DOI: 10.14529/ctcr170201

APPLYING BIO-INSPIRED ALGORITHMS TO ROUTING PROBLEM SOLUTION IN FANET

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The advances in Unmanned Aerial Vehicles (UAVs) development provide new opportunities for their civil application. UAVs are an integral part of the scientific research nowadays. UAVs implementation requires that a group of interacting UAVs takes part in the task completion. Organizing a multi-UAV network calls for special routing algorithms developed with due concern of their features. The article gives a brief review of the existing routing algorithms for ad hoc networks based on swarm intelligence. The test analysis has been carried out proving that bio-inspired algorithms can be effectively applied to solve the routing problem in FANET networks. This has been proved on the example of BeeAdHoc and AntHocNet, modeling the natural behavior of bees and ants.

Keywords: UAV, swarm intelligence, routing protocols, flying ad hoc network, FANET, BeeAdHoc, AntHocNet, network simulation.

Introduction

Recently, the interest in Unmanned Aerial Vehicles (UAVs) has increased largely. UAVs are currently an integral part of scientific investigations, and they are gradually entering the market of civil application. Modern UAVs are equipped with a computer vision system and a body of information sensors, providing an integral representation of the current situation. The obtained data allow UAVs to navigate in surroundings and make decisions on actions, necessary for the given task completion, without external control.

Implementation of autonomous mobile UAVs calls for simultaneous participation of several interacting UAVs in the set task completion.

Nevertheless, the multi-UAV systems have several problems to be investigated. The development of an autonomous multi-UAV system requires a reliable connection between all the nodes. Therefore, it demands constructing a wireless Ad Hoc Network taking unique UAV characteristics into account.

Analogous to mobile peer-to-peer network MANET (Mobile Ad Hoc Network) and vehicular peer-to-peer network VANET (Vehicular Ad Hoc Network), FANET (Flying Ad Hoc Network), is a special type of peer-to-peer Ad Hoc Networks based on UAVs. Table 1 compares these types of Ad Hoc Networks [1].

Table 1

Comparison of FANET, VANET and MANET

Criteria	Ad-Hoc network types		
	FANET	VANET	MANET
Node mobility	High compactness	Medium compactness	Low compactness
Mobility model	Usually predetermined, but special mobility models for independent multi-UAV systems	Steady	Arbitrary
Node density	Low thickness	Medium thickness	Low thickness
Topology change	Rapid and speedy	Average speed	Slow and steady

Table 1 (end)

Criteria	Ad-Hoc network types		
	FANET	VANET	MANET
Radio propagation model	High above the ground level, LoS (Line of Sight) is accessible for most of the cases	Close to ground, LoS is now accessible for all cases	Very close to ground, LoS is not accessible for all cases
Power consumption and network lifetime	Needed for mini UAVs, but now needed for small UAVs	Not needed	Need of energy efficient protocols
Computational power	Very big	Average	Limited
Localization	GPS, AGPS, DGPS, IMU	GPS, AGPS, DGPS	GPS

Amont FANET's characteristics are dynamically-changing topology, high nodes mobility, and movement in 3D-space. Nodes interaction is restricted by the assigned frequency resources, power capacity, radiowave propagation conditions, and others. Network nodes interact at random, and a pair of nodes can connect through a chain of intermediaries. This imposes a set of additional constraints for network organization and calls for specialized routing protocols.

1. UAVs group application

UAVs group application provides large opportunities. Single UAV has a limited amount of onboard power supply and functional units, and available data on surrounding conditions are restricted by the onboard sensors features. At the same time, when in group, UAVs may exchange the obtained data on surroundings, largely increasing information awareness of every vehicle. With available amount of onboard power supply, the group can perform a larger scope of work and the breakdown of one or several UAVs results in no task failure but leads only to a decrease in group efficiency.

UAVs group is of practical concern in solving such issues as video monitoring, false target forming, site data gathering, mapping, reconnaissance, search for disaster victims, measuring the level of radiation or chemical contamination, security system, continuous area status monitoring (for forest areas, transport routes, oil and gas pipelines, frontiers, etc.), electronic jamming, mobile communication networks development, mobile phased array development, and others. Fig. 1 shows project ANCHORS (UAV – Assisted Ad Hoc Networks for Crisis Management and Hostile Environment Sensing). The ANCHORS project started in 2012 as a joint project of France and Germany. The project objective is to organize an autonomous network consisting of various unmanned systems that can be used as an independent communication infrastructure for emergency services [2].

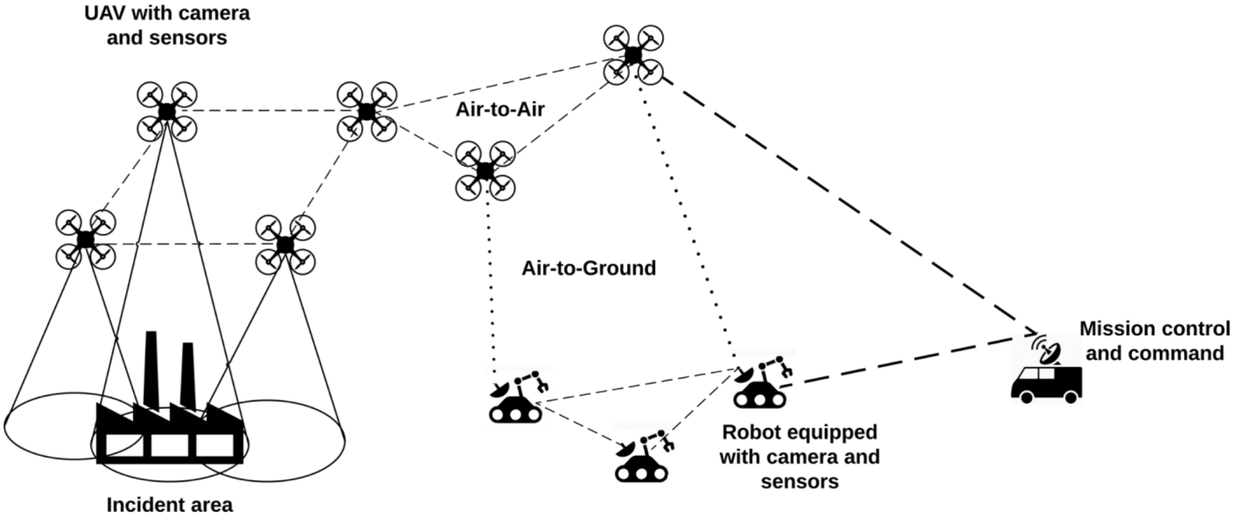

Fig. 1. Functional diagram of the ANCHORS project operation

2. Controlling a group of UAVs

The analysis of the existing solutions has shown that to solve a complicated task by UAVs group under conditions of uncertainty, the groups should be organized not as a centralized system but as distributed decentralized one. In this case the group control is carried out through data exchange between the agents, and data processing is performed by the system control center.

Since the group includes a large number of UAVs, real-time centralized control has such shortcomings as low operational reliability of the system, heavy radio-channel load, and high computational resources consumption of the system control center. Moreover, centralized approach is inefficient if operating area conditions are changing rapidly. Such shortcomings are absent in the second, decentralized approach to tasks distribution in the group of robots, i.e. multiagent control. It implies that robots distribute the tasks among themselves autonomously as a result of "negotiations" and by following the optimality criterion (Fig. 2). In this case each robot forms price array$\{c_{ij}\}$, where $i = 1, 2, \dots, n$ is the robot numbers, and $j = 1, 2, \dots, m$ is task numbers.

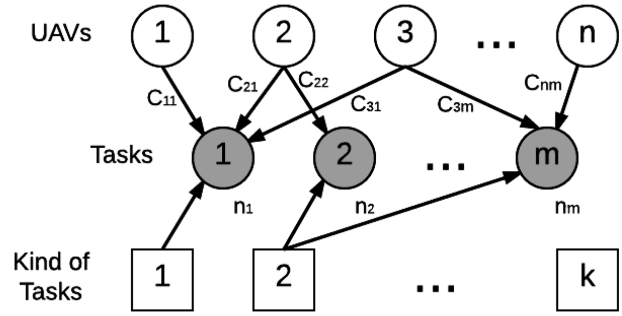

Fig. 2. Multiagent distribution of the tasks in the group

The realization of the distributed decentralized system provides equal distribution of the robots in working area during its investigation for emergencies, and the robots movement to the required target locations for technological operation [3].

Multiagent control allows the system self-organization and increases its operational reliability.

3. Swarm intelligence

Self-organization and complex behavior occur in multiagent systems, even if each agent has a rather simple behavior strategy. It underlies the so-called "swarm intelligence" (SI) [4].

The concept "swarm intelligence" describes the collective behavior of a decentralized self-organized system consisting of multiple agents, and it is considered an optimization method in artificial intelligence theory [5]. The agents follow very simple rules of behavior in the environment. Their simple interaction affects collective adaptation.

Collective system can solve complicated dynamic issues in collaborative work. Under varying circumstances a single element of the system cannot solve such problems without an external management, control or coordination.

To realize SI systems, one uses the so-called "swarm algorithms" (SA). These algorithms are based on modeling the social behavior of birds or fish in flocks and insects in swarms. Swarm algorithms are used successfully to solve complex optimization problems. To settle such problem means to find the optimal solution for the target function (precision, distance, price, time, etc.) optimization (the discovery of the maximum or the minimum) in a discrete set of the possible solutions.

Various algorithms have been developed, based on the swarm intelligence, and are currently used. Among them are the ant colony optimization, the bee colony algorithms, the particle swarm optimization algorithms, and others [6].

Bees and ants behavior resembles that of the nodes in wireless Ad Hoc Networks.

4. Problem representation in the algorithms based on the bee colony

This algorithm belongs to the sub-class of bio-inspired algorithms, and it consists in modeling natural bee behaviour (Fig. 3) [7].

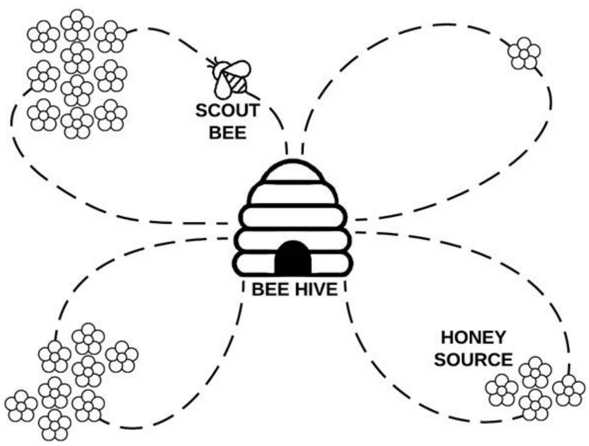

Fig. 3. The diagram of natural bee colony behavior

The bee swarm is based on the self-organization that allows achieving the common goals thanks to low-level interaction. The bee colony makes use of two level strategy as its main paradigm. On the first level, the scouts locate a set of promising sites, i.e. they randomly search for new nectar sources. On the second level, forager-bees explore the sites neighbourhoods and share the data on the located sites quality with onlookers, while onlookers remain in the beehive and receive the information on the object under research from the employed bees only through a special language of "waggle dance". The bee moves during the dance show to the other bees the exact location of the food source and the amount of the pollen or nectar there. The waggle dance is based on the Sun location (Fig. 4).

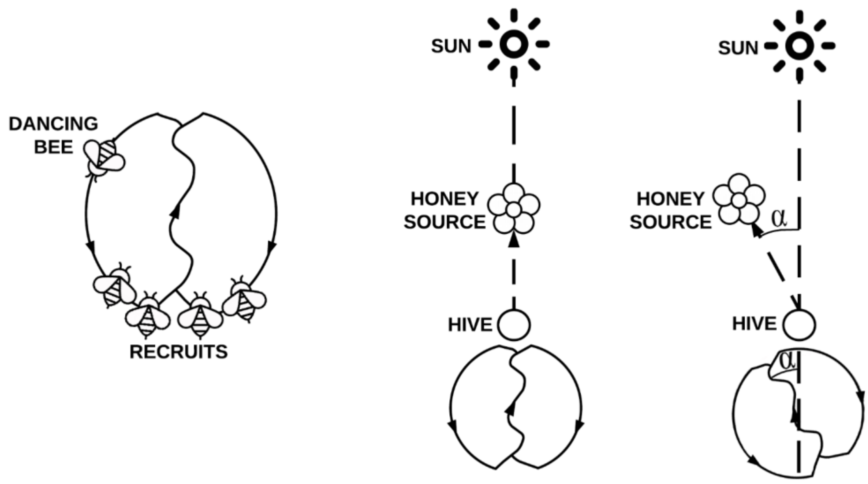

Fig. 4. Schematic representation of the "waggle dance"

The bee colony tries to find the source with the maximal nectar amount, which is the target function of the optimization problem [8].

A point (site) in the search space represents every solution in the investigated algorithm. The target function (TF) value at this point is the determined amount of the nectar (Fig. 5).

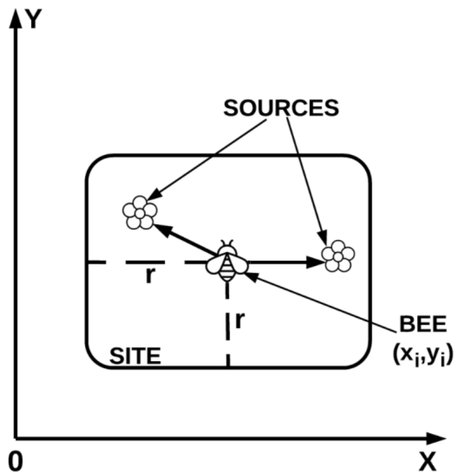

Fig. 5. The model for determining the nectar search site

Let the search space be a two-dimensional space, where x_i, y_i are the bee coordinates (function parameter), r is the radius (size) of the site, n is the number of function parameters. As for this particular case, it is the variant with two parameters – x and y. As seen in Fig. 5, the bee may move to the other nectar sources only within the territory of a single site retricted by the given radius. The nectar amount is inversely proportional to the function value at coordinates x and y. And the agent is looking for another solution similar to the previous one.

Fig. 6 shows the flow chart of Artificial bee colony algorithm (ABC algorithm) [9].

The number of onlookers is determined as $\frac{1}{2} \cdot m$, and the search site is chosen according to the formula:

$$v_{ij} = x_{ij} + \phi_{ij} * (x_{ij} - x_{kj}), \tag{1}$$

where m is the search site; x_i is a random initial location; ϕ_{ij} is a random number from the range $[-1; 1]$; k is the subscript of the solution chosen at random from the colony ($k = int\,(rand * m) + 1$); and $j = 1, \dots, D$,D is the problem dimension. When the site v_i is determined, the obtained solution is compared to x_i, and the employed bee travels to the best (elite) site of the two.

As for the elite sites neighborhoods, the solutions are chosen with probability calculated by the expression:

$$p_i = \frac{fit_i}{\sum_{j=1}^{S} fit_i}, \tag{2}$$

where fit_i is the value of the target function x_i.

Scouts continue searching randomly and evaluate TF. Onlookers of the site become scouts, and the solutions are chosen randomly by the formula:

$$x_{ij} = x_j^{min} + (x_j^{max} - x_j^{min}) * rand, \quad (3)$$

The best (elite) site is chosen for each bee among the ones, the bee has been visiting since the first iteration, as well as the target function fit_i value at this site.

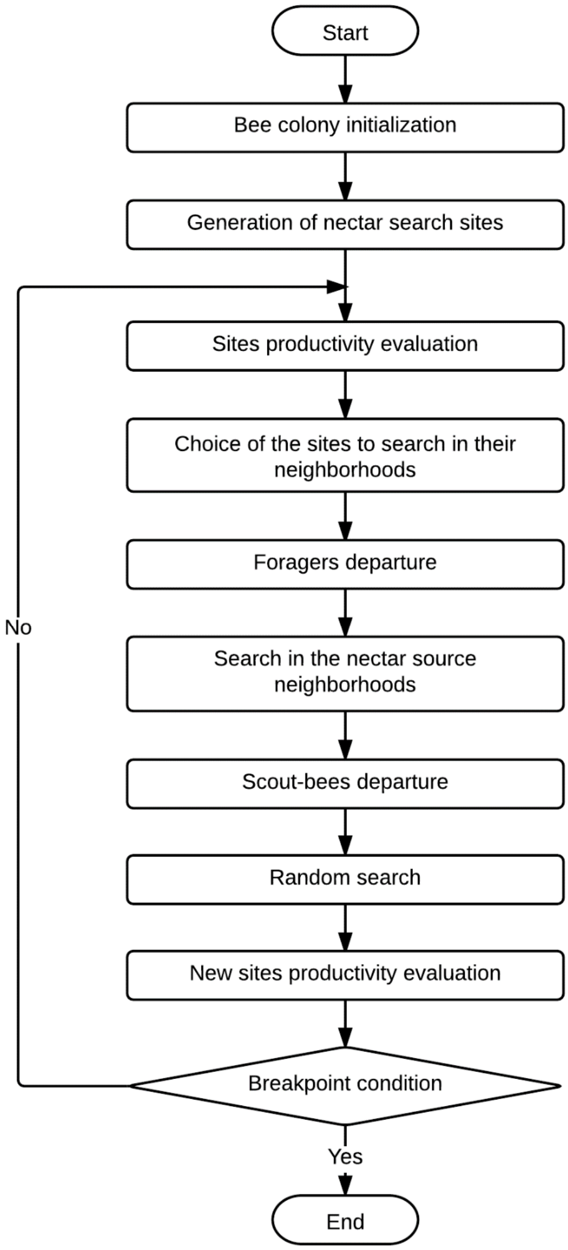

Fig. 6. The flow chart of ABC algorithm

5. Problem representation in the algorithms based on the ant colony

Ant Colony Optimization (ACO) algorithm is a metaheuristic swarm method used to solve the combinatorial optimization polynominal problems by a graph model [10].

The given algorithm adopts natural ant behavior. Two types of interaction among the ants are:

– direct interaction (food exchange, visual contact, chemical contact, etc.);

– indirect interaction, or stigmergy, i.e. two species interact indirectly: one modifies the environment and the other reacts to the modification gradually. In nature, indirect interaction is performed with the help of pheromone that is a special steady secretion. It is left as a trail when the insect moves.

The higher the pheromone concentration is on the path; the larger number of ants follows it. After some time, the pheromone evaporates, and the ants modify their behavior according to the environment changes.

Fig. 7 demonstrates a generalized diagram of the ant colony algorithm operation.

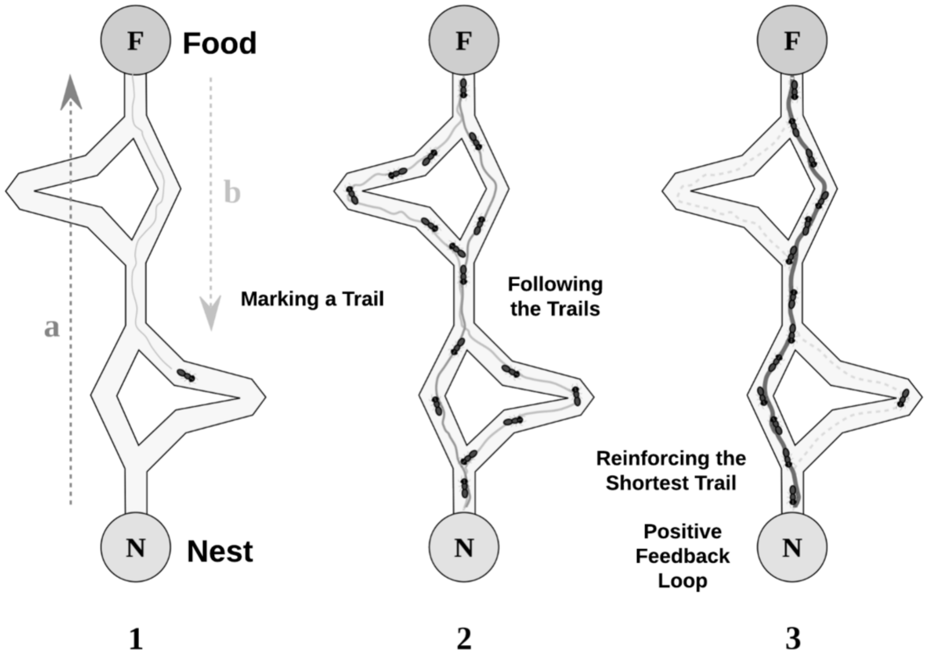

Fig. 7. Operation mechanism for ant colony optimization algorithm

For algorithm operation one should develop the rules (methods) for:
– initial positioning of the ants in the graph vertices;
– constructing the acceptable alternative solutions (the graph route);
– determining the probability of the ant movement from one graph vertex to the other;
– pheromone update on the graph edges (vertices);
– pheromone evaporation.

The flow chart for the ACO algorithm is given in Fig. 8 [11].

The probability k of an ant moving from vertex i to vertex j is estimated by the following ratio:

$$\begin{cases} P_{ij,k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum_{l \in J_{i,k}} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}(t)]^{\beta}}, j \in J_{i,k} \\ P_{ij,k}(t) = 0, j \notin J_{i,k} \end{cases}, \quad (4)$$

where α, β are the parameters affecting the pheromone trail weight. At time moment t the pheromone level on edge D_{ij} corresponds to $\tau_{ij}(t)$. Parameters α and β estimate the relative significance of the two parameters and their impact on the equation. They determine "greed" of the ant. At $\alpha = 0$ the ant tends to choose the shortest edge, while at $\beta = 0$ it chooses the edge with the highest amount of the pheromone.

The ants have "sight" inversely proportional to the edge length:

$$\eta_{ij} = 1/D_{ij}. \quad (5)$$

Pheromone evaporation is estimated by:

$$\tau_{ij}(t+1) = (1-p) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij,k}(t), \quad (6)$$

where m is the ants number; p is the evaporation coefficient ($0 \leq p \leq 1$), determining the amount of the pheromones left after every iteration.

The remaining pheromone amount is in inverse proportion to the route length:

$$\Delta\tau_{ij,k}(t) = \begin{cases} \frac{Q}{L_k(t)}, (i,j) \in T_k(t) \\ 0, (i,j) \notin T_k(t) \end{cases}, \quad (7)$$

where T_k stands for the route finished by agent k, L_k is the route $T_k(t)$ length, l is the iteration number, Q_i is the total pheromone amount, left by the ant on the edges of route D_k.

Pheromone evaporation on the graph edges occurs according to the following equation:

$$f_{ik} = f_{ik}(l - p), \quad (8)$$

where ρ is the update coefficient. After all actions at the iteration, the agent with the best solution is determined, and the solution is memorized. Then the agent moves to the next iteration.

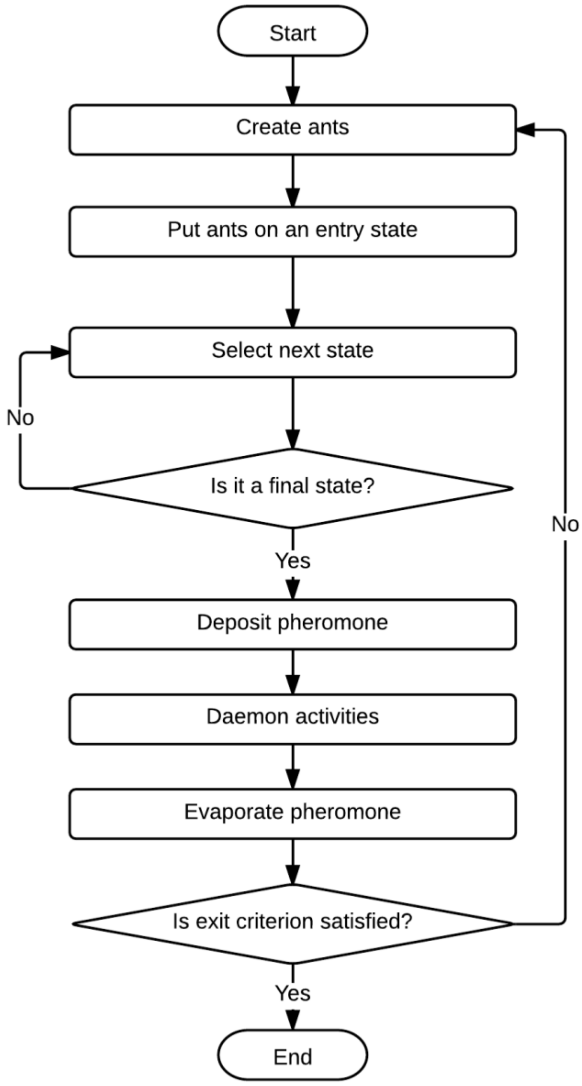

Fig. 8. The flow chart of ant colony algorithm

6. Swarm intelligence in ad hoc networks

To realize multiagent task distribution, each UAV should have an opportunity to share information with the other UAVs of the group. Under real-life conditions these requirements are hard to meet, since working area may contain numerous obstacles and noises interrupting information exchange.

The principles of swarm intelligence have proved their efficiency in solving the routing problems in such self-organized networks as MANET, VANET, and WSN.

It was mentioned earlier that swarm intelligence is one of the sub-fields in artificial intelligence domain, and it includes several algorithm groups, such as ant [13] and bee algorithms [14].

6.1. Ant routing algorithms

Applied for routing in Ad Hoc Networks, ant algorithms differ from the traditional ones. The hybrid algorithms, including reactive and proactive components, provide the best results [15].

The reactive component is performed only on demand and reacts to the events requiring the algorithm usage, namely, the information acquisition on destination sites involved in the communication session. This can be compared to the process of food search performed by an ant in natural environment.

The proactive component operates periodically. Its function is to maintain and improve the connection and to update the information about the existing routes during the communication session. The reactive component differs from the proactive one since it operates only when the existing known routes become faulty (come out of action). This is similar to the way improvement between the ant-hill and the food source in nature.

Pheromone tables store the routing information. These tables are represented as distance-vector two-dimensional matrices. The pheromones in nature perform the same function. With these tables, the control packets and data forwarding occurs stochastically (Fig. 9). The given network node has neighbouring nodes X, Y and Z, while all network nodes act as destination ones. The network includes N nodes.

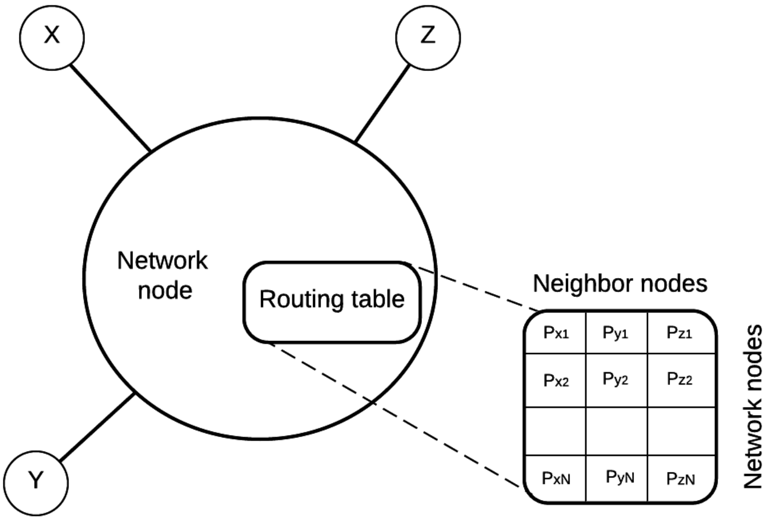

Fig. 9. The node routing information is stored in pheromone table

ACO algorithms gather the routing information through the iterative sampling of the possible routes between the source node and the receiver node using the control packets, i.e. ants.

Table 2 contains the most known modifications made for Ad Hoc networks based on the ant colony.

Table 2

ACO-based routing algorithms

MANET	VANET	WSN
ARA [16]	Time-Ants [17]	EEABR [18]
AntHocNet [15]	MAZACORNET [19]	AORA [20]
HOPNET [21]	VACO [22]	OD-PPRP [23]
Ant-DSR [24]	TACR [25]	FAMACROW [26]

6.2. Bee routing algorithms

The bee algorithms represent another important class of bio-inspired algorithms. When watching bee colonies, the scientists noticed some interesting features. These features proved to be useful for wireless Ad Hoc Networks.

The first stage is called “scouting”, divided into forward and backward scouting. Forward scouts inspect the network, looking for the head-end presence. They carry four categories of information. They are the scout ID (Identification Number), the source node ID, minimal residual energy (initially equal to infinity), and the number of hops (equal to zero). The scouts are sent to all source node neighbourhoods and so on. Upon arriving at another intermediate node, the counter of hops number is increased by 1.

Once the destination node is found, the backward scout returns to the source node, and multiple channels are created between the source and head-end.

The algorithm checks the scout characteristics at each visited node, and thus draws a conclusion on the route efficiency. It is a rather complicated procedure, and it includes several verification steps.

When the scouting procedure is completed and the route is determined, "dance formula" is used to calculate the number of forager-bees necessary for the route.

Then, another stage begins, known as "resource foraging". The foragers transfer the data in a way, similar to the real bees transporting the food.

Data transmission process is rather complicated as well. The data are transmitted from the source node to the destination one, while the number of forager-bees may vary. The probability distribution table is employed for probabilistic calculation.

The intermediate nodes making no decisions on routing is the main difference from the ant colony optimization algorithm, since all decisions come from the source node. In ACO algorithm each intermediate node contains the pheromone tables. The calculations on the network operation improvement and the decisions are also made in such nodes.

To return to the source node, the foragers should merge in a single swarm. This merge takes place on the same ID of the foragers' route. The routes number is determined during the comeback, and inefficient routes are removed from the routing tables.

Table 3 presents the applications and algorithms modeling the bees behavior in wildlife, which have been developed for such peer-to-peer networks as VANET, WSN, and MANET.

Table 3

Routing algorithms based on ant colony

MANET	VANET	WSN
BeeAdHoc [27]	Bee Life Algorithm [28]	BeeSensor [29]
BeeIP [30]	QoSBeeVanet [31]	Bee-Sensor-C [29]
BeeAIS [32]	HyBR [33]	ICWAQ [34]
Bee-MANET [35]	MQBV [36]	Artificial Bee Colony [37]

Therefore, bio-inspired algorithms modeling the bees and ants behavior in wildlife are efficient, and they provide good results. In many cases they surpass the traditional routing algorithms in productivity when applied in such types of peer-to-peer networks as VANET, WSN, and MANET. Moreover, bio-inspired algorithms allow to improve the intelligence in wireless Ad Hoc Networks.

7. Modeling

7.1. Modeling environment

Computer imitation modeling plays an important role in scientific and research work. The researchers often apply it in network design as a tool allowing to understand the protocols behaviour and to evaluate the network productivity.

One of the most important tasks is to choose a suitable network simulator. Nowadays, there are a lot of network simulators. The most popular ones are ns-2, ns-3, OMNET++, GloMoSiM, and QualNet. All mentioned systems are used for imitation modeling of Ad Hoc Networks and allow:

– enhancing the development efficiency;
– conducting an experiment without real network deployment;
– conducting scientific research in this field;
– reducing the development and real network deployment costs dramatically.

These simulators are remarkably popular in scientific society.

7.2. Modeling parameters

This section describes the parameters for test analysis of the routing protocols AntHocNet and BeeAdHoc for FANET.

AntHocNet is an adaptive hybrid multipath routing algorithm for MANET, and it is based on modeling natural ant behavior [38].

While BeeAdHoc is a power efficient routing algorithm for mobile peer-to-peer networks. The algorithm models bee behaviour in natural habitat [27].

Input data for the simulation modeling of all protocols were identical (Table 4).

Table 4

Modeling parameters

Parameter	Value
Simulated area	1500 m × 1500 m
Mobility model	Random waypoint
UAV number	10, 20, 30, 40, 50
Simulation runs	10
Simulation duration	20 s
Nodes velocity	20–50 m/s
Traffic type	CBR
MAC layer protocol	802.11
Signal Propagation Model	Friis
Data links antenna	Omni
Antenna coverage range	150, 200, 250, 300, 350 m
Transport Protocol	UDP
Packet size	512 Kbytes

The routing protocols were investigated in network simulator ns-2. In modeling, we used version 2.35 with pre-installed protocols AODV, DSDV, and DSR.

7.3. Performance evaluation parameters

The following metrics were used for the algorithms performance analysis:

- Throughput – it characterizes the maximal possible rate of successful packet delivery via the communication channel [39].
- End-to-End delay – it is the delay between the first sent byte and the last received one. It includes process queue delay, transmission delay, and propagation delay [40].
- Routing overhead – it is a route discovery overhead and a routing table construction [41].

7.4. Modeling results

As seen from Fig. 10, for the protocols AntHocNet, BeeAdHoc, DSR, and AODV, the throughput increases when the nodes amount rises to 40, but afterwards it declines. While for the protocol DSDV, the throughput lowers when the nodes amount increases.

In Fig. 11 one can see that the increase in the nodes amount lead to routing overhead increase for all protocols under investigation. Moreover, DSR and DSDV demonstrate a weaker increase when in comparison with the other protocols. At the same time, the protocol AODV has the biggest increase.

Fig. 12 shows the protocols behavior pattern regarding the ratio of the end-to-end delay to the nodes amount. BeeAdHoc is slightly inferior to AODV and DSR protocols. The protocol AntHocNet shows decent results when the nodes number is lower than 30, a delay being less than in AODV. DSDV has the best parameters because it is a proactive/table-driven protocol and store all node routes are stored in its routing tables.

Fig. 13 and Fig. 14 demonstrate that if the nodes rate slightly changes from 20 to 50 m/s, the protocols are not affected by heavy loads due to the routing overhead caused by an increased nodes mobility, and the throughput remains almost the same. Therefore, in the present experiment the protocols DSR and AODV are the optimal ones in terms of the throughput.

BeeAdHoc has longer delay time compared to the other protocols (Fig. 15) because it needs to find a new route to the destination node. Though the figures for the other protocols differ only slightly, the protocol DSR is the best one in terms of the delay.

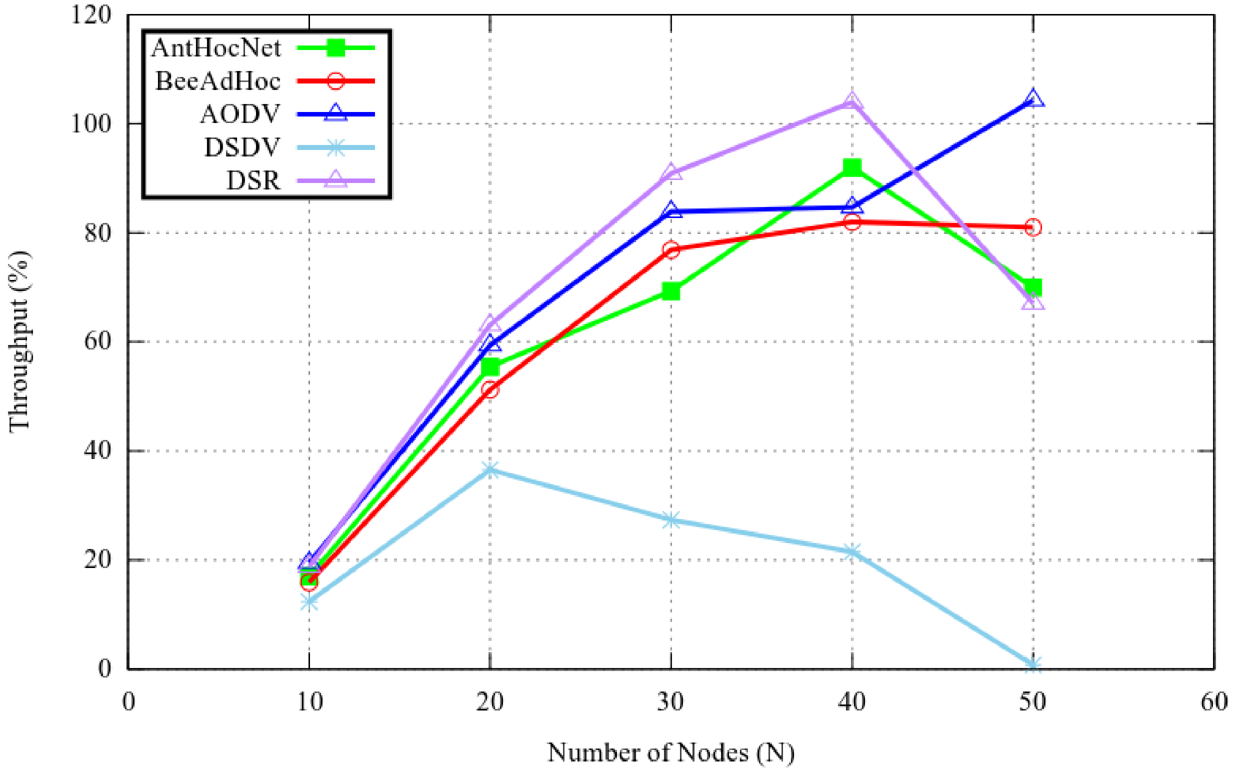

Fig. 10. Number of Nodes vs Throughput

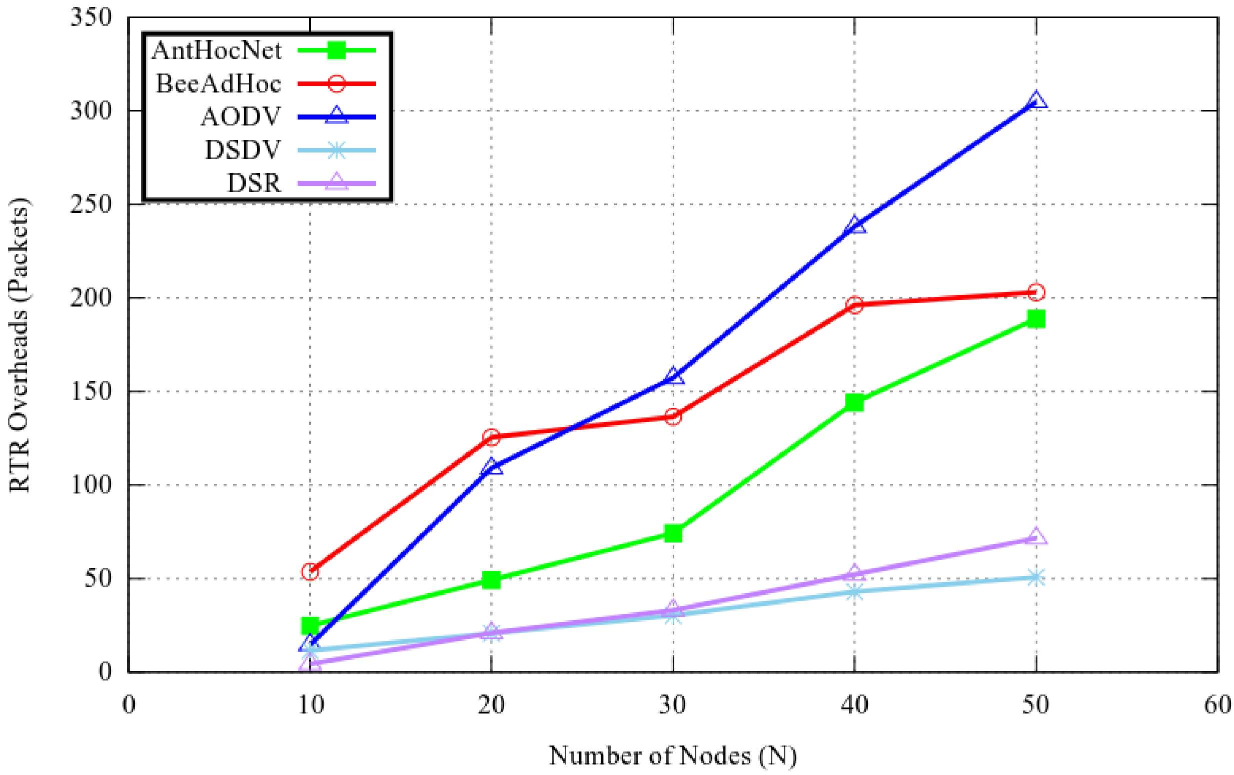

Fig. 11. Number of Nodes vs Routing Overhead

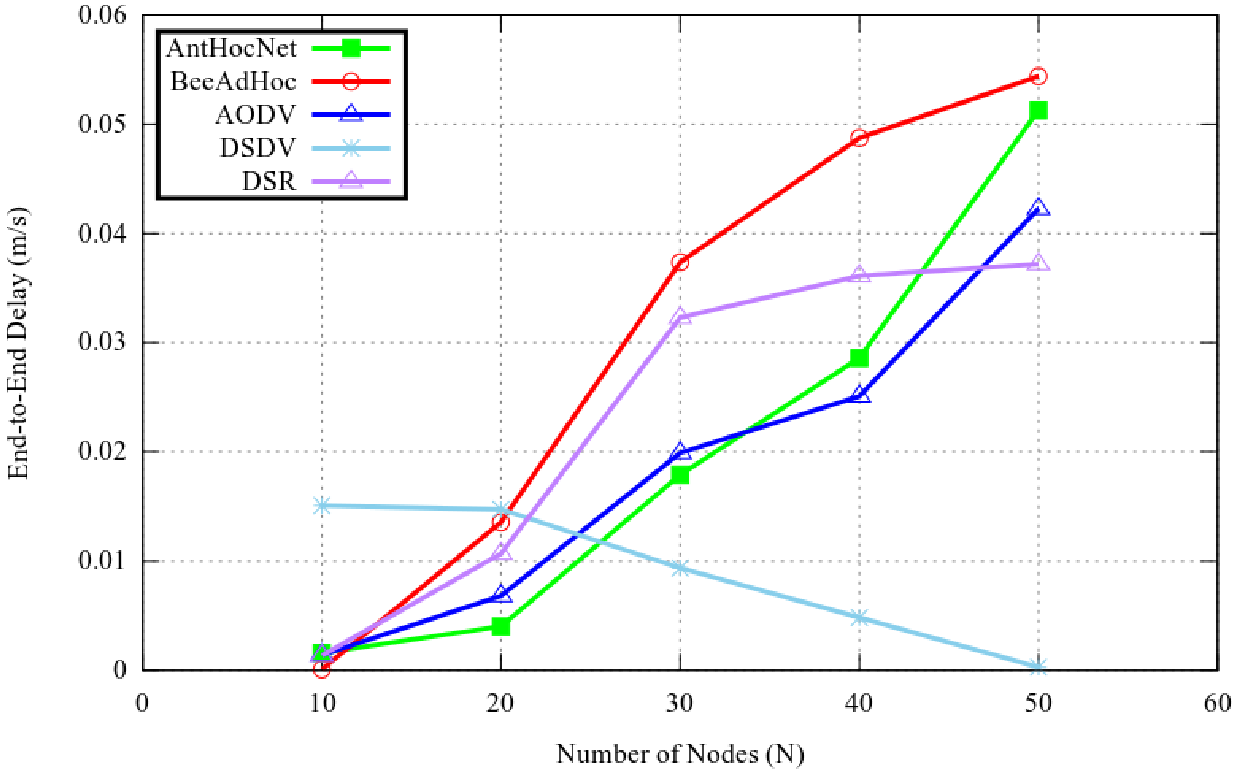

Fig. 12. Number of Nodes vs End-to-End Delay

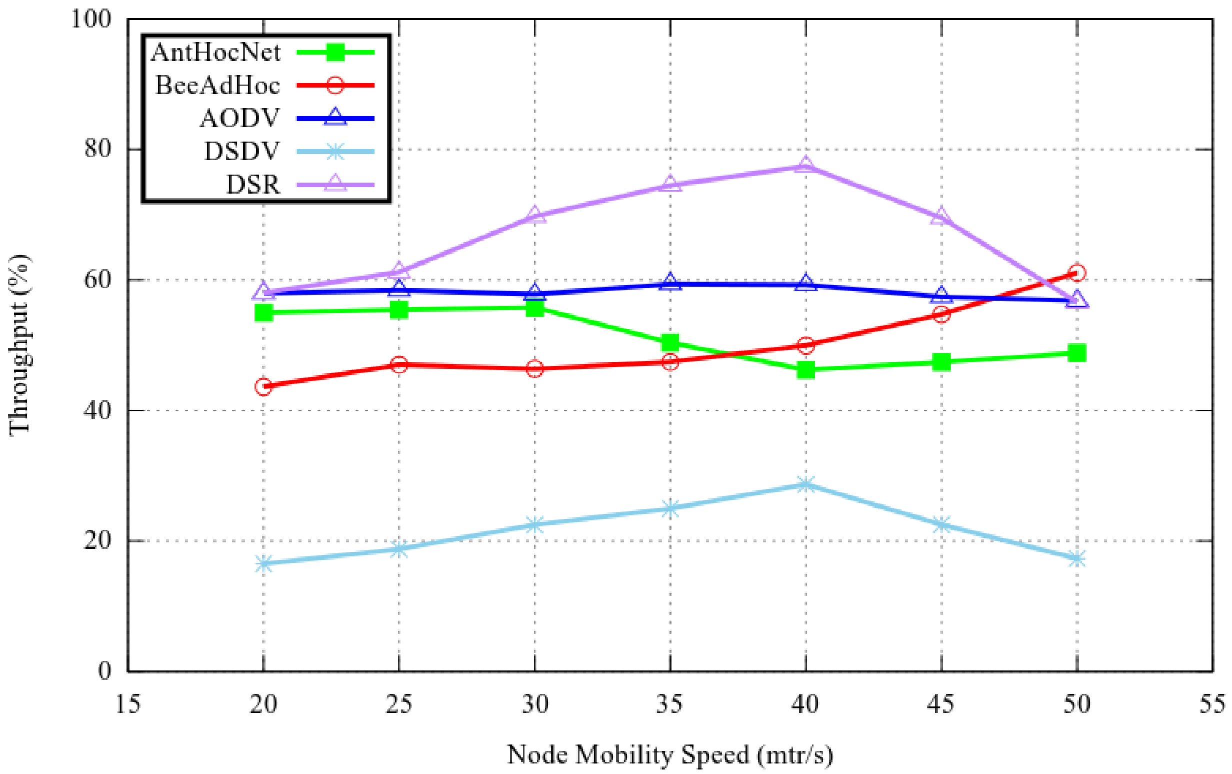

Fig. 13. Node Mobility vs Throughput

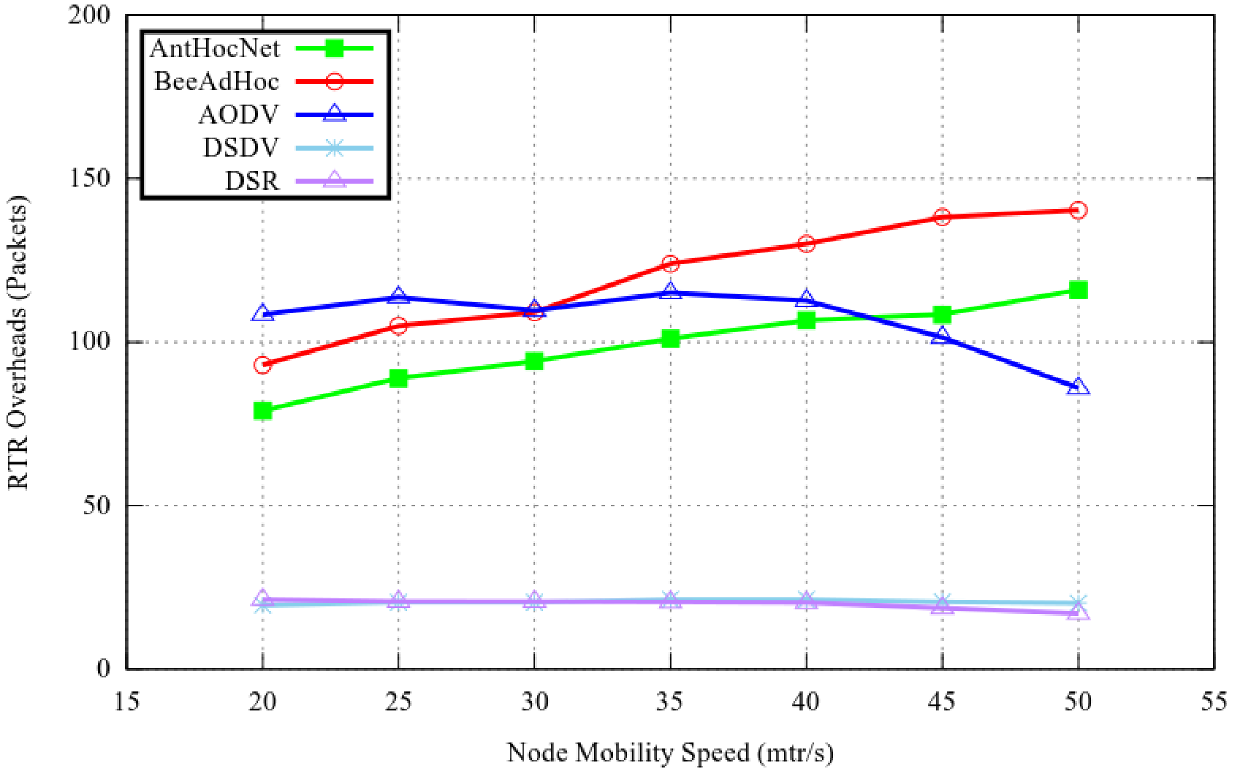

Fig. 14. Node Mobility vs Routing Overhead

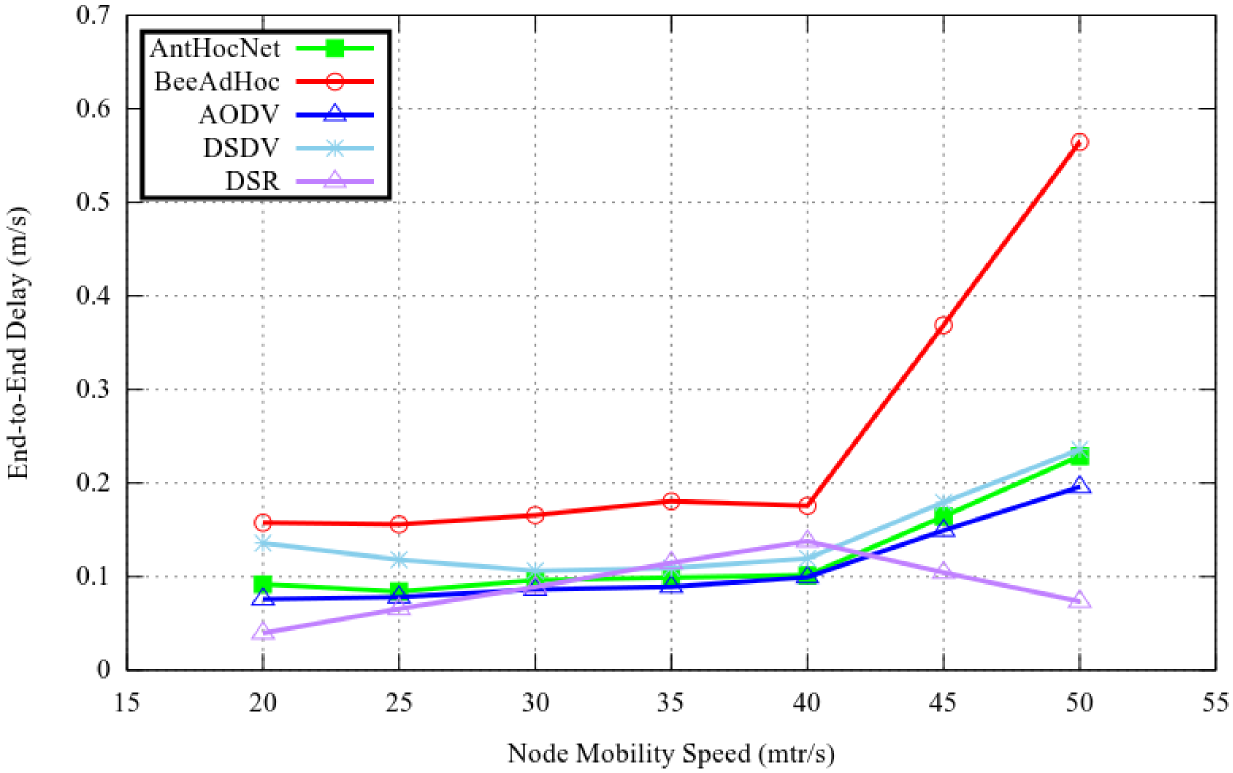

Fig. 15. Node Mobility vs Routing Overhead

The modeling results indicate that the performance of AntHocNet and BeeAdHoc as a whole is comparable to that of the protocols DSR, DSRV and AODV.

BeeAdHoc is as good as DSR and DSDV in throughput and routing overheads, but its delay is worse.

As for the protocol AntHocNet, it shows good figures in networks with high nodes agility. Moreover, AntHocNet possesses fine scalability.

Currently, it is impossible to determine the most universal and effective solution of the routing problem, but it has been proved above that the solutions based on ant and bee colony algorithms are efficient in comparison with the other algorithms.

Conclusion

The development of robotic technology and, namely, UAVs has reached a new level where the researches have moved from the remote control for mobile self-contained units to the control incorporating UAVs as a major part of the process.

Therefore, robotic devices allow solving a broader range of issues than before. The system, however, becomes more complicated, because it has a high level of independence and opportunities relating to artificial intelligence. The main issues revolve around the computing technology functionality, since it should be capable of evaluating the current situation and controlling UAVs on a real time basis in the context of high velocity.

Group control theory for intelligent self-contained units is at the initial development stage.

The article has described the routing problem solution for FANET. The comparative analysis of the existing FANET algorithms has been given, as well as of the algorithms based on the swarm intelligence (of the ant and bee colonies).

Nowadays, there is no universal solution of the routing problem in FANET, thus the results of the performed modeling clearly demonstrate that the solutions based on bio-inspired algorithms AntHocNet and BeeAdHoc prove to be efficient in comparison with the traditional routing algorithms AODV, DSDV, and DSR.

The obtained results demonstrate that bio-inspired algorithms may be recommended for FANET networks organization.

The promising prospect for the future research in this field seems to be the development and realization of the hybrid algorithm based on the bee and ant colony algorithms.

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Received 20 February 2017

УДК 621.391 :: 519.863 **DOI: 10.14529/ctcr170201**

ПРИМЕНЕНИЕ БИОПОДОБНЫХ АЛГОРИТМОВ ДЛЯ РЕШЕНИЯ ЗАДАЧИ МАРШРУТИЗАЦИИ В СЕТЯХ FANET

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Успехи, достигнутые в разработке беспилотных летательных аппаратов (БПЛА) открывают новые возможности для их гражданского применения. На сегодняшний день БПЛА составляют важную часть научных исследований. Практическое применение БПЛА привело к необходимости одновременного участия в выполнении поставленных задач не одного, а группы взаимодействующих БПЛА. Для организации сети мульти-БПЛА необходимо использовать специальные алгоритмы маршрутизации, разработанные с учетом их специфических особенностей. В статье представлен краткий обзор существующих алгоритмов маршрутизации для Ad Hoc Networks, основанных на интеллекте роя (муравьиных и пчелиных колоний). Для решения задачи маршрутизации в сетях FANET проведен экспериментальный анализ, подтверждающий возможность эффективного использования биоподобных алгоритмов на примере протоколов BeeAdHoc и AntHocNet, имитирующих поведение пчел и муравьев в природе.

Ключевые слова: БПЛА, роевой интеллект, протоколы маршрутизации, беспроводная самоорганизующаяся сеть БПЛА, FANET, BeeAdHoc, AntHocNet, имитационное моделирование.

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Поступила в редакцию 20 февраля 2017 г.

ОБРАЗЕЦ ЦИТИРОВАНИЯ

Leonov, A.V. Applying Bio-Inspired Algorithms to Routing Problem Solution in FANET / A.V. Leonov // Вестник ЮУрГУ. Серия «Компьютерные технологии, управление, радиоэлектроника». – 2017. – Т. 17, № 2. – С. 5–23. DOI: 10.14529/ctcr170201

FOR CITATION

Leonov A.V. Applying Bio-Inspired Algorithms to Routing Problem Solution in FANET. *Bulletin of the South Ural State University. Ser. Computer Technologies, Automatic Control, Radio Electronics*, 2017, vol. 17, no. 2, pp. 5–23. DOI: 10.14529/ctcr170201