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DEVELOPMENT OF A ROUTING METHOD FOR GROUND-AIR AD-HOC NETWORK OF SPECIAL PURPOSE

The object of the study is the process of forming control decisions to ensure the operation of the ground-air communication network routing subsystem based on neural network algorithms. The carried-out research is based on the application of the numerical-analytical approach to the selection of modern scientific and applied solutions for building management models for promising Ad-Hoc communication networks. In the Google Collab simulation environment, using the Python programming language, it was possible: firstly, to simulate the operation of a ground-to-air communication network based on previously obtained models and a routing process management system based on the FA-OSELM algorithm. Secondly, in accordance with the scenario of route construction and maintenance described in the article, to experimentally determine the communication metrics of the proposed method of intelligent routing of the ground-air Ad-Hoc special-purpose network, in order to assess its efficiency, adequacy and reliability of the results obtained. Thus, in order to evaluate the effectiveness of the proposed solutions, a comparative analysis of the application of three existing routing methods (FLCA, Q-Routing, Neuro Routing) used in Ad-Hoc networks relative to the developed method was conducted.

The result of the experiment showed that the proposed routing method MAODV-FA-OSELM provides significant advantages over analogs. Thus, the method exhibits the best network throughput (2.12e+06), the lowest average network latency (0.12), the lowest packet loss (6.32), the lowest bit error rate (2.41), and the lowest overhead (0.10e+06). However, it should be noted that a promising direction of further research may be the study of the computational complexity of the routing management process and the determination of the minimum allowable representative sample of initial data to ensure online decision-making.

Keywords: *ground-air communication network, neural network, machine learning with reinforcement, routing method, throughput.*

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1. Introduction

In the military sphere, especially in the conditions of a full-scale invasion of the Russian Federation, one of the rapidly developing innovative scientific and applied directions is the development of methods, techniques, algorithms for the use of unmanned aerial vehicles of various types and purposes. Most of the developments in this area are reconnaissance and attack unmanned aerial vehicles or complexes. At the same time, drones are also used as «flying» repeaters, to communicate with hard-to-reach areas, zones and objects when direct visibility is not enough. Such tasks, in the classical sense, can be performed by powerful air control points in terms of their equipment, however, the high dynamics of hostilities requires a constant search for ways to solve problems with limited economic resources. Publications [1–4] demonstrate the high practical interest of using unmanned aerial vehicles of various classes in terms of weight and dimensions for their use as communication aerial platforms, united in groups to expand the area of radio coverage and ensure information exchange of a given quality. In general, an increase in the structural reliability of the network is accompanied by an increase in the complexity of organizing the compatibility of two sub-networks – ground and air [5].

From the point of view of the implementation of the management process, decentralization of the information and communication system of a certain unit (structure) limited to a district or area of performance of certain tasks, one of the approaches is the use of MANET-class networks and FANET-class air networks. Which, along with numerous advantages, is a difficult task due to its dynamic nature, high mobility of nodes, limited resources, and determines the need to form two main classes of control solutions – movement and communication at different levels of the open systems interaction model [5].

The question of building the topology of Ad-hoc networks is the subject of many scientific publications [6–8], however, most of them have a fragmentary nature of solving a separate defined task – bandwidth, delay time, energy efficiency of the air or ground communication network, etc.

The main aggravating factor of management organization in the considered communication systems is the high dynamics of the environment, therefore it is necessary to react quickly in the form of optimal or, more often, suboptimal management solutions.

One of the tasks of ground-air communication network management is routing management, with the aim of building and maintaining routes for the transmission of useful information of a given quality while meeting the requirements for their operation (minimizing service traffic, reducing battery energy consumption, etc.). In order to implement operational management tasks, it is necessary to ensure the fulfillment of network management goals at the FANET level.

The classic methods of routing – proactive (DSDV, OLSR, TBRPF), reactive (AODV, DSR, TORA) and hybrid (ZRP, HSLS) [9–12], has its own features, advantages and disadvantages, which determine their acceptability from the point of view of application in the military sphere or special ground-air networks. It is determined that the MAODV protocol has significant advantages in terms of ensuring the specified bandwidth, delay time and energy saving of nodes [11]. However, the analysis of modern scientific approaches to the construction of air-level network routing protocols for UAVNET [13] and FANET [14] allows to conclude that the ground communication network protocols of the MANET class are poorly adapted for aerial networks [5].

In this regard, the scientific task of developing a routing method that is a synthesis of the MAODV protocol and neural network algorithms for the predicted reduction of the volume of service information, adapted for both the ground and air subnets, is relevant.

The aim of research is to carry out a synthesis of the routing method of the special purpose ground-air communication network.

2. Materials and Methods

Communication network parameters: the network is represented by a directed graph $G^{\psi}=(V^{\psi},E^{\psi})$, with a set vertices $V^{\psi}=\{\vartheta_i\}$ and a set of edges $E^{\psi}=\{(i,j)|d_{ij}\le r_i \wedge d_{ij}\le r_j\}$, $i,j=\overline{1,N_{\psi}}$, $i\ne j$, $\psi=\overline{1,3}$ (1 – ground communication network GCN, 2 – mobile base stations network MBS, 3 – flying communication network FCN).

Total number of communication nodes ψ-th level – N_{ψ}, d_{ij} – distance between nodes, $r_i(p_i^{\psi})$ – radius (power) of transmission $i,j=\overline{1,N_{\psi}}$, $i\ne j$, $\psi=\overline{1,3}$.

As a control system of the ground-communication network GCN a complex hierarchical intelligent control system is adopted, which is conditionally divided into three main control levels: executive, nodal and network, and consists of the q-th number of subsystems. And include subsystem for managing routing, topology, load, security, QoS, flight/MBS movement, radio resource, energy resource costs.

Nodes parameters: each node of the graph ϑ_i^{ψ}, at some point in time t, is described by a set of parameters:

– location coordinates (x_i,y_i,z_i);

– velocity of movement is represented by the velocity vector at the point $\bar{v}(t)$, at time t;

– acceleration vector $\vec{a}(t)=(a_x(t),a_y(t),a_z(t))$;

– direction of movement $\vec{d}(t)=\bar{v}(t)/|\bar{v}(t)|$, where:

$$|\bar{v}(t)|=\sqrt{(v_x(t)^2+v_y(t)^2+v_z(t)^2)};$$

– transmitter power that can change adaptively:

$$p_i^{\psi}(t)\le p_{\max};$$

– capacity at each moment of time t, which cannot be higher than some maximum value $e_{bi}(t)\le e_{bi\max}$;

– Θ_i – width of the directional pattern of the antenna of the i-th node;

– the routing table of the shortest paths $\mathbf{L}_i=l_{\eta}(\pi_{ij}^k)$, where $\eta=\overline{1,H}$ – routing table metrics (availability of radio connectivity, bandwidth, transmission delay, transmission power, Euclidean distance, etc.), $\pi_{ij}^k=\{0,\ 1\}$ – route variable that determines the existence of a route from the sender to the addressee through an intermediate node. The intensity of incoming flows is determined by:

– the gravity matrix $\mathbf{\Gamma}=\gamma_{jk}$,

$$\sum_{j=1}^{N_{\psi}}\sum_{k=1}^{N_{\psi}}\gamma_{jk}\le\gamma_{\max},\ j\ne k;$$

– bandwidth of the radio channel $s_{ij}\le s_{ij\max}$, $\forall(i,j)\in E^{\psi}$;

– $\Pi_{\xi ij}$ – priority ξ-th type of traffic $\xi=\overline{1,3}$, (1 – video, 2 – voice, 3 – data) in the channel ij; the receiver of each mobile node is characterized by a sensitivity threshold p_{sl}, which determines the minimum signal strength $p_{i\min}^{\psi}(t)$, which can be received by the node. As part of each mobile node, an intelligent control system functions, the main task of which is the initialization of its own state vectors $X_{1qr}(k)=\{x_{1qr}^a(k)\}_{a=1}^{a_{1qr}}$ – for GCN, $X_{KA1qr}(k)=\{x_{KA1qr}^a(k)\}_{a=1}^{a_{1qr}}$ – for FCN [15].

Objective functions must be divided into two subgroups: the first describes objective functions in relation to network requirements (network objectives):

– $S_{\max}=\max_{s\in S}S(s)$ – function of maximum network bandwidth;

– $\bar{t}_{delay\min}=(1/|M|)\min_{m_{ab}\in M}\sum t_{delay}(m_{ab})$ – function of the minimum average network delay time, M – set of network routes;

– $\min_{m\in M}\bar{P}(m_{ab})$ – the function of the minimum average cost of the network capacity;

– $\min_{E_i\in E}\bar{E}$ – function of the minimum average energy consumption of the i-th number of network nodes.

The second group of target functions describes the process of node resource management in order to fulfill the network goals of the ground-air communication network FANET-MANET:

$$F_1=F_{seg}=\min\begin{pmatrix}\alpha\sum_{i=1}^{N_{seg}}Z(n_{seg})+\\+\beta\sum_{m_{ik}\in M}\bar{t}_{delay}(m_{ik})+\gamma\sum_{i\in E}\bar{E}_i\end{pmatrix}$$

– the function of building a segmented topology (the network is divided into subnets (segments) that communicate with each other through FCN);

$$F_2=F_{rout}=\min\begin{pmatrix}\sum_{m_{ik}\in M}(\beta_1\bar{t}_{delay}(m_{ik})+\\+\beta_2 PL(m_{ik})+\beta_3\bar{E}_i(m_{ik}))\end{pmatrix}$$

– route search function for finding optimal data transmission paths between the sending node (addressee) and end nodes (addressees). Optimal paths can minimize the number of hops, delay, energy consumption, and routing overhead;

$$F_3=F_{delay}=\min_{(m_{ik}\in M)}\begin{pmatrix}\gamma_1\bar{t}_{delay}(m_{ik})+\\+\gamma_2\sigma_{\bar{t}_{delay}(m_{ik})}+\gamma_3\Xi_{\bar{t}_{delay}(m_{ik})}\end{pmatrix}$$

– the function of the minimum delay time required for the transmission of data packets from the addressee to the addressee;

$$F_4 = F_{PL} = \min_{(m_{ik} \in M)}\left(\delta_1 \overline{PL} + \delta_2 \sigma_{PL} + \delta_3 \Xi_{PL}\right)$$

– the function of minimum packet loss in the process of building subnets and evaluating network performance;

$$F_5 = F_{BER} = \min_{(i \in N)}(\varepsilon_1 \overline{BER_i} + \varepsilon_2 \sigma_{BER_i} + \varepsilon_3 \Xi_{BER_i})$$

– bit error rate minimum function, where N_{seg} – number of subnets, $Z(n_{seg})$ – connectivity n_{seg} subnet, which is the ratio of the number of possible connections in the subnet, $n_{seg} = \overline{1, N_{seg}}$, $\overline{t}_{delay}$ – average network latency, σ – standard deviation, Ξ – probability distribution of the corresponding metric, $\overline{PL}$ – average packet loss in the network, $\overline{BER}$ – average network bit error rate, $\overline{E_i}$ – the node's battery energy, thus a set of weights – $\Upsilon_{U_2} = \{\alpha_1, \alpha_2, \alpha_3, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, \delta_1, \delta_2, \delta_3, \varepsilon_1, \varepsilon_2, \varepsilon_3\}$ – to find and evaluate a suboptimal solution by a network layer agent.

Admissions and limitations: the principle of ground-air communication network (GAN) management is mixed (decentralized in the process of exchanging useful information), with the possibility of manual monitoring and management (exchange of official information) $N_1 \leq 80$. $N_2 \leq 2$. $N_3 \leq 8$. Area of operation GAN – MAP_{GAN} determined in advance (physical obstacles and topography of the area are known). GAN nodes are divided by ranks P_i^{GCN}, $i = \overline{1,7}$, at the same time, each rank has its own limited area of functioning at the initial stage, then the location of NCM nodes can change randomly within MAP_{GAN}, and occupy a different area of operation for a while, each node is equipped with SDR radio stations with MIMO technology. Unmanned aerial vehicles must perform a flight task in the absence of visual surveillance by their own forces (means).

The control system of each communication node is built and divided into conditional subsystems, intelligent, has a knowledge base obtained at the stage of planning the communication network using the mobility model [16]. The UAVs are assembled on rotor-type UAVs that move at a constant speed, the dependence of the battery discharge on the increase in speed is linear. MBSs are equipped with high-precision topographic reference equipment and are placed in a weighted average point of radio accessibility to mobile GCM users. The CAPs are equipped with an inertial navigation system and a GPS receiver for correcting control effects with GNSS reference parameters to reach the given hovering coordinates calculated at the planning stage and reduce the positioning deviation at the operational control stage. During the operation of the CAPs, GPS correction channels may be under the influence of the enemy's REB in the form of spoofing and jamming attacks, the task of controlling the CAPs is carried out according to the method described in [17, 18] with a sufficient level of quality. CAPs are evenly spaced relative to the area of operation of ground communication nodes.

Today, the scientific problem of ensuring communication quality requirements is solved using neural network algorithms, machine learning algorithms based on a priori data, and combined hybrid methods. To simulate the process of functioning of FANET-MANET networks, scientists, as a rule, use simulation environments NS-3, NS-2, SimNET with mobility models of the Random Waypoint Model type. But they which do not fully reflect the real operating conditions of the studied communication networks; therefore, the effectiveness of the proposed method was evaluated in the Google Collab environment and the Python programming language. It is known that to ensure the interaction of FANET-MANET networks at the channel and network level, routing protocols are used, which can be divided into three main categories: proactive, reactive and hybrid.

Proactive protocols maintain an up-to-date routing table for each network node, which contains information about optimal routes relative to other nodes in the topology construction process. Proactive protocols can provide low-latency transmission of data packets in the process of interaction between mobile users, but at the same time, high computational costs and energy consumption increase. Examples of proactive protocols are: Destination Sequenced Distance Vector (DSDV), Optimized Link State Routing (OLSR) and Topology Broadcast based on Reverse-Path Forwarding (TBRPF) [19].

Reactive protocols initiate the route construction process taking into account the node's requirements during interaction with other network nodes. Also, reactive protocols can reduce computing costs and increase throughput, and reduce the energy consumption of network nodes. However, if to take into account the dynamic, unpredictable nature of the process of movement and interaction between mobile network users, it is necessary to expand (add) the parameters to reflect the nonlinearity of the processes, while the increase in the time interval for the transmission of data packets is fixed. Examples of reactive protocols are Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR) and Temporally Ordered Routing Algorithm (TORA) [20].

Hybrid protocols combine the functions of both proactive and reactive protocols, and typically decompose the network into zones or clusters, and use different routing strategies. Hybrid protocols can balance the trade-off between overhead and latency, and adapt to network size and density. Examples of hybrid protocols are: Zone Routing Protocol (ZRP), Cluster Based Routing Protocol (CBRP) [21] and Zone-based Hierarchical Link State (ZHLS).

Most existing routing protocols for MANETs are not suitable for FANETs because they do not take into account the specific characteristics of FANETs, such as high mobility, three-dimensional topology, frequent link breaks, and node heterogeneity. Therefore, some routing protocols have been proposed specifically for FANET, which take into account the peculiarities of FANET and try to improve the performance of the network. Example, Fuzzy Logic based Routing Protocol (FLRP) [22] uses fuzzy logic to choose the optimal hop search, taking into account speed, node positioning, and link quality. Also, among such protocols Genetic Algorithm based Routing Protocol (GARP) [23], that uses a genetic algorithm to find the optimal path based on a fitness function that takes into account the number of hops, link stability, and node energy. However, these routing protocols are still based on fixed rules or predefined metrics and may not be able to adapt to dynamic and complex network conditions and achieve optimal performance. There are also many solutions based on machine learning algorithms. Machine learning is used to solve network optimization problems such as routing, resource allocation, load balancing, congestion control, information security, and quality of service.

One of the machine learning methods that is widely used for multi-criteria optimization problems is machine learning with reinforcement (RL) [24]. At its core, RL is a type of machine learning that allows an agent to learn from its own experiences and interactions with its environment and find the optimal policy or action that can maximize the cumulative reward over time. It should be noted that RL algorithms usually do not require any prior knowledge, and it can work with dynamic and stochastic environments. Today, there are many examples of RL application for solving problems of multi-criteria optimization of MANET-FANET mobile networks and modification of routing algorithms.

Thus, Q-Routing is an RL-based routing protocol that uses Q-learning [25] to find the optimal routing table for each node based on the evaluation of state vector data such as queue lengths and delays.

AntNet [26] is a routing protocol that is also based on an RL machine learning algorithm that uses ant agents to learn the optimal routing table for each node based on the level of pheromones and network traffic. Neuro Routing [27] is an RL-based routing protocol that uses a neural network to learn the «optimal» routing table for each node based on network state and network feedback. However, these RL-based routing protocols are mainly designed for MANETs and may not be able to handle high-dimensional and non-stationary data, as well as feature variations and strategy drifts (node- and network-level user requirements) that are common in MANET scenarios. FANET.

Initial conditions of the routing process in general:

– *at the first stage* – in order to build new routes, it is necessary to solve the multi-criteria problem of determining the necessary target function of the ground-air communication network;

– *in the second stage* – selection of routing type (single user or multicast);

– *in the third stage* – the number of routes is selected (one or several) depending on the requirements for the quality of traffic service. The possibility of selecting the number of information transmission routes between the sender and the addressee will increase the reliability of information delivery, increase the security of information transmission, however, it may increase the volume of service traffic;

– *in the fourth stage* – the method of sending service information is selected based on a statistical sample of metrics of mutual placement of GAN nodes at the planning stage (availability and relevance of such information).

Probable scenario of the investigated process. Further, in the case of the need to transmit information, the sending node contacts the routing management subsystem. The presence of a route in the statistical sample (knowledge base) of the intelligent management agent of the nodal level is checked. In the absence of a route of the specified quality in the knowledge base, the agent of the sender node receives a «penalty» and initiates the creation of a probe-request to the head node of a cluster of mobile users operating within the same rank. In the case when it is possible to provide a route of the required quality through this head node, then it forwards the probe to the destination with the estimated values of the route parameters, and the agent of the sender node will receive the «reward». In the event that the head of the cluster does not have a route to the specified addressee, it initiates the sending of a probe to the mobile base station, in the event that there is a route through the MBS, the agent of the head of the cluster (group leader – GL) of the addressee node and the agent of the network layer receive a «reward» and the former accepts the formed response probe from the latter, which is transmitted to the sender. Next, an assessment of the level of compliance with network level restrictions (predicted given quality of information exchange according to the selected criteria) is carried out, a decision is made regarding the selected route – ground node (GN) – GN-GL – MBS – GN, or GN – GN-GL – MBS – CAP – GN, or other combinations. For successful route selection, the network layer agent (MBS – agent) receives a «reward». In the case when there is no route to GN, but the MBS has an alternative route through the air-level CAP, the nodal air-level agents (CAP – agent) are «rewarded» and form a probe in response to the addressee. In the event that the CAP agents do not have up-to-date information about the addressee, then the CAP agents receive «fines» and form a multicast message within radio range to update the table of current routes.

The process algorithmization of the proposed routing method.

The logic of routing management decisions within the framework of the developed method is determined by the Feature Adaptive Online Sequential Extreme Learning Machine (FA-OSELM) algorithm [28], and the Multicast Ad hoc On-Demand Distance Vector (MAODV) routing protocol is chosen as the prototype algorithm. Network nodes use MAODV logic for routing, which is a reactive and efficient routing protocol [11], which can support multicast communication and reduce the computational overhead of the routing process.

Parameterization of the Feature Adaptive Online Sequential Extreme Learning Machine (FA-OSELM) algorithm for the routing problem.

The main advantage of FA-OSELM is that the selected algorithm can adapt to the variations of network data features, that is, it is an online learning algorithm. That is, FA-OSELM can adjust the weights and biases according to the dynamic variations of network data characteristics by using a forgetting mechanism, which allows it to quickly adapt to the demands of mobile users.

The essence of the routing decision-making algorithm.

Network data is represented by a feature vector $x \in R^d$, where d – dimension of the feature space, and the target vector $y \in R^m$, where m – dimension of the target space. A vector of features x includes network parameters.

The essence of the algorithm is the process of adjusting the actions of the agent r_t, which lead to the maximization (or minimization) of the sum of reinforcement signals, the search for optimal gain coefficients to form a suboptimal solution.

Iterative formula of the algorithm Reinforcement learning – FA-OSELM:

$$Q_{t+1}(s,a) = (1-\eta)Q_t(s,a) + \\ +\eta\left[r_t + \gamma(U)\max_{a_{t+1}} Q_t(s_{t+1},a_{t+1})\right], \quad (1)$$

where r_t – immediate reinforcement signal, which is the profit (sum of reinforcements) received over time, $\mathrm{Y}_{U_2} = \{\alpha_1,\alpha_2,\alpha_3,\beta_1,\beta_2,\beta_3,\gamma_1,\gamma_2,\gamma_3,\delta_1,\delta_2,\delta_3,\varepsilon_1,\varepsilon_2,\varepsilon_3\}$ – a set of weighting coefficients for the search, assessment by the agent of a suboptimal solution, taking into account the result of

FA-OSELM work, and γ – discount factor on the interval $0 \le \gamma \le 1$, which affects the future state of the agent at the time of decision, η – the learning factor, which controls the rate of interval learning $0 < \eta < 1$, $Q(s,a)$ – a value that provides an estimate of how satisfied the condition is for the agent to enter the state (s) to perform an action (a).

At the training stage, the input vector is formed n random training samples $(s_t, a_t, Q_t), (s_t, a_t) = [x_{t1}, x_{t2} \ldots x_{tn}]T \in R^n$, and output data $Qt = Yt = [y_{t1}, y_{t2} \ldots y_{tn}]T \in R^m$.

The state of the network is represented by a state vector $s \in R^n$, where n – dimension of the state space, and the network reward can be represented by a reward scalar $r \in R$.

State vector s may include node parameters.

The learning process is presented:

1. *Initialization stage*. At this step, the initialization process takes place, the function of the value of the agent's action $Q(s,a) \in R$, where a – action, and the speed of learning $a \in (0,1]$. A reinforcement learning algorithm also determines the speed of application of a possible solution $\varepsilon \in [0,1]$, which controls the trade-off between network state prediction. The agent reinforcement technique also obtains the first state of the network $s_1 \in R^n$ and the first network reward $r_1 \in R$.

2. *Action selection stage*. An agent reinforcement technique selects an action a_t for the current network status s_t, using the policy ε-greedy. Policy ε-greedy chooses a random action with probability ε and chooses the action that maximizes the value-action function with probability $1-\varepsilon$.

3. *Action execution stage*. The agent searches for reinforcement when performing the selected action a_t for the current network status s_t, by changing the transmission power, modulation method, or antenna direction of the node or communication channel, according to network conditions and user requirements. The agent then observes the next state of the network $s_{t+1} \in R^n$ and the following reward $r_{t+1} \in R$.

4. *Action evaluation stage*. In this step, the agent calculates the selected action a_t for the current network status s_t, updating the value-action function $Q(s_t, a_t)$, using time difference learning.

5. *Iteration stage*. The agent repeats algorithm steps 2–4 until the network state reaches a terminal state or the algorithm terminates.

As a result, the learning algorithm is built Q-matrix used for the functioning of the agent performing the target task.

MAODV-FA-OSELM algorithm.

1. *Formation of a multicast (multicast) group*. At this step, the process of forming a multicast group takes place, which is a set of nodes built according to the «one-to-many» or «many-to-many» principle. Each multicast group is then assigned a unique identifier (M-GID) and the group leader (GL) assignment process takes place, the group sequence number (G-SN) and hop count (G-HC) are also assigned.

2. *Discovery of a multicast route* between source nodes and destination nodes.

3. *Transmission of M-RREQ messages*. The sending node broadcasts an M-RREQ message to its neighboring nodes, which contains the following information: Source Node ID (S-ID), Source Node Sequence Number (S-SN), Source Node Hop Count (S-HC), Multicast Group ID (M-GID), group sequence number (G-SN) and group hop count (G-HC). The sending node also creates a multicast group reverse path entry in its routing table that records the previous hop, next hop, group leader, group sequence number, and number of group hops for the multicast group.

4. *Forwarding M-RREQ*. In this step, each intermediate node that receives an M-RREQ message performs the following actions:

1) checks whether the M-RREQ message is a duplicate and discards it if so;

2) checks whether it is a member of a multicast group and sends an M-RREP message back to the source node if it is;

3) updates its routing table with the reverse path entry for the multicast group and forwards M-RREQ messages to neighbors if it is not.

5. *M-RREP unicast*. Next, each destination node or intermediate node that is a member of the multicast group sends an M-RREP message back to the source node, which contains the following information: destination node identifier (D-ID), destination node sequence number (D-SN), number destination node hops (D-HC), multicast group identifier (M-GID), group sequence number (G-SN), and group hop count (G-HC). The destination node or intermediate node also creates a forward route entry for the multicast group in its routing table that records the previous hop, next hop, group leader, group sequence number, and number of group hops for the multicast group.

6. *M-RREP forwarding*. In this step, each intermediate node that receives an M-RREP message performs the following actions:

1) checks whether the M-RREP message is a duplicate and discards it if so;

2) updates its routing table with a forward path entry for the multicast group and forwards an M-RREP message to the previous hop if it is not.

7. *M-RREP reception*. A destination node receives an M-RREP message from a destination node or an intermediate node that is a member of a multicast group and updates its routing table with a forward route entry for the multicast group. The sending node also sends a MACT message to the next hop that contains the following information: source node ID (S-ID), destination node ID (D-ID), and multicast group ID (M-GID). The MACT message is used to activate a multicast route and join a multicast group.

8. *Maintenance (support) of a multicast route*. At this step, the MAODV logic maintains multicast routes, which are routes connecting the sender and destination nodes in a multicast group.

9. *M-RERR broadcast*. Each node that detects a link failure or node failure in a multicast route sends an M-RERR message to its neighbors that contains the following information: Multicast Group ID (M-GID), Group Sequence Number (G-SN), and Group Hop Count (G-HC). The node also removes the corresponding path entry for the multicast group in its routing table and leaves the multicast group if it is not a source node or a destination node.

10. *M-RERR forwarding*. Each intermediate node that receives an M-RERR message does the following:

1) checks whether the M-RERR message is a duplicate and discards it if it is;

2) updates the routing table with the new group sequence number and the new number of group hops for the multicast group, and forwards M-RERR messages to neighbors if not.

11. *M-RERR reception*. In this step, each sending node that receives the M-RERR message does the following:

1) updates its routing table with the new group sequence number and the new number of group hops for the multicast group;

2) initiates a new multicast route discovery process for the multicast group by broadcasting a new M-RREQ message with the updated group sequence number and the updated number of group hops.

12. *MACT unicast*. Each node that receives a MACT message from a previous hop does the following:

1) checks whether it is a member of a multicast group and joins the multicast group if it is not;

2) updates the routing table with the previous hop and the next hop for the multicast group;

3) sends a MACT message to the next hop if it is not an end node.

Therefore, the MAODV-FA-OSELM algorithm makes several key improvements and extensions to the classic MAODV (Multicast Ad hoc On-Demand Distance Vector) protocol, namely:

– intelligent routing management with FA-OSELM, an algorithm that uses machine learning to predict and optimization of routes depending on current network conditions and variable parameters, which allows the network to adapt to changes in topology and data transmission conditions in real time and ensure a reduction in overhead costs for providing and supporting network routes;

– ensuring the formation of multicast groups with unique identifiers and group leaders and ensures more efficient use of network resources and increases the reliability of multicast transmission.

3. Results and Discussion

A mobility model is used to simulate and verify the adequacy of the proposed method [16], for the representativeness of the results of the experiments, the following scenario is proposed, which consists of stages according to *the probable scenario described above*. The simulation time is 30 min, and the simulation scenario is dynamic, which means that the network topology, network traffic, and network state change over time. To *evaluate the effectiveness* of the proposed method, the metrics listed below were used and a comparison was made with existing methods such as: Q-Routing, Fuzzy Logic-Based Clustering Algorithm and Neuro Routing [29].

It should be noted that the experiment was conducted 15 times, which made it possible to obtain statistical indicators: the average and standard deviation of indicators for each of the routing methods.

Modeling metrics:

– network bandwidth, which is the total amount of data that is successfully delivered to destination nodes in the network (bit/s);

– network delay, that is, the average time required for the delivery of data packets from addressee nodes to destination nodes in the network(s);

– packet loss, that is, the ratio of data packets that are lost or dropped during transmission in the network (%);

– network bit error BER, that is, the ratio of bits that are damaged or changed during transmission in the network (%);

– network overheads represent the total amount of service traffic (packets) generated and transmitted in the network (bit/s).

The simulation results are shown in Table 1 and in the graphs of Fig. 1 and Fig. 2.

The obtained results confirm the analytical conclusions that the proposed method shows the best throughput (2.12e+06) among all the investigated methods. In addition, this method has the lowest latency (0.12), the lowest packet loss (6.32), the lowest bit error rate (2.41), and the lowest overhead (0.10e+06). These results indicate that the proposed method is the most effective among those studied.

Thus, the proposed method makes it possible to optimize the target functions of constructing a segmented topology, finding routes, minimizing delay time, packet loss, and bit error, due to the synthesis of machine learning with the reinforcement of decisions (actions) of intelligent agents.

The proposed method can adapt to the dynamic change of the network by using FA-OSELM algorithm for control and MAODV logic for routing. The proposed method can also handle function variations, communication failures, node failures, and provide the process of multicast information exchange in the ground-air communication network.

Limitations of the study. To implement the developed routing method, it is necessary to study its operation under the conditions of directed influences of the enemy's radio electronic warfare in real conditions. Actually, at first it will be useful to collect a statistical set of influences in a combat situation for further research.

The direction of further research is to determine the size of the minimally necessary representative sample of statistical data of the metrics of the mobility model of the terrestrial communication network, to ensure training at the planning stage of the network and to reduce the learning time on the stage of operational management.

Impact of martial law. It should be noted that the transience of hostilities on the territory of Ukraine, and the analysis of combat experience, allows to conclude that the scientific community should implement the latest scientific and technical solutions on average every 2–3 months to maintain technological «initiative» and superiority on the battlefield. Potentially existing institutions make it possible to do this by increasing the level of communication.

Table 1

Simulation results

Method routing	Bandwidth (bit/s)	Delay (s)	Packet loss (%)	Bit error rate (%)	Overhead (bps)
FLCA	1.23e+06±0.12e+06	0.32±0.05	12.45±2.34	3.21±0.65	0.56e+06±0.08e+06
Q-Routing	1.18e+06±0.11e+06	0.35±0.06	13.67±2.54	3.54±0.71	0.65e+06±0.09e+06
Neuro routing	1.15e+06±0.10e+06	0.38±0.07	14.89±2.73	3.86±0.77	0.52e+06±0.07e+06
Proposed	1.42e+06±0.14e+06	0.12±0.04	1.87±1.87	1.41±0.48	0.18e+06±0.06e+06

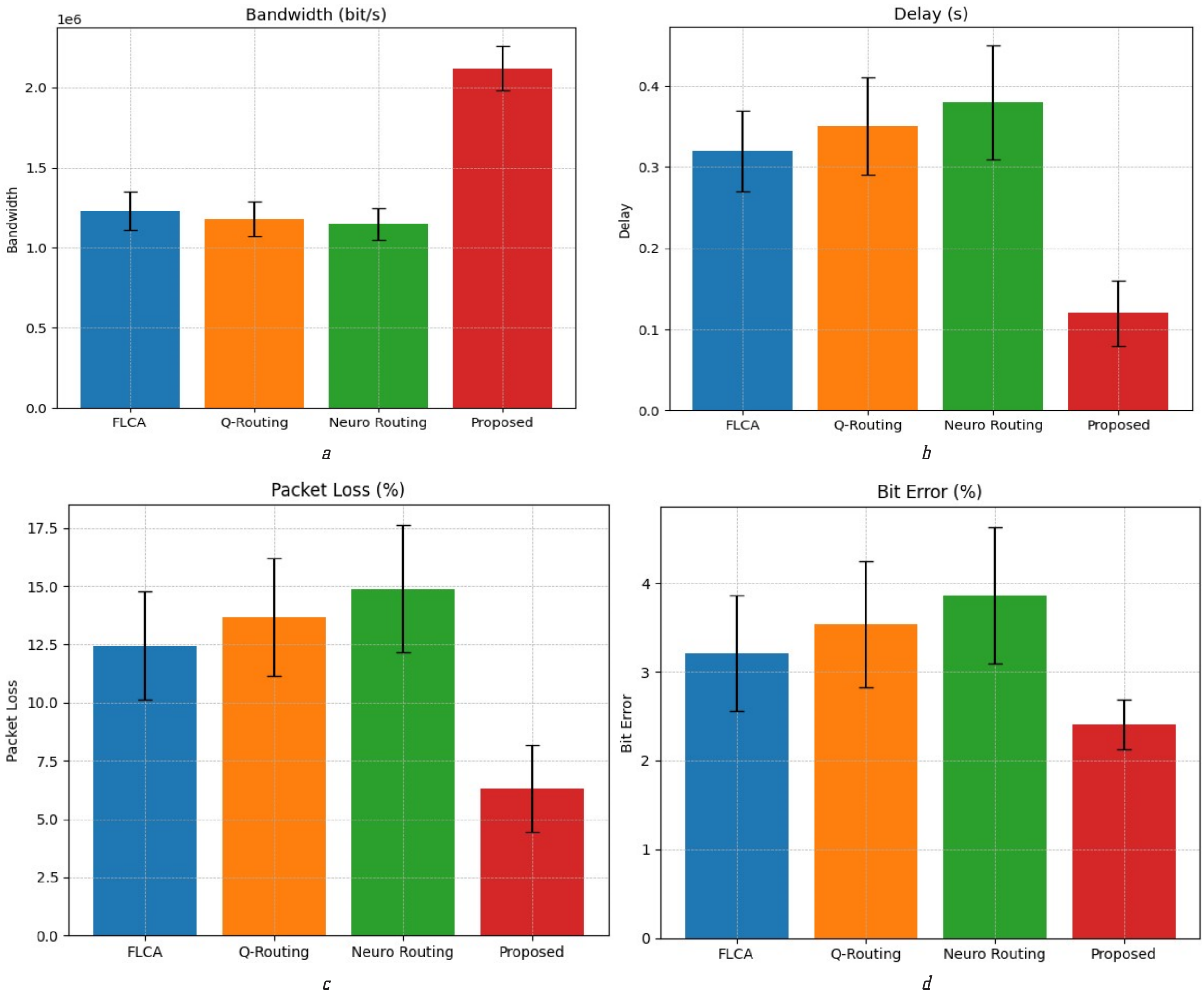

Fig. 1. Diagrams of communication metrics obtained as a result of simulation of FLCA, Q-Routing, Neuro routing and MAODV-FA-OSELM routing methods: *a* – network bandwidth; *b* – network delay; *c* – packet loss; *d* – network bit error

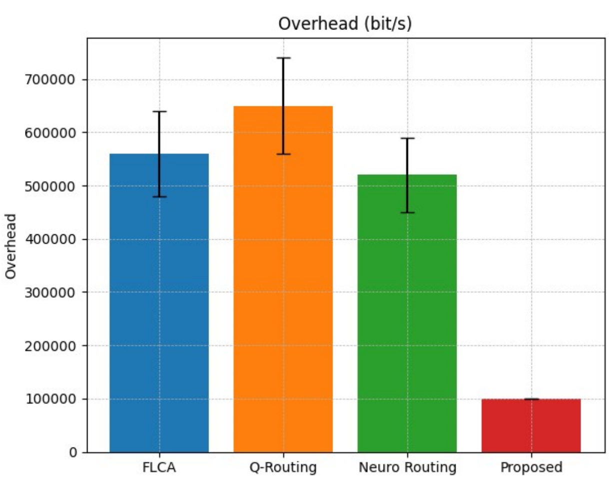

Fig. 2. Diagrams of network overheads obtained as a result of simulation of FLCA, Q-Routing, Neuro routing and MAODV-FA-OSELM routing methods

4. Conclusions

The article shows the mathematical model of the ground-air communication network, and formalizes the target functions of managing the communication metrics of the network. The process of making routing decisions using a neural network algorithm of machine learning with reinforcement and the process of forming service traffic and information exchange at the stage of route construction and their support based on the MAODV prototype protocol are algorithmized.

Simulation was carried out in the Google Collab environment using the Python programming language based on the output data of the hierarchical control model of the ground-air communication network, the model of the mobility of ground communication nodes, the model of the movement control of the movement of communication aerial platforms of the FANET class air network, to study the process of routing management in the ground-air special purpose communication network using FA-OSELM neural network machine learning algorithm to improve MAODV prototype routing protocol.

Adequacy and reliability of analytical conclusions of the proposed method were studied. Other routing methods such as FLCA, Q-Routing and Neuro Routing showed lower throughput, higher delay, higher packet loss, higher bit error rate and higher overhead compared to the proposed method. This indicates that the above-mentioned methods have certain limitations, namely the difficulty of adapting to the dynamic requirements of mobile users, and as a result have a significant deterioration in overall efficiency.

Conflict of interest

The author declares that he has no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The author confirms that he did not use artificial intelligence technologies when creating the current work.

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