of the routing protocol. Some of the existing works (Zhong 2016; Jabbar et al. 2009; Luo et al. 2017 and Sakhaee et al. 2006c) make the flooding of position information messages for neighbor discovery through Route Request Advertisement. In this work, ADS-B takes part in neighbor discovery whereby the aircrafts, which are in the transmission, range of the source is easily found with their coordinates, speed, and direction. In the routing metrics aspect, the link and node stability are mandatory for ensuring successful packet delivery. Excluding any one of these aspects also leads to poor network performance. The relative distance between source and neighbor toward an intended destination, relative speed, and queuing capacity is used to assess the link and node stability in the proposed systems. This work focuses on load balancing by calculating the queuing delay of every neighbor to reduce the packet loss rate. Moving toward managing the huge flight traffic, applying conventional ways for finding the appropriate next hop will be costly in terms of time and computation. Training aircraft as intelligent for automatically choosing the next hop in midst of need is a novel idea of this proposed work. To the best of our knowledge, this is the first work to make use of DL techniques in the field of AANET routing. This proposed work consists of three phases as shown in Fig. 4.

4.1 Neighbor discovery

4.1.1 ADS-B

ADS-B is a new aeronautic surveillance technology that has been applied broadly around the world in recent years (Strohmeier et al. 2014). ADS-B system consists of ground infrastructures and onboard transponders. This system provides two different services: ADS-B Out and ADS-B In as shown in Fig. 5. The ADS-B Out service uses onboard transponders to broadcast the aircraft position as well as other important flight information periodically down to the ground, or other interested receivers such as communication satellites and other aircraft. The ADS-B In service allows aircraft to receive ADS-B messages from nearby aircraft, and therefore to benefit from a clear understanding of the surrounding traffic situation. ADS-B Out service has been well developed in practical applications, as installation of qualified transponders has been mandatory in several countries, while ADS-B In-service remains an operational choice for airline operators. It has better precision, a higher refresh rate, and lower cost than traditional secondary radar (Schafer et al. 2016). Therefore, it is envisaged as a potential solution for air traffic surveillance in the context of nowadays-growing traffic.

Three different categories of ADS-B are available, namely 1090 MHz Mode S Extended Squitter (1090 ES), Universal Access Transceivers (UAT), and VHF Data Link Mode 4 (VDL Mode 4) (Lester 2007). The civil aircrafts make use of 1090 ES ADS-B systems, while the general aviation use UAT. In general, all geographical routing protocols start with the neighbor discovery phase to gather the eligible neighbors for packet forwarding to the destination. The existing routing methods adapt the beaconing procedure to ensure the availability of nodes in their transmission range. The identified neighbors are maintained in a table with the collected information by flooding beaconing messages periodically. To keep the discovery phase in higher accuracy, the beacon messages are kept on flooding by the source within a shorter time duration that results in higher traffic overhead and increases the end-to-end delay. This drawback has been resolved in this work by utilizing the ADS-B, which is GPS-enabled equipment available in the aircraft.

This ADS-B module sends its own aircrafts information such as position, speed, and unique identifier through its *Out* module to nearby aircrafts with a time interval of one second. The moving aircrafts receive this information through *In* module and display in cockpit part. The smaller frequency of time in updating the position information ensures the accuracy of the neighbor table and drastically reduces the traffic overhead. The physical layer specification of ADS-B and AANET is different, thus there is no interference between AANET data forwarding and ADS-B message transfer.

4.2 Next-hop selection

ANFIS, one of the deep learning algorithms is used to make decision-making on the next-hop selection within a short time efficiently in this study. In addition, the routing metrics for the next-hop selection must be framed in such a way that they should account for the conditions of both nodes and links available between source and destination. The existing work partly focused on this aspect either in node or in the link. In this work, both link stability between source and destination and the node capacity in terms of queuing delay for data forwarding is taken into account to ensure the QoS enhancement. The routing metrics are calculated as described below.

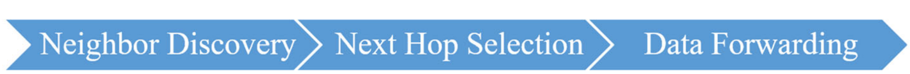

Fig. 4 Phases of ANFIS based routing

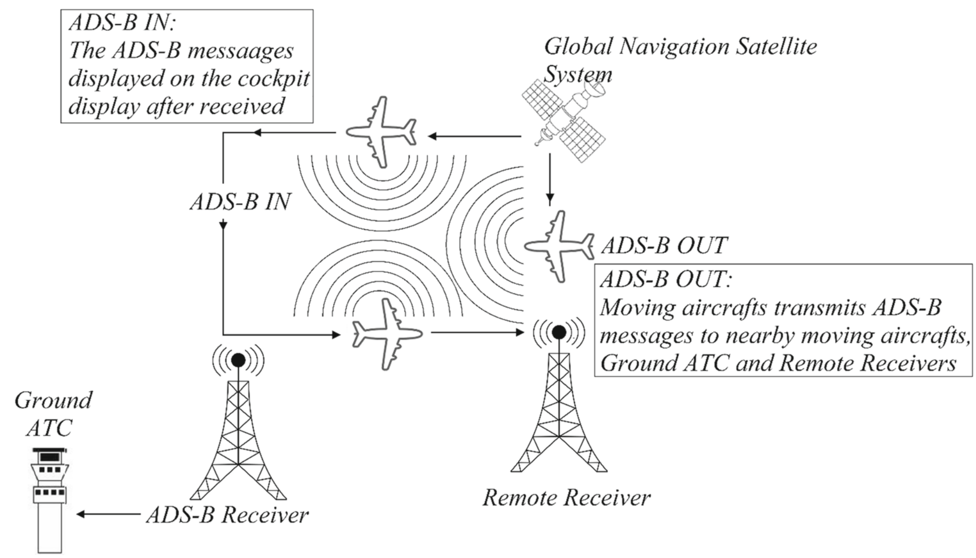

Fig. 5 Working of ADS-B system

4.2.1 Computation of the routing metrics

The source aircraft node of the packet is required to calculate the routing metrics of neighbors such as distance between the source and next hop, the distance between the next hop and destination, relative velocities of the nodes, and queuing delay of the neighbors to find the best next hop.

4.2.1.1 Distance between nodes Euclidean distance formula has been used to calculate the distance between two nodes as shown in (6).

$$ED_{m,n}(t) = \sqrt{(x_n(t) - x_m(t))^2 + (y_n(t) - y_m(t))^2 + (z_n(t) - z_m(t))^2} \quad (6)$$

where (x_m, y_m, z_m) and (x_n, y_n, z_n) are the positions of the node m and n, at time instance 't'.

4.2.1.2 Relative velocities of the node The relative velocity of two nodes 'm' and 'n' moving in same direction as shown in Fig. 6 is calculated using Eq. (7)

$$RV_{m,n} = v_m(t) - v_n(t) \quad (7)$$

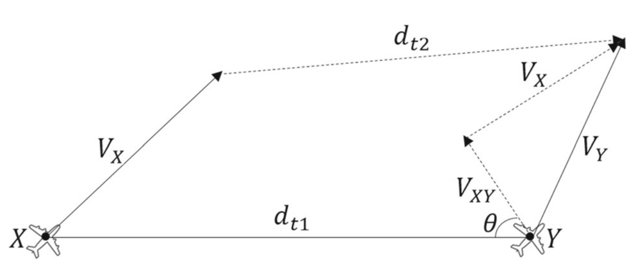

Fig. 6 Relative velocities of aircrafts

4.2.1.3 Queuing delay When a node is a common neighbor to more than one node, a bottleneck situation may arise as illustrated in Fig. 7. In such a situation, the node may be unable to forward the packets as the node is overwhelmed with too many packets in the queue, which leads to packet dropping and network congestion. To avoid this situation, the load is mitigated to nearby suitable neighbors by considering queuing delay by analyzing the queuing system of aircraft.

This work assumes that the aircraft system is implemented with multiple parallel servers, which has the following characteristics:

1. The arrival rate λ and service rate μ follow the Poisson distribution.
2. The utilization factor is $\rho = \frac{\lambda}{\mu}$

According to the M/M/1 model, the queuing delay of a node is calculated as,

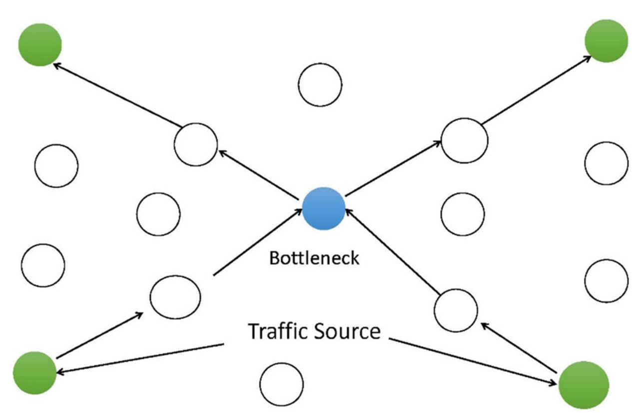

Fig. 7 Bottleneck situation in aircrafts

$$Q_n = \frac{\rho^2}{1-\rho} \tag{8}$$

where ρ is the utilization factor. As per Little's law, the number of packets is directly proportional to the waiting time.

In this work, ANFIS (Jang 1993) uses one input layer for feeding inputs, two hidden layers for processing the fuzzy rules, and one output layer for getting final crisp output as shown in Fig. 8. The network is trained with network moving scenarios and varying densities. The ANFIS attempts to find the next-hop with different combinations of distance, speed, and queuing delay. Upon receiving the fuzzy rules from the fuzzy inference module, the weights are adjusted in Layer-3 for normalization. The normalization helps to speed up the training of ANFIS, thus results in faster convergence. The normalized fuzzy rules are fed as input to the next layer, where defuzzification is done to get the final output. To find the next hop, the rules are framed by refining through the hidden layers of ANFIS by analyzing the different routing patterns of AANET.

Layer 1: Fuzzification

After calculating the routing metrics, the linguistics variables are framed as shown in Table 1. by analyzing patterns of the dynamic variations of the metrics with trapezoidal and triangular membership functions.

The triangular membership function is defined as,

$$\mu_A(x) = \left\{ \begin{array}{ll} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x \geq c \end{array} \right\} \tag{9}$$

The trapizoidal membership function is defined as,

$$\mu_A(x) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{10}$$

The nodes in this layer are adaptive and the aforementioned membership functions are applied over the routing metrics using (9) and (10). The output of this layer is in form as shown in (11)

$$O_{1,i} = \begin{cases} \mu_{Ai-2}(x), & for\, i = 1,2 \\ \mu_{Bi-2}(y), & for\, i = 3,4 \end{cases} \tag{11}$$

In this work, the value of i is five for all the inputs. Ai denotes the linguistic variable assigned to the routing metrics (such as Nearest, Far, Less and more).

Layer 2: Fuzzy rule formation

In Layer-2, the fixed nodes are labeled as π and each node performs fuzzy operation AND to fuzzify the given inputs (x, y). In this work, four inputs are used, namely distance between source and next hop, the distance between next-hop and destination, relative speed, and queuing delay. The output of this layer is named as firing strength of the fuzzy rules as it helps to conclude the precise output by reasoning the given inputs. It is represented as shown in (12),

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad i = 1,2 \tag{12}$$

The formed fuzzy rules are in the form as described as follows:

$$\begin{array}{l} \text{Rule}_{(1)}: \text{IF } x \text{ is } A_1 \text{ AND } b \text{ is } B_1, \text{ Then } F_1 = r_1 a + s_1 b + t_1 \\ \text{Rule}_{(2)}: \text{IF } y \text{ is } A_2 \text{ AND } b \text{ is } B_2, \text{ Then } F_2 = r_2 a + s_2 b + t_2 \end{array} \tag{13}$$

where, x, y are the inputs, A_1, B_1 are the fuzzy sets, F_i is the outputs of the fuzzy rule, r_i, s_i, t_i are design parameters that are decided in the course of the training. According to

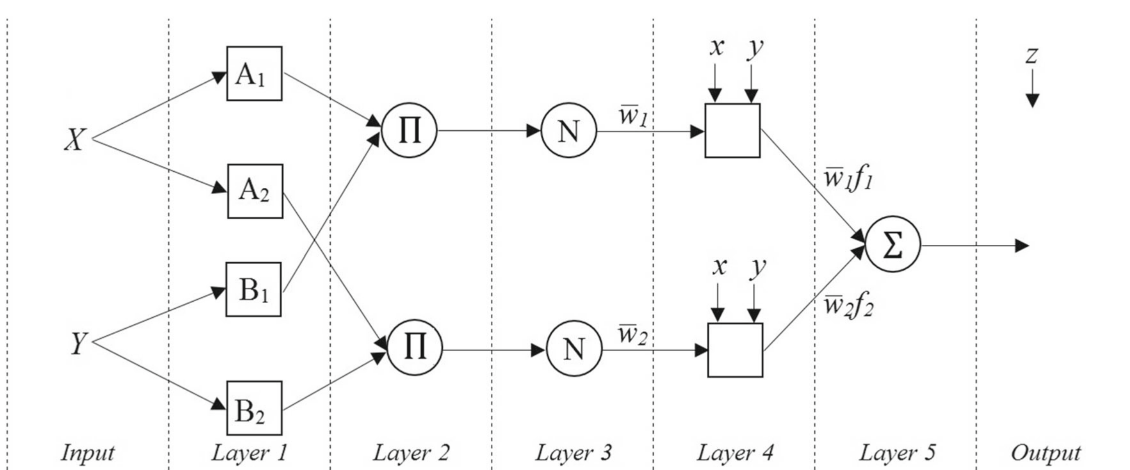

Fig. 8 Typical ANFIS Layered Architecture

Table 1 Linguistic variables

Crisp input	Linguistic variables	Membership function
Dist (S,Neigh) & Dist (Neigh, D)	0–20%: Nearest	Trapmf
	15-35a% %:Medium Nearest	Trimf
	35–45%: Medium	
	45–70%: Less Far	
	70–100% Far	Trapmf
RV & QC	0–15%: Very Less	Trapmf
	15–30%: Less	Trimf
	30–45%: Average	
	45–67%: More Average	
	67–100%:More	Trapmf

Table 2 Fuzzy rules

Dist.(S, Neigh)	Dist.(Neigh, D)	RV	QC	Next hop choice
Nearest	Nearest	Very Less	Very Less	Very Strong
Nearest	Nearest	Very Less	Less	Strong
Nearest	Nearest	Very Less	Average	Less Strong
Nearest	Nearest	Very Less	More Average	Highly Medium
Nearest	Nearest	Very Less	More	Medium
Medium Nearest	Medium Nearest	Very Less	Very Less	Less Strong
Medium Nearest	Medium Nearest	Very Less	Less	Highly Medium
Medium Nearest	Medium Nearest	Less	Very Less	Strong
Medium Nearest	Medium Nearest	Less	Less	Less Strong
Medium Nearest	Medium Nearest	Less	Average	Highly Medium
Medium Nearest	Medium Nearest	Less	More Average	Medium
Medium Nearest	Medium Nearest	Less	More	Less Medium
Medium	Medium Nearest	Very Less	Very Less	Strong
Medium	Medium Nearest	Very Less	Less	Less Strong
Medium	Medium Nearest	Less	Very Less	Highly Medium
Medium	Medium Nearest	Less	Less	Medium
Medium	Medium Nearest	Less	Average	Less Medium
Medium	Medium	Very less	Very less	Highly Medium
Medium	Medium	Average	Very Less	Medium
Medium	Medium	More Average	Less	Less Medium
Medium	Medium	More	Average	Less Weak
Medium	Medium	More	More Average	Weak
Medium	Less Far	Average	Average	Less Weak
Less Far	Less Far	Average	Average	Less Weak
Less Far	Less Far	Average	More Average	Weak
Far	Far	More Average	More Average	Less Weak
Far	Far	More	More	Very Weak

patterns of the routing metrics, the fuzzy rules are formed as shown in Table 2.

Layer 3: Normalization

In Layer-3, nodes are fixed labeled as 'N' as it involves with normalization role to fire the strength to the next layer. The output of the layer is denoted as,

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \; i = 1, 2 \tag{14}$$

Each node calculates the ratio of firing strength of its own rule with the sum of all rule's firing strength.

Layer 4: Aggregation

In Layer-4, nodes are adaptive where each adaptive node produces output as the product of normalized firing strength from the previous layer as shown in (15),

$$O_{4,i} = \overline{w}_i f_i = \overline{w_i}(r_i x + s_i y + t_i),\ i = 1,\ 2 \tag{15}$$

Layer 4: Defuzzification

In Layer-5, the fixed node labeled as Σ performs a summation of all inputs from the previous layer. The step deals with centroid defuzzification of the previous layer output and expressed as,

$$O_{5,i} = \sum_i \overline{w} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{16}$$

Finally, Reachable Time (RT) is observed from ANFIS for all the neighbors identified in the neighbor discovery phase. A neighbor with a less RTi value is chosen as the appropriate next hop for packet forwarding.

$$RT_i = \sum_{i=1}^{N} \min(O_{5,i}) \tag{17}$$

4.3 Data forwarding

When an aircraft has data to send, it searches for the eligible neighbors from ADS-B messages as described in (Sect. 4.1). The aircraft which is more optimum to forward the data to its intended destination identified by the deep learning assisted next-hop selection in (Sect. 4.2). The data are forwarded through the identified neighbor as per the procedure mentioned below in Fig. 9.

5 Results and discussion

The proposed work was simulated with real-time ADS-B datasets collected from Open Sky Network, which aims to provide live aircraft information. The simulation parameters for routing are shown in Table.3. This work evaluates the network performance concerning the node distribution of nodes, namely Sparse and Dense networks. The observed routing metrics, namely, the distance between source and next hop, the distance between next-hop and destination, relative speed, and queuing delay are fed as inputs to the fuzzy inference module to get fuzzified output. The linguistic variables of the input variables are discussed in the previous section. For all routing metrics, the lower and higher values of linguistic variables have been calculated by using trapezoidal membership functions to filter the best and worst options with wider coverage. The middle values of linguistic variables are calculated based on the triangular membership functions to accurately pick the aircrafts in moderate capacity. Due to the nature of easy computation and suitability to real-time implementations, these two membership functions have been used here. For each routing metric, lower and upper bound are computed by applying trapezoidal membership functions and the intermediate values are calculated by using triangular membership functions. Figure 10 shows the linguistic values for the distance between source and neighbor and neighbor to destination. The fuzzy set values are Nearest, Medium Nearest, Medium, Less far, and Far. Figure 11 shows the linguistic values for the Relative Velocity, namely Very Less, less, More Average, More. Figure 12 shows the linguistic values for the Queuing Capacity, namely Low, Average Low, Average, More Average, More. Figure 13 shows the linguistic values or the Member Choice, namely Very Weak, Weak, Less Weak, Less Medium, Medium, High Medium, Less Strong, Strong, and Very Strong. Figure 14 shows the Neuro-Fuzzy approach followed by the proposed work for approximating nonlinear functions. This model takes one input and produces output for the next layer. Figure 15 shows the distribution of moving aircrafts in the simulation area.

The impact of communication range in average time to link breakage is shown in Fig. 16. This figure depicts how reliable the proposed method when increasing the communication range and helps to identify the optimal communication range in civil AANET. The smaller transmission range exhibits greater link interferences in the network due to which the link fails too shortly. The reliability measures how much time the link is available between two pairs of nodes. When the communication range is very less, the possibilities of having interference are very high, which will negatively impact packet transmission. When the transmission range is extended, the number of nodes for packet forwarding will be more. This reduces the congestion and interferences among links, which increases the time for link breakages. When the transmission range goes beyond 300 km above, the time links take to break gradually increases with any number of nodes. In contrast, the link existence between pairs of aircrafts is shown in Fig. 17. The higher transmission range and the larger number of nodes help to retain the links among nodes and possibly reduce the number of relays or hops to reach the destination.

5.1 Proposed method evaluation

The performance of the proposed approach is evaluated under varying packet sizes and packet inter-arrival rate in dense civil AANET, where nodes are thickly scattered. As shown in Fig. 18a–c, the packet size varies from 128 to 1024 Kbytes. Generally, the small packets consume less amount of time for complete transmission, also able to cover larger distances. Because of the dense nature and

Fig. 9 Pseudo code for data forwarding

Data Forwarding Algorithm

```
Input: S,D, List_neigh, n_h
List_neigh ← List of neighbor aircrafts in the transmission range
of S
n_h ← $, initialized to $ for storing the next hop
Begin
While (D)
    search ( List_neigh)
    n_h ← execute ANFIS(List_neigh)
      If (n_h==D)
          forwardData(D)
      else
         repeat
          S:forwardPacket(data, n_h)
      End If
End
```

Table 3 Simulation parameters

Parameters	Values
Simulation Area	500 × 50 km
PHY Layer	IEEE 802.11 a
CBR Packet Size	4096 Kbits
CBR sending rate	200 kbps
Propagation model	Free Space
Transmit power	51 dBm
SNR Threshold	6 dBm
Antenna Used	Omni Directional
Path Loss Model	Free Space
Average Speed	250 m/s
Simulation Time	15 min

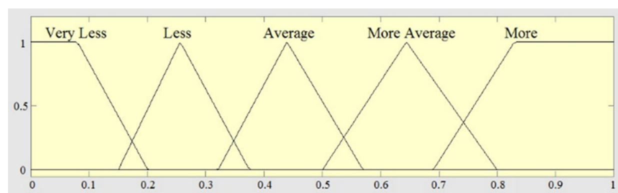

Fig. 11 Linguistic values for relative velocity

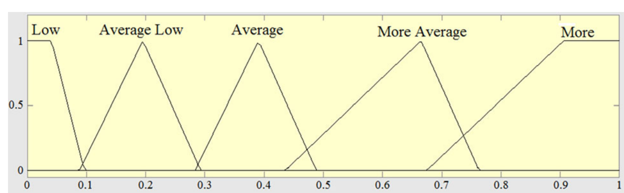

Fig. 12 Linguistic values for queuing capacity

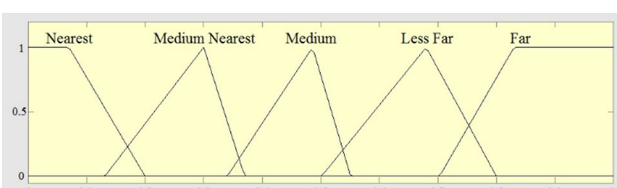

Fig. 10 Linguistic values for distance between Source and neighbor

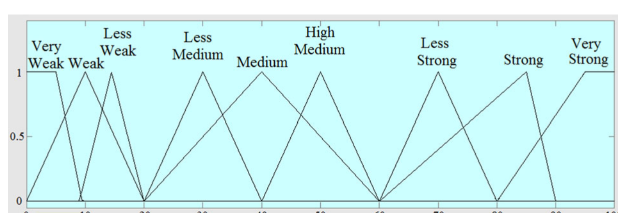

Fig. 13 Linguistic values for member choice

high transmission range with more reliable links as shown previously, the e2e delay is greatly reduced. The reason is source and destination can reside between the large communication range (R = 500 km), hence reduces the end-to-end delay. Increasing the packet sizes leads to more processing at each hop, specifically in a dense environment, which results in more end-to-end delay. Therefore, the 1024 KB packets lead to a 230 ms end-to-end delay on

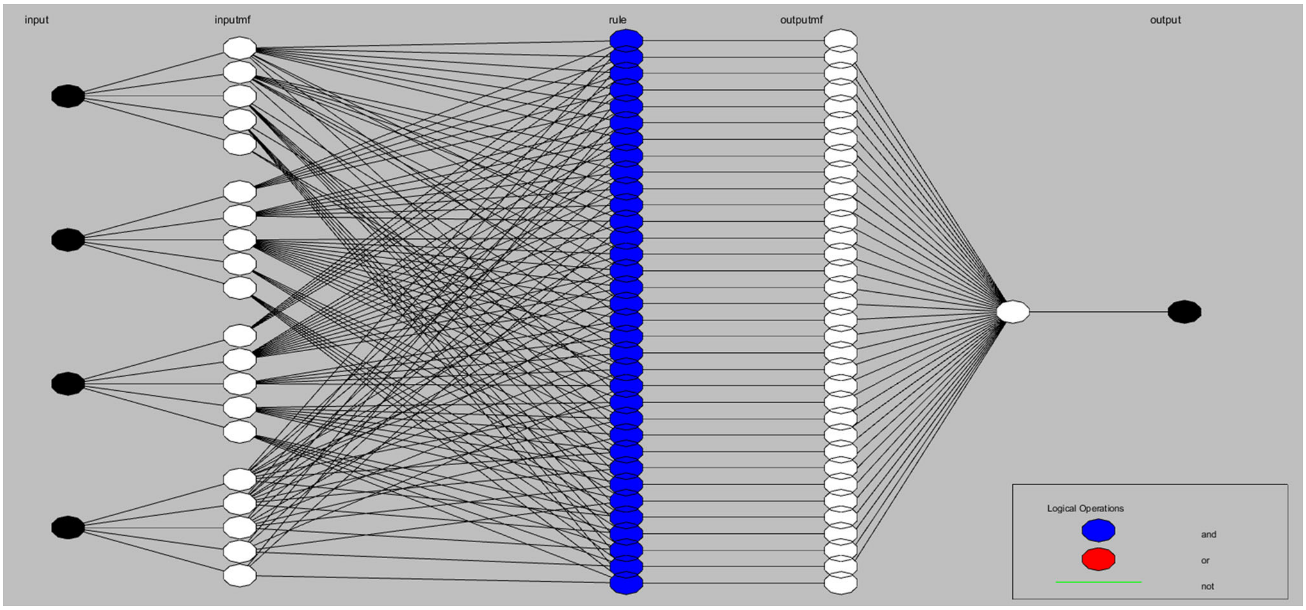

Fig. 14 Neuro-Fuzzy process of proposed approach

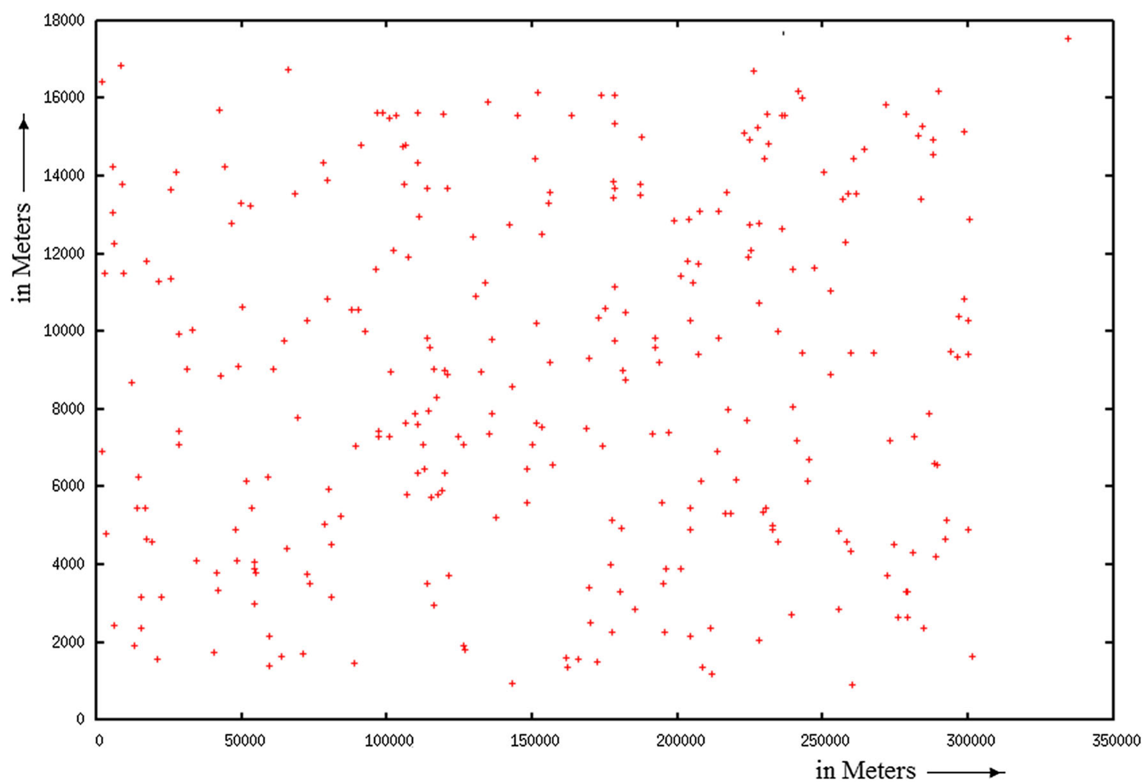

Fig. 15 Distribution of aircrafts

average when the packet inter-arrival time goes beyond 4 secs as shown in Fig. 18a. In the case of traffic overhead, the ADS-B module of the proposed work plays a significant role in drastically reducing the traffic overhead. Due to this, the QoS performance in terms of overhead is improved considerably. For instance, with short packet inter-arrival time and small packet sizes, the overhead is increasing gradually and takes an average overhead of 2.7 Mb/s in dense civil AANET as shown in Fig. 18b. With huge packet sizes also, the overhead is slowly increased which produces significant outcomes in the proposed QoS routing. The QoS in terms of PDR under different packet sizes

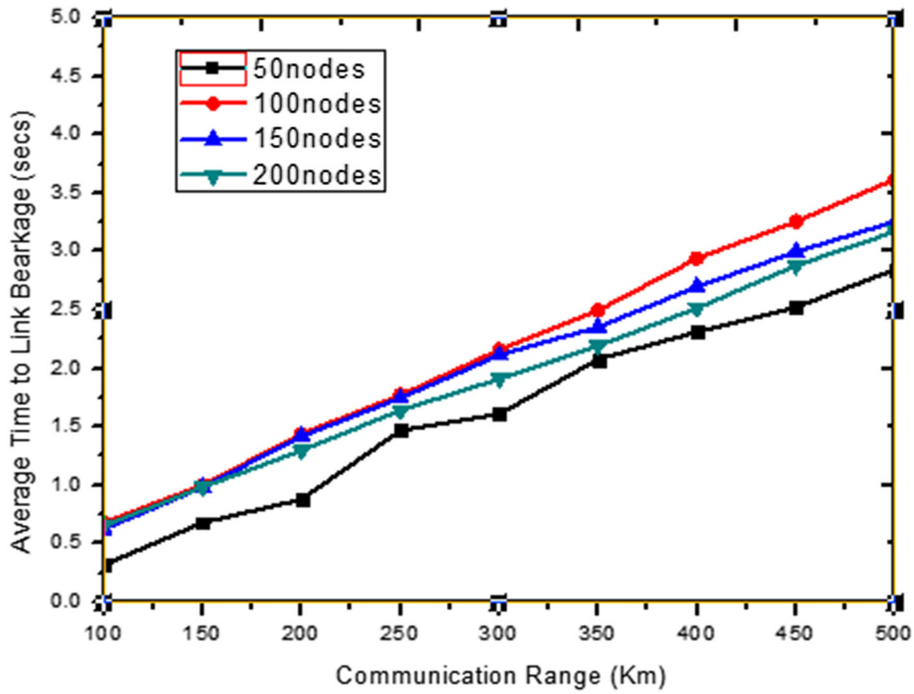

Fig. 16 Average time to link break

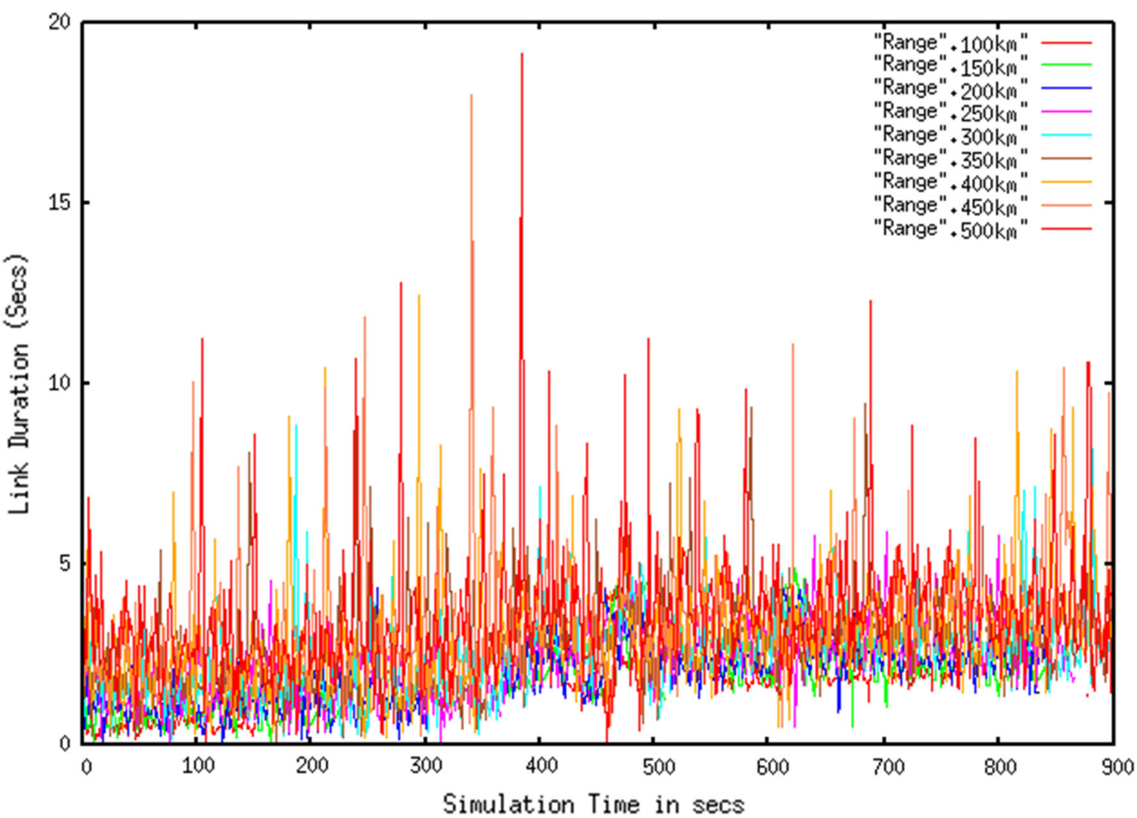

Fig. 17 Link duration between pairs of aircrafts

is shown in Fig. 18c. Generally, in a congested medium, increasing the packet sizes leads to decrease PDR. To cope up with this situation, this method considered the possible cause of congestion as mentioned earlier. Hence, increasing the packet sizes and inter-arrival time shows less difference in PDR when compared with small packet sizes.

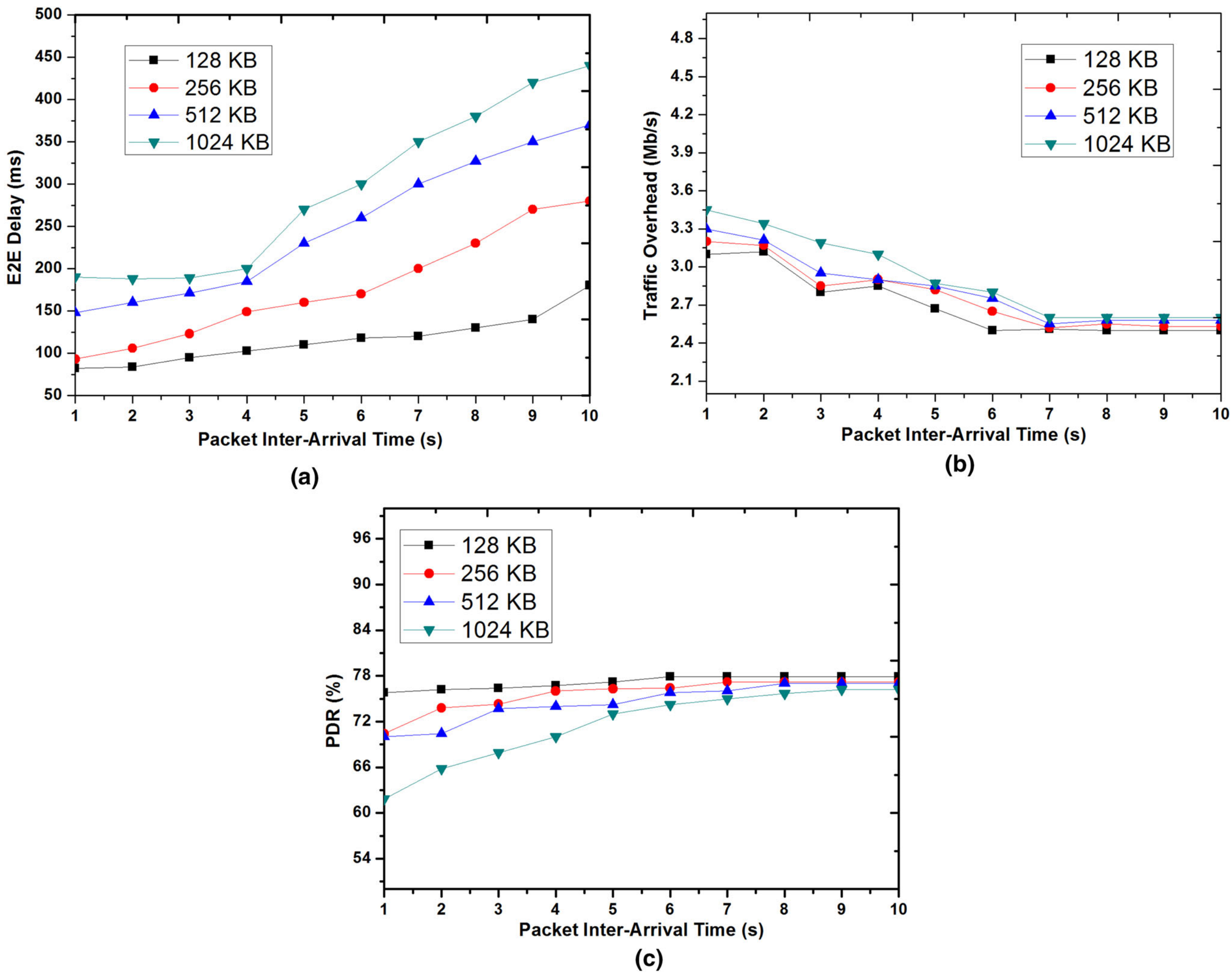

Fig. 18 QoS performances with varying packet sizes

The evaluation of the proposed approach under three different network scenarios (sparse, moderate, and dense civil AANET) has been carried out and shown in Fig. 19. In the sparse AANET, the nodes are thinly scattered and fewer nodes exist inside the communication range. In the case of moderate civil AANET, a considerable amount of nodes could be inside the communication range, whereas in the dense AANET, the nodes are thickly scattered. All three different scenarios have the same transmission range with the different random distributions of nodes. Connectivity plays a major role in networks with different node distributions (Liu et al. 2015). In a dense network, nodes are thickly connected, which indirectly means that the network is connected always. As a result, possibilities of the source and destination pair existence inside the transmission range have a high probability. This leads to better QoS performances in terms of PDR, traffic overhead, and end-to-end delay in a dense network. The reasons are first, the possible congested nodes are identified and neglected to be next hop by the proposed work, hence packets drops are reduced. Second is, the ADS-B based neighbor discovery aids in improving the accuracy of overall routing through the update of the global state of the network every second. The third is the hybrid learning method of the neuro-fuzzy method finds the accurate relay nodes with sufficient resources. In moderate civil AANET, the probability of connectivity is 0.5, which means there are link breakages due to which PDR, traffic overhead, and end-to-end delay are affected as shown in Fig. 19a–c. Hence, the possibilities of suitable relays nodes are less than the dense network. As a result, the moderate network exhibits average QoS performances. In a sparse network, the network is highly disconnected because of the unavailability of links among nodes. Due to insufficient resources, routing in a sparse network degrades QoS performances in terms of PDR and end-to-end delay. Simultaneously, less overhead is experienced as less number of nodes inside the

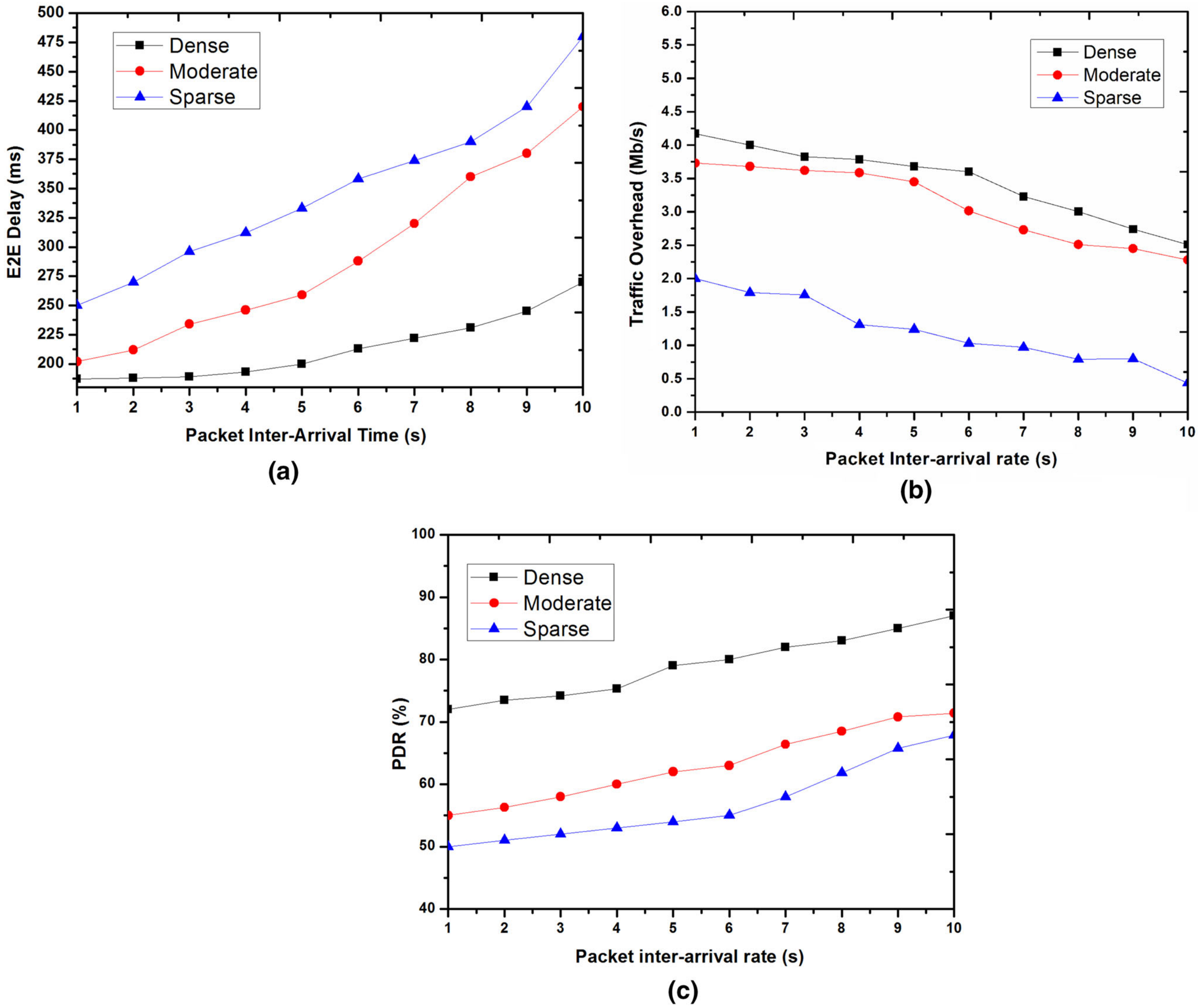

Fig. 19 QoS performances with different network densities

transmission range. The neuro-fuzzy model refines the result with less accuracy with the small number of data.

5.2 Comparative analysis of proposed with existing methods

The proposed method compares QoS performances with existing methods A-GR (A novel Geographic Routing) and GRAA (Geographic Routing Protocol for Aircraft Ad hoc Networks) in terms of packet delivery ratio, end-to-end delay, traffic overhead concerning the increasing number of nodes, packet inter-arrival time. Figure 20a, b illustrates the proposed method's QoS performances in terms of packet delivery ratio (PDR) concerning increasing the number of nodes. In the dense network shown in Fig. 20a, all the routing protocols (proposed, A-GR and GRAA) face difficulty when the number of nodes increases. Amid the increasing crowd, the proposed approach achieves a higher packet delivery ratio up to 69% which is higher than A-GR and GRAA in a stable manner even after with increasing nodes as the Neuro-fuzzy module classifies the scenarios well with larger dataset size and fairy allocate loads to nodes. Due to the lack of queue management aspects in the existing approach, their PDR is suddenly reduced when the number of nodes started increasing. In the case of A-GR, ADS-B assistance is utilized for accomplishing neighbor discovery, it also shows a stable increase in PDR than GRAA but lesser than the proposed approach. The GRAA follows the broadcasting of messages to collect the neighbor information; it starts to degrade in its PDR as the number of nodes reaches 55 as all the nodes periodically broadcast the beacon messages. In addition, the network is easily congested with its broadcasting nature has no facility

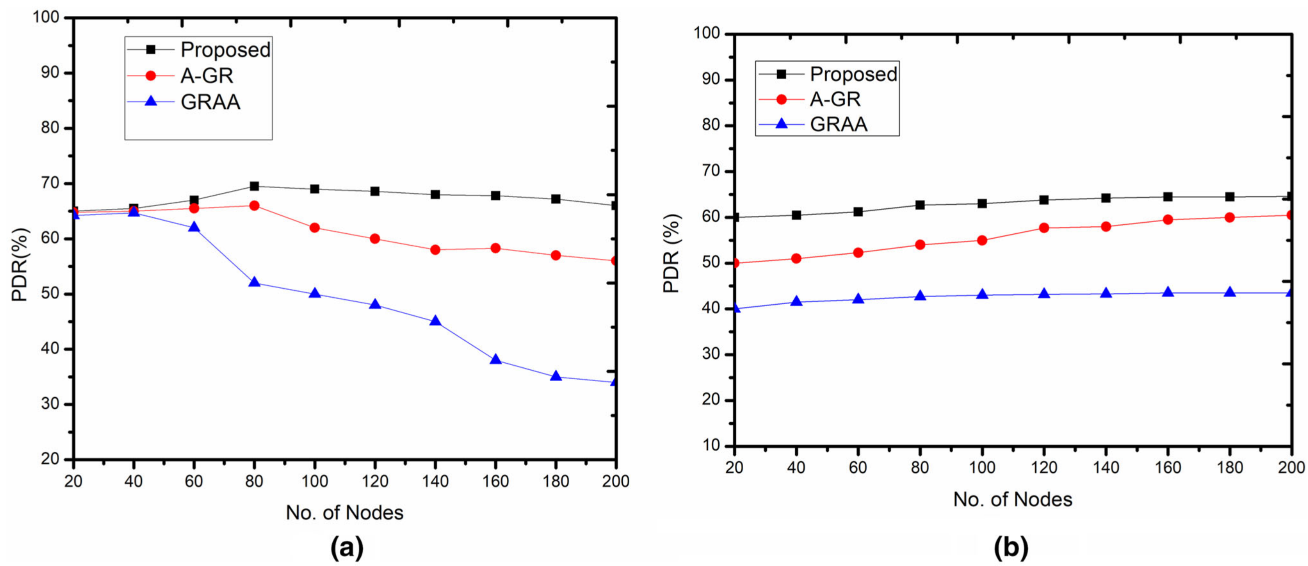

Fig. 20 QoS performances in terms of PDR concerning the number of nodes **a** Dense network Scenario, **b** Sparse network Scenario

to relaxing the bottleneck situation; it fails to achieve greater PDR.

The sparse network shown in Fig. 20b leads to poor PDR when employing all the routing protocols due to the nature of scatterings of node distribution. The proposed approach exhibits a slow increase in PDR even with an increasing number of nodes. Nevertheless, the accuracy of Neuro-Fuzzy with an increasing number of data samples helps to predict the optimal path, as a result, it can attain a higher 65% PDR comparing with the existing approach. In contrast, A-GR achieves considerable PDR than GRAA due to the accuracy of ADS-B assisted neighbor discovery phase. The GRAA starves to achieve PDR as it relies on the traditional way for collecting neighbor information that often produces inaccurate data, as the nodes are highly mobile.

Figure 21a and b shows the proposed method's QoS performances in terms of end-to-end delay concerning increasing the number of nodes. In the context of end-to-end delay, the Neuro-Fuzzy approach shows lesser end-to-end delay than A-GR and GRAA due to the intelligent decisions made by each node on the optimal selection on next hop on receiving the accurate position, speed, and direction information. With the increasing number of nodes, NFRP finds more options to find a suitable neighbor that aids to deliver the packets in less time. However, when nodes are below 80, NFRP shows increased delay than A-GR. In the case of A-GR, its delay is overlapped with the proposed work when the number of nodes is less. When the number of nodes starts to increase, the delay in A-GR also starts to increase because of the non-availability of the load balancing mechanism, whereas GRAA shows a gradual increase in its end-to-end delay. In a sparse scenario, the delay is considerably increased for all the routing protocols due to the scarcity of neighbors. In addition, due to link unavailability or highly disconnected nature leads to poor performance in finding the next hop, which in turn greatly increases the overall end-to-end delay in all the methods. However, the neighbor discovery phase and the consideration of congested nodes the proposed method helps to improve the end-to-end delay.

Figure 22 shows the QoS performance of the proposed method in terms of traffic overhead with an increasing number of nodes. In the simulation, routing overhead includes the position, velocity information of neighbors, and beacon messages used for neighbor discovery. As NFRP and A-GR assisted with the ADS-B module, it shows lesser overhead than GRAA. In the proposed method, every node broadcasts its position and velocity information through their ADS-B Out module and ADS-B In modules receives the nearby neighbors every second. Hence, the global state of the network is updated accurately without any need for beacon messages. This module helps to attain appropriate next-hop with lesser overhead compared with existing methods. The NFRP shows very less routing overhead than A-GR as the load balancing mechanism. Due to the lack of advanced methodologies for neighbor discovery and load balancing GRAA gives higher overhead than A-GR and proposed work. In a sparse network scenario, all the routing approaches result in reduced overhead than that of a dense network as the neighbors within the transmission range will be very less with poor routing capabilities. Hence, few nodes are probable to take part in forwarding. However, with the aid of intelligent decisions, the proposed work can find an appropriate hop

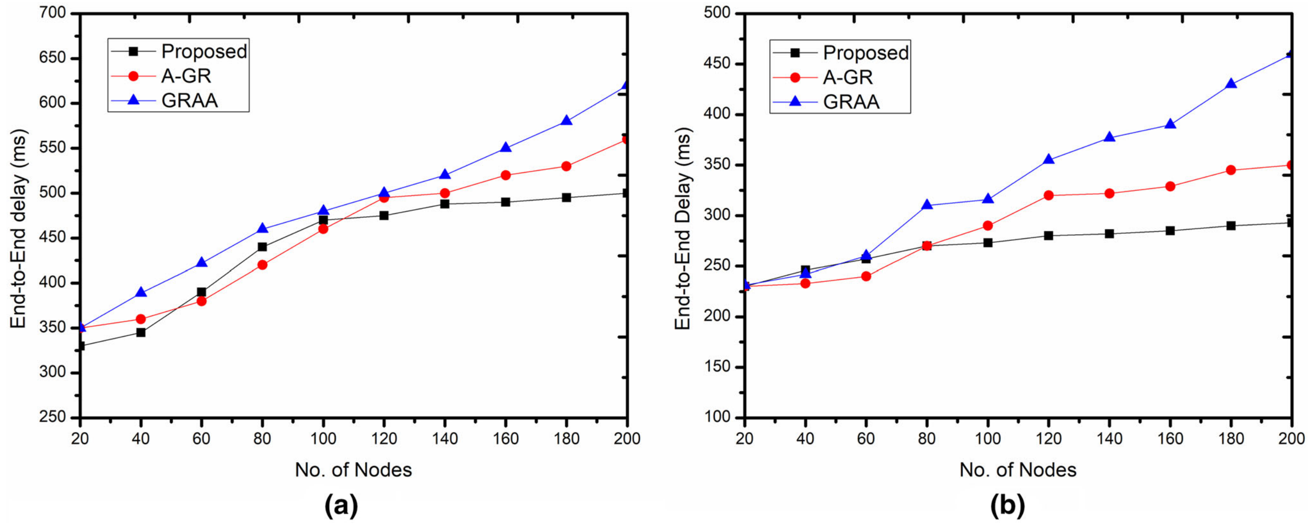

Fig. 21 QoS performances in terms of end-to-end delay concerning the number of nodes **a** Dense network Scenario, **b** Sparse network Scenario

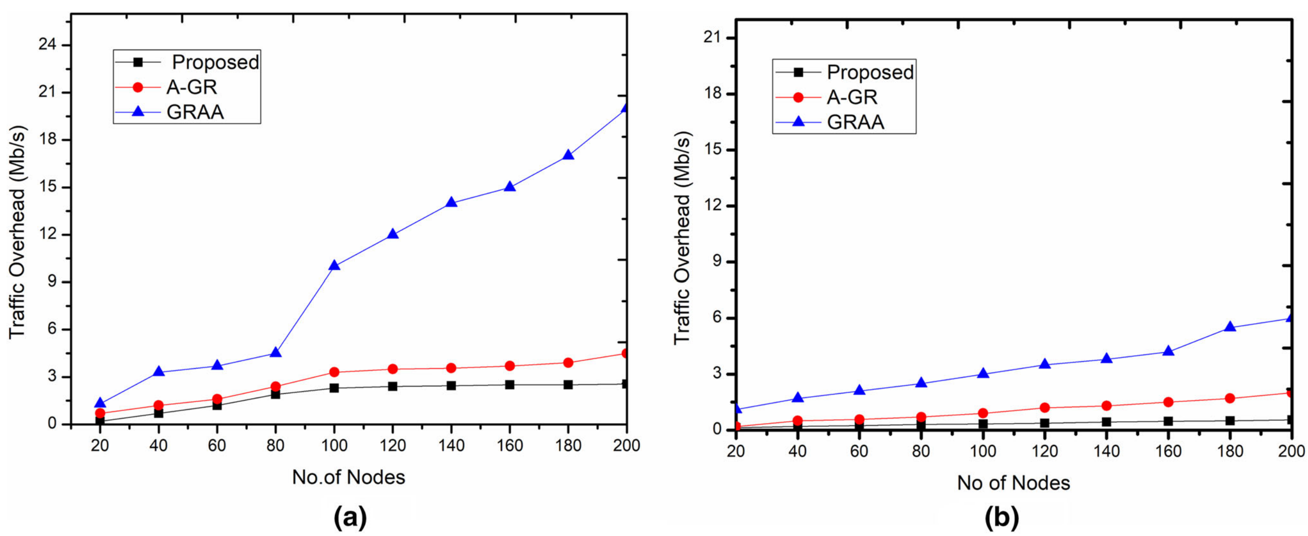

Fig. 22 QoS performances in terms of traffic overhead concerning the number of nodes **a** Dense network Scenario, **b** Sparse network Scenario

toward a destination without accumulating the packets anywhere in between source and destination.

5.3 One-way ANOVA statistical test

One-Way ANOVA (Analysis of Variance) has been carried to draw the conclusion, where the Null Hypothesis and Alternative Hypothesis are clearly shown below the table. Sparse and dense network scenarios are taken into account to derive the conclusion of the QoS performances as sparse denotes highly disconnected, and dense denotes highly connected network. The alpha value considers being 0.05.

Table 4 compares the proposed method's performance of QoS with A-GR, and GRAA methods in sparse network scenario and dense network scenario. In a comparison of sparse network scenario, the PDR of the proposed method has been improved by 11.29% compared to A-GR and 32.24% compared to GRAA. The end-to-end delay of the proposed method has been reduced by 9.27% from the end-to-end delay of the A-GR method and 12.81% from the end-to-end delay of the GRAA method. The traffic overhead of the proposed method has been reduced by 66.67% from the traffic overhead of the A-GR method and 89.46% from the traffic overhead of the GRAA method.

In a comparison of the dense network scenario, the PDR of the proposed method has been improved by 9.06% compared to A-GR and 26.83% compared to GRAA. The end-to-end delay of the proposed method has been reduced by 7.62% from the end-to-end delay of the A-GR method and 19.74% from the end-to-end delay of the GRAA

Table 4 Descriptive statistics

	Sample size	PDR			E2e delay			Traffic overhead		
		Mean	SD	SE of Mean	Mean	SD	SE of Mean	Mean	SD	SE of Mean
One-Way ANOVA Statistical Test in Sparse Network										
Proposed	10	62.90	1.75	0.55	442.30	64.23	20.31	0.35	0.14	0.04
A-GR	10	55.80	3.87	1.22	487.50	85.54	33.89	1.06	0.58	0.18
GRAA	10	42.62	1.14	0.36	507.30	104.95	56.86	3.34	1.59	0.50
		PDR			E2e delay			Traffic overhead		
	Sample size	Mean	SD	SE of Mean	Mean	SD	SE of Mean	Mean	SD	SE of Mean
One-Way ANOVA Statistical Test in Dense Network										
Proposed	10	67.36	1.51	0.77	270.60	20.41	6.45	1.87	0.86	0.27
A-GR	10	61.26	3.86	1.22	292.92	46.79	14.80	2.84	1.28	0.41
GRAA	10	49.29	11.62	3.67	337.13	78.74	24.90	10.08	6.54	2.07

**SD*, Standard Deviation; *SE*, Standard Error

method. The traffic overhead of the proposed method has been reduced by 34.03% from the traffic overhead of the A-GR method and 81.44% from the traffic overhead of the GRAA method. The overall ANOVA statistical test results are listed in Table 5 for both sparse network scenario and dense network scenario.

The statistics test finalizes that the conclusion can be drawn as the methods are significantly different in all the QoS parameters considered. In addition, the empirical correlation analysis depicts the strength and the direction of the relationships among the parameters. Table 6 describes the strength of the correlation coefficients, where the possible correlation coefficients range from = 1 to − 1.

6 Conclusion

Cellular-based AANET can be used as an alternative communication system for satellite-based AANET over remote or oceanic regions to realize In-Flight Wi-Fi. The distinguishing features of AANET such as higher mobility, frequent topology changes, node distribution, limited bandwidth, and the drastic growth of air traffic urge the researchers to come up with efficient as well as intelligent decision-making in the course of routing to ensure the quality of service. For capturing the reality of moving aircrafts, ICAO separation standards are incorporated in Gaussian mobility modeling. In this work, one of the deep learning techniques called ANFIS is employed for efficiency and intelligence in the routing process. A complementary system of radar called ADS-B is used in the neighbor discovery phase. The neighbor information is updated every second in moving aircrafts through the In/Out mode of ADS-B, thus ensures accuracy in location information of fast-moving aircrafts. The routing metrics play a vital role in selecting the next-hop to achieve greater performance in routing. This work takes four metrics, namely distance between source to the neighbor, the distance between neighbor to destination, the relative speed between source and neighbor, and the queuing delay of the neighbor into account. To avoid the situation of overwhelming nodes, queuing delay is considered in this work. The fuzzification step produces the linguistics values for routing metrics, followed by fuzzy rules are framed. The process of refining fuzzy rules is done in hidden layers of the ANFIS method and then the centroid defuzzification is applied to get the final output. The results section shows the effect of updated Gaussian mobility modeling in terms of the average time for link breakages and link availability between pairs of source and destination aircrafts and performance of the proposed routing protocols in terms of packet delivery ratio, end-to-end delay, and traffic overhead with varying packet sizes and packet inter-arrival time. The proposed method has maximum improvement in PDR, end-to-end delay, and traffic overhead of 32.24%, 19.74%, and 89.46%, respectively, in comparison with GRAA. And in comparison with A-GR, the proposed method has improvement in PDR, end-to-end delay, and traffic overhead of 11.29%, 9.27%, and 66.67%, respectively. This is a notable improvement in civil AANET. As increasing the accuracy of the system, the computational complexity also increases proportionally, which is the limitation of this work. More routing metrics and fuzzy rules will make the system computationally complex, results in higher accuracy. This method is highly advantageous in complementary civil AANET for QoS routing

Table 5 Overall ANOVA test

	DF	PDR SS	PDR MS	PDR *F* value	PDR $P > F$	E2e delay SS	E2e delay MS	E2e delay *F* value	E2e delay $P > F$	Traffic overhead SS	Traffic overhead MS	Traffic overhead *F* value	Traffic overhead $P > F$
One-way ANOVA statistical test in sparse network													
Between Groups	2	2118.00	1059.00	164.26	7.77 E-16	153,429.50	5682.57	0.94	0.07132	48.80	24.40	25.35	6.3504E-07
Within Groups	27	174.06	6.45			10,380.80	5190.40			25.99	0.96		
Total	29	2292.08				163,810.30				74.79			
One-way ANOVA statistical test in dense network													
Between Groups	2	1690.05	845.03	16.66	1.94E-05	22,932.34	11,466.17	3.91	0.03236	402.65	201.32	13.39	9.1152E-05
Within Groups	27	1369.44	50.72			79,253.27	2935.31			405.92	15.03		
Total	29	3059.49				102,185.61				808.57			

*DF, Degree of freedom; SS, Sum of squares; MS, Mean Squares; F, F-statistics; P, Probability

Null Hypothesis: The means of all levels are equal

Alternative hypothesis: The means of one or more levels are different

At the 0.05 level, the population means are significantly different

Table 6 Correlation between network density and QoS performances

Correlation coefficient	Description
+ 1.0	Perfect positive + Association
+ 0.8 to 1.0	Very strong + Association
+ 0.6 to 0.8	Strong + Association
+ 0.4 to 0.6	Moderate + Association
+ 0.2 to 0.4	Weak + Association
0.0 to 0.2	Very Weak + or No Association
0.0 to − 0.2	Very Weak−or No Association
− 0.2 to − 0.4	Weak−Association
− 0.4 to − 0.6	Moderate−Association
− 0.6 to − 0.8	Strong−Association
− 0.8 to − 0.1	Very strong−Association

because of the capability of dealing with increasing air traffic.

In the future, the work will be extended in the following directions,

i. Cross layered approach is to be adapted by coupling the Network and MAC layer, where the channel allocation and routing will be combined to properly utilize channels.
ii. Software-Defined Networking (SDN) for monitoring the state of the AANET properties concerning the QoS requirements of the corresponding applications. Also, it manages the forwarding of data packets to flows according to the service priorities.
iii. Investigation on QoS routing optimization problems and ε-constraint multi-objective optimization will be employed by considering the tradeoff among conflicting parameters of AANET.

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Declarations

Conflict of interest The author declares that he has no conflict of interest.

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