Inter-Object Navigation of Unmanned Aerial Vehicles to Increase the Efficiency and Accuracy of Inspection of Power Lines

Tymochko O.[1], Fustii V.[2], Kolesnyk G.[1], Olizarenko S.[1], Kalashnyk G.[1], Kulish R.[1], Tymoschuk O.[3], Galinskji D.[1]
[1]Flight Academy of the National Aviation University
Kropyvnytskyi, Ukraine
[2]Kharkiv National Air Force University named after Ivan Kozhedub
Kharkiv, Ukraine
[3]State University of Infrastructure and Technology
Kyiv, Ukraine

Abstract. The purpose of the work is to improve the accuracy and efficiency of a power line section inspection for a fault detection using unmanned aerial vehicles. The goal was achieved by using a unified computing and measurement platform on multicopter and aircraft drones and by simplifying the interaction between them and by using the inter-object navigation sensors. The most significant results were the development of a method of route planning by drones over different parts of the power grid and a method of inter-object navigation. The drone route planning problem was represented by a multi-agent variation of the classical traveling salesman problem and was solved by the ant colony method. The method of inter-object navigation was distinguished by the representation of the power grid topology by high and low intensity graphs, involving a different number and types of drones in the inspection process. The application of the developed methods made it possible to increase the accuracy of power line inspections by 27-73%, and the efficiency by 2-8 times. Solving the problem of multi-criteria optimization of the drone team flight route planning made it possible to reduce the cost of monitoring critical infrastructure facilities while improving its efficiency and accuracy. Thus, the conducted research has shown the effectiveness of the proposed approach for the monitoring of power facilities, route selection, number and composition of search teams. The direction for further research is to improve the ant algorithm.

Keywords*:* power grid, navigation, unmanned aerial vehicle, accuracy, efficiency, monitoring, ant algorithm.
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Navigarea între obiecte a dronelor aeriene fără pilot pentru a crește eficiența și precizia inspecției liniilor electrice

Timocico O.[1], Fustii V.[2], Kolesnik G.[1], Olizarenko S.[1], Kalașnik G.[1], Kuliș R.[1], Tymoșuk O.[3], Galinski D.[1]
[1]Academia de zbor a Universitătii Naționale de Aviație, Kropivnytskyi, Ucraina
[2] Universitatea Națională a Forțelor Aeriene Ivan Kojedub Harkiv, Harkiv, Ucraina
[3]Universitatea de Stat de Infrastructură și Tehnologie, Kiev, Ucraina.

***Rezumat*.** Scopul lucrării este de a crește precizie și eficiența inspectării unei secțiuni a rețelei electrice pentru a detecta o defecțiune folosind dronele aeriene fără pilot. Acest obiectiv este atins prin utilizarea unei platforme unificate de calcul și măsurare pe drone aeriene care implementează diverse scheme de zbor - multicopter și aeronautice și simplificarea interacțiunii dintre ele. Mai mult, o creștere a eficienței detectării defecțiunii se realizează prin inspectarea simultană a diferitelor secțiuni ale rețelei de către mai multe diferite tipuri de dispozitive, iar o creștere a preciziei localizării defecțiunii se realizează prin utilizarea senzorilor de navigație între obiecte. Cele mai importante rezultate sunt elaborarea unei metode de planificare a rutei pentru survolarea diferitelor secțiuni ale rețelei electrice de către drone, ceea ce face posibilă creșterea eficienței inspectării prin prezentarea problemei de planificare a rutei ca o problemă clasică de vînzare în varianta multi - agent și rezolvarea variației revizuite prin metoda coloniei de furnici, și elaborarea unei metode de navigare inter-obiect care diferă în topologia descrierii rețelelor electrice cu grafice de intensitate mare și scăzută, implicarea în inspectarea diverse cantități și tipuri de drone fără pilot, ceea ce permite obținerea cîștigului în precizia inspectării liniilor electrice cu 27-73% și eficiența inspectării rețelelor electrice de 2-8 ori. Semnificația rezultatelor obținute constă în rezolvarea problemei de optimizare multicriterială a planificării rutelor de zbor pentru un grup de drone fără pilot pentru monitorizarea obiectelor de infrastructură critică, ceea ce va reduce costurile de monitorizare sporind în același

timp eficiența și precizia acesteia.
Cuvinte-cheie: rețea electrică, navigație, dronă aeriană fără pilot, precizie, eficiență, monitorizare, algoritm pentru colonii de furnici.

Межобъектная навигация беспилотных летательных аппаратов для повышения оперативности и точности инспектирования линий электропередач

Тимочко А.[1], Фустий В.[2], Колесник А.[1], Олизаренко С.[1], Калашник А.[1], Кулиш Р.[1], Тимощук Е.[3], Галинский Д.[1]
[1]Летная академия Национального авиационного университета, Кропивницкий, Украина
[2]Харьковский национальный университет Воздушных Сил имени Ивана Кожедуба, Харьков, Украина
[3]Государственный университет инфраструктуры и технологий, Киев, Украина

Аннотация. Целью работы является повышение точности и оперативности инспектирования участка электросети для выявления неисправности с использованием беспилотных летательных аппаратов. Поставленная цель достигается путем использования унифицированной вычислительной и измерительной платформы на беспилотных летательных аппаратах, реализующих различные полетные схемы – мультикоптерную и самолетную, и упрощения взаимодействия между ними. Причем повышение оперативности обнаружения неисправности достигается путем одновременного инспектирования разных участков сети несколькими разнотипными аппаратами, а повышение точности локализации места неисправности – путем использования датчиков межобъектной навигации. В основу построения алгоритма оценки вектора состояния беспилотного аппарата положены результаты объединения информации об измерении и моделирования. Наиболее важными результатами являются разработка метода планирования маршрута облета беспилотными аппаратами разных участков электросети, что позволяет повысить оперативность инспектирования за счет представления задачи планирования маршрута как классической задачи коммивояжера ее многоагентным вариантом и решения рассмотренной вариации методом муравьиных колоний, и разработка метода межобъектной навигации, который отличается описанием топологии электросетей графами высокой и низкой интенсивности, привлечением к инспектированию различного количества и типов беспилотных летательных аппаратов, что позволяет получить выигрыш в точности инспектирования линий электропередач на 27-73% и оперативности инспектирования электросетей в 2-8 раз. Значимость полученных результатов состоит в решении задачи многокритериальной оптимизации планирования маршрута полета группы беспилотных летательных аппаратов для мониторинга объектов критической инфраструктуры, что позволит снизить затраты на мониторинг, одновременно повысив его оперативность и точность. Таким образом, проведенные исследования показали эффективность предложенного подхода для мониторинга объектов электроэнергетики, подбора маршрута, численности и состава групп поиска, что позволит создать действенную систему мониторинга за состоянием объектов наблюдения.
***Ключевые слова*:** электросеть, навигация, беспилотный летательный аппарат, точность, оперативность, мониторинг, муравьиный алгоритм.

INTRODUCTION

The development of modern civilization has entered the phase of smart cities construction. Their elaboration requires integration and the best usage in practice of several intellectual solutions in various regions. In this context, recently the studies of 'smart' power grids were carried out. This advanced generation of the energy systems must maintain the optimum output throughout all the cycle stages, including energy consumption and energy transmission.

Rapid economic development of territories and urbanization have led to an abnormal increase in demand for electricity consumption, which requires a high level of electrical supply reliability. High-voltage power transmission lines, as the connecting element between production and consumption nodes, play an important role in the overall performance of the electrical grid.

Most of the high-voltage transmission lines, for reasons of environmental protection, safety, cost savings in construction, etc., are located far from main roads, production, and residential centers. Therefore, the search for more efficient and cost-effective ways of inspecting transmission lines is one of the most important stages in electricity management.

To check electrical equipment, pedestrian patrols or helicopter surveys are usually carried out [1, 2, 3]. The first method is quite slow and mainly ineffective. Helicopter inspections are much faster. However, since they cannot hover at a short distance from energy systems, it is quite problematic to get reliable measurements visually or with other sensors.

The rapid development of automation and artificial intelligence technologies in recent years has highlighted the inspection of transmission lines with unmanned aerial vehicles (UAVs) as a viable alternative method [4, 5].

Power lines are extensively inspected using UAVs in China. In the provinces of Shandong and Ganzhou, intelligent control systems based on small drones equipped with HD cameras and infrared thermal imaging are successfully applied to 220 kV and 500 kV transmission lines [6].

To maintain optimal power network performance, it is necessary to reduce the time it takes to detect and repair faults on the network. Known power line inspection methods can be replaced or improved with the use of recent advances in science and technology. With this goal in mind, it is proposed to investigate the construction of a UAV-based robot for monitoring conditions and, if possible, carrying out some urgent maintenance procedures on various components of energy systems.

The aim of the article is to increase the accuracy and speed of inspecting a power network section to detect faults using UAVs.

We will consider existing approaches to solving similar problems.

PUBLISHED LITERATURE ANALYSIS

In most of the analyzed studies [7-11], the UAVs are only considered as an element of the system for checking the state of high-voltage transmission lines. If any defects are detected in them, no technical maintenance scenario is carried out.

Attempts have been made to determine the mission of the drone to improve its planning efficiency and pre-model the inspection [12].

Primitive methods of digital image processing are used to locate the connections of transmission lines: background subtraction and morphological operations. However, this method is considered unstable when consecutive images of the same scene from different scales or orientations are captured [7].

The Kalman filter and the Hough transform are used to track the state of transmission lines based on the flow of the video stream [9]

Acceptable results were obtained in the study of the state of power grids using a multi-channel ground-matching BPL system relying on a laser radar [10].

When moving along cables to read the state of electrical components from close range and achieve the required maintenance quality, an alpine robot [13] is proposed. However, this type of platform is slow and has many mechanical difficulties when moving along lines located in the forest.

Recently, a hybrid alpine-flying robot has been proposed, which combines the advantages of UAV and ROW robots on one platform [14].

The verification of power transmission lines usually takes place in two stages: data collection and fault detection. The key direction of the research is the automation of the verification process. It is also carried out in two ways - a) selection of the type of robotic platform and b) development and modification of computer vision algorithms.

During autonomous data collection, computer vision methods and technical means were studied on unmanned aerial vehicles (UAVs) and remotely piloted vehicles for visual inspection [15], tracking power transmission lines [16], electrical masts [17], [18], and obstacle detection [19].

At the second stage, faults in the power line infrastructure [20] are usually detected at the base station using automation tools, specifically in electrical wires [21], supports [22], insulators, conductors, clamps, etc.

Currently, research on detecting power transmission lines themselves to identify sags and proximity to vegetation or man-made constructions is relevant. The image pre-processing strategy is to detect line candidates and segments search, which form the electric transmission lines' parts [22], [23] Some researchers have also focused on detecting and segmenting electrical poles on images [16] [17], [22], [23]. Similarly to the detection of the electric transmission lines, the pre-processing stage in this case usually includes the determining of location of line sections on the image.

Therefore, the analysis conducted suggests the feasibility of using unmanned aerial vehicles to solve specific tasks in the energy sector. The unresolved issues remain the inter-object navigation of a group of unmanned aerial vehicles inspecting power lines to achieve the required speed and accuracy of the procedures.

METHODS, RESULTS, AND DISCUSSION

Universal Computational Platform for Unmanned Aerial Vehicle

In any sufficiently developed electrical grid, there are extended stretches between base stations that sometimes reach hundreds of kilometers (Fig. 1). For automated inspection, a universal platform is proposed where all measurements and calculations are performed. The UAV is proposed to be implemented on two different flight schemes - multicopter and aircraft. This will allow for efficient inspection of fundamentally different parts of electrical grids. For long stretches of the network, the aircraft-type UAV is applicable due to its advantage in flight range without recharging. Short network sections and sections with complex interchanges and obstacles are proposed to be checked using multicopter UAVs due to their maneuverability advantage. The use of a group of UAVs allows for simultaneous inspection of various parts of the power grid. Accordingly, it is possible to find the number of UAVs (or kilometers of power line per UAV) that will allow for the most efficient detection of faults in a given area. To increase the accuracy of fault localization, a method described in [25] is proposed.

Navigation tasks are solved using a visual-inertial navigation system (VINS) [26], and UAV control is based on the PX4 autopilot [27].

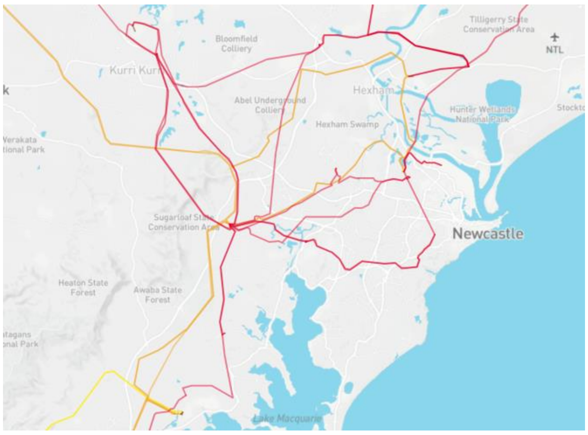

Fig. 1. An example of transmission line infrastructure in Newcastle, Australia.

The PX4 hardware consists of an STM32 H7 MCU and a combined accelerometer and gyroscope IMU BMI088 with an 8GB memory card for logging. The IMU sensor is responsible for low-level position control and sending inertial sensor data to the high-level navigation block. This block, performing localization, planning, high-level control, and other navigation functions, requires sufficient computing power.

In the proposed platform, the NVIDIA Xavier NX is used - a powerful computer for embedded and peripheral systems with a six-core processor, a 384-core graphics processor, and 8 GB of RAM (Fig. 2). In experiments, except for multi-view video, the load on the processor and graphics processor was less than 40%. That is, there are significant computational reserves for additional potential use.

Fig. 2. External view of the hardware of the proposed UAV control system.

The Intel Realsense D430 camera [28] outputs depth images for mapping and gray-scale stereo images for localization. The UWB module is a Nooploop LTPS with a DW1000 radio chip inside, which allows for the use of the UAV inter-object navigation method described in [25]. The functional diagram of the proposed UAV is shown in Fig. 3.

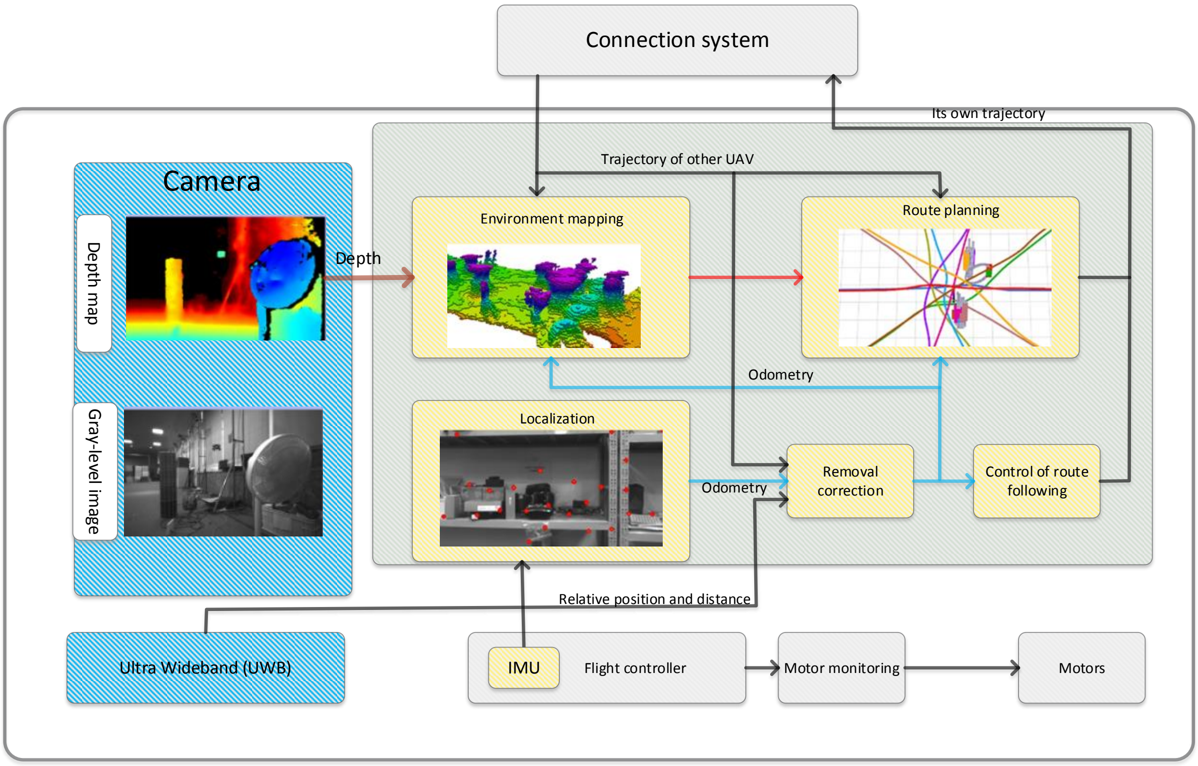

Fig. 3. Functional diagram of the proposed UAV.

Inter-object navigation and the traveling salesman multi-agent task.

Traditionally, the UAV navigation system consists of a satellite navigation module, inertial measurement systems (accelerometer, gyroscope), barometer, and magnetometer. In recent years, SLAM (simultaneous localization and mapping) technologies, which use stereo cameras or a depth scanner and camera to build a model of the environment and determine their own location, are increasingly being used.

As an additional source of navigation information, we propose using UWB transceiver modules. The principle of this system is described in [25] based on [29-32].

With this set of modules, information exchange between UAVs is possible and the relative location can be determined with high accuracy. The location determination error is significantly less than in other navigation methods and does not exceed tens of centimeters.

But with this method, only the relative position can be determined. However, the known position of the UAV relative to the global navigation system and inertial sensors, using the Kalman's filter, allows us to compare the information and increase its accuracy [33]. Let's imagine the UAV's position estimate as:

$$\mathbf{x} = \begin{bmatrix} p \\ s \end{bmatrix};$$
$$\mathbf{x}' = \mathbf{F}x_{k-1} + \mathbf{B}\mu_{k-1} + \nu, \tag{1}$$

where $\mathbf{x}'$ is the predicted state of the system;

p is the position of the UAV;

s – is the velocity;

$\mathbf{F}$ is the transition matrix;

$\mathbf{B}$ is the control matrix;

μ_{k-1} is the monitoring vector at the previous moment of time;

ν is the process noise.

The transition matrix **F** is necessary to map the traffic model to the object. Suppose there is a model that provides the position and velocity of an unaccelerated object. Then the new value of x and p over time Δt is calculated as:

$$\begin{aligned} s' &= s; \\ p' &= p + s\Delta t. \end{aligned} \tag{2}$$

Then matrix **F** will look like as follows:

$$\mathbf{F} = \begin{pmatrix} 1 & \Delta \\ 0 & 1 \end{pmatrix}. \tag{3}$$

The control matrix **B** describes the changes in the state of an object through the influence of external or internal forces, such as gravity or friction.

Now let's consider the equation for extrapolating the error covariance matrix:

$$\mathbf{P}' = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^{\mathrm{T}} + \mathbf{Q}, \tag{4}$$

where $\mathbf{F}^{\mathbf{T}}$ is the transposed matrix of transition;

$\mathbf{Q}$ is the noise matrix.

Suppose the object changes direction of motion or may accelerate or decelerate. Therefore, after time Δt the uncertainty will increase by $\mathbf{Q}$.

Let's consider the step of updating the value of the UAV position. Let's start by describing the difference between the measured value and the predicted state value:

$$y = z - \mathbf{H}x', \tag{5}$$

where z is the actual measurement value;

$\mathbf{H}$ is the transition matrix;

$\mathbf{x}'$ is the predicted state value.

Matrix **H** is also known as the transition matrix. It can be used to discard unnecessary information from the predicted state value. Technically, **H** performs the same job as **F** in the extrapolation step.

Let's find the common error in determining the system state:

$$\begin{aligned} &\mathbf{S} = \mathbf{H}\mathbf{P}'\mathbf{H}^{\mathbf{T}} + \mathbf{R}, \\ &K = \mathbf{P}'\mathbf{H}^{\mathbf{T}}\mathbf{S}^{-1}, \end{aligned} \tag{6}$$

where $\mathbf{R}$ is the noise measurement;

K is the Kalman gain coefficient.

Values of the Kalman gain coefficient are in the range from 0 to 1. If the error in measurement is large, the value of the coefficient is closer to 0. This means that the extrapolated value is closer to the real value than the measured one. If the error in extrapolation is large, the value of the coefficient is closer to 1, i.e., the measured value is closer to the real value than the extrapolated value.

We shall obtain the aposteriori estimates of the state vector and the error covariance matrix:

$$\begin{aligned} &\mathbf{x} = \mathbf{x}' + Ky; \\ &\mathbf{P} = \left(1 - K\mathbf{H}\right)\mathbf{P}'. \end{aligned} \tag{7}$$

The algorithm described above allows estimating the UAV vector based on the results of combining information on measurements and modeling results.

The choice of the navigation information source determines a different measurement error matrix $\mathbf{R}$. This ultimately allows for a gain in measurement accuracy by combining heterogeneous observations.

The improvement of the efficiency of inspection of different parts of the power grid is achieved by using multiple UAVs. To solve the route planning problem for the UAVs, we will represent the power grid as a weighted graph (Fig. 4). Assuming that the arc weight includes the distance between the nodes of the power grid. Then the route planning problem becomes a classic traveling salesman problem with its multi-agent variant.

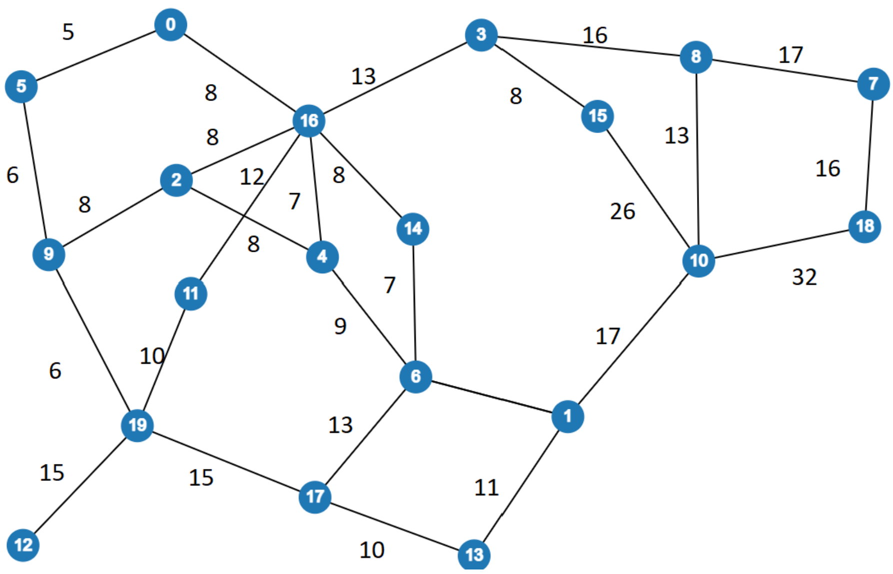

Fig. 4. Image of the power supply system in the form of a weighted graph.

As a solution option, let's consider the variation of the ant colony method for the multi-agent case [34]. According to the rule of the ant colony method, the amount of pheromone deposited on the edges of the graph, the edges selected by each ant on its path, and the rate of evaporation of pheromone on each edge are determined. An ant *k* located in node *i* decides to move to node *j* using the "pseudo-random proportional rule"

$$j=\begin{cases}\arg\max_{l\in N_i}\left(\left(\tau_{i,l}\right)^{\alpha}\left(\eta_{i,l}\right)^{\beta}\right), \text{ если } & q\le q_0;\\ J, & \end{cases} \tag{8}$$

where α is the parameter monitoring $\tau_{i,j}$ effect $\tau_{i,j}$;

$\tau_{i,j}$ is pheromone amount, on (i,j) arc;

$\eta_{i,l}$ is arc reachability (i,j), which is calculated as the inverse arc weight value $1/w_{i,l}$;

β is the parameter, monitoring $\eta_{i,l}$ effect;

q is the random variable with uniform law of distribution on section $[0,1]$;

q_0 is the parameter q initial value;

J is the random node, selected according to the distribution law (9);

N_i – set of neighboring nodes of i node.

Probability $p_{i,j}$ that the ant located in node i, occasionally decided to move to node j is

$$p_{i,j}=\frac{\left(\tau_{i,l}\right)^{\alpha}\left(\eta_{i,l}\right)^{\beta}}{\sum_j\left(\tau_{i,l}\right)^{\alpha}\left(\eta_{i,l}\right)^{\beta}}. \tag{9}$$

From the analysis of formula (8), it follows that the ant makes the best possible move (marked by a large amount of pheromone) with probability q_0. And it makes a random choice of a suboptimal arc with probability (1 − q_0). If q_0 = 0, it means that the focus is on searching for the best solution, avoiding convergence to the suboptimal as much as possible. Therefore, only probability (9) should be used to determine the next transition in the proposed approach.

The best solutions should be marked by a large amount of pheromone along the path. Therefore, when t_k determines a new path V_k with cost L_k, the ant will increase the strength of the pheromone on each edge of the tour by a value inversely proportional to the cost of the path:

$$\Delta\tau_{i,j}^{k}=\begin{cases}1/L_k \text{ if arc } (i,j) \text{ belongs to}\\ \text{the way found } V_k;\\ 0,\end{cases} \tag{10}$$

where L_k – cost of k path.

When an ant travels along a given path at a constant speed, it takes time proportional to the distance traveled. Pheromones are volatile substances. It will take the ant longer to travel a longer distance. Consequently, over a longer time, more pheromones will evaporate, implying better solutions that will be discovered in the future. It's evident that incorporating pheromone evaporation into the model can be useful for solving the traveling salesman problem. The path (arc) traveled by the ant is marked with pheromones. The update will also consider pheromone evaporation. The change in the amount of pheromones is taken into account as follows:

$$\Delta\tau_{i,j}^{k}=\left(1-\rho\right)\tau_{i,j}+\rho\Delta\tau_{i,j}^{k}, \tag{11}$$

where ρ is the pheromone evaporation level,

$0 \le \rho < 1$.

For the probabilistic determination of the next step of the ants, formula (9) is used. Therefore, the arc with the highest pheromone content is chosen, i.e., the probability of exploring other paths is low. The solution consists in reducing the pheromone content on the arcs selected by the ants, i.e., applying a local evaporation process. This makes them less interesting for the ant, increasing the degree of exploration of still unselected arcs. Each time an ant crosses an arc, it uses local evaporation, updating the pheromone as follows:

$$\tau_{i,j} = (1-\xi)\tau_{i,j} + \xi\tau_0, \tag{12}$$

where ξ is the local level of pheromone evaporation, $0 \le \xi < 1$,

τ_0 is the initial pheromone amount on each arc.

A good heuristic for initializing the pheromone trails is to set them to a value slightly higher than the amount of pheromone deposited by ants in one iteration. To approximate this value, we need to tune $\tau_0 = 1/(nC)$, where n is the number of nodes and C is the cost of the path. Thus, if w_{awg} is the average edge cost, then it can be set to $C = nw_{awg}$. To monitor the impact of evaporation on the solutions, a pheromone update scheme that does not include evaporation is also considered. In this case, equations (11) and (12) are replaced with

$$\tau_{i,j} = \tau_{i,j} + \Delta\tau_{i,j}^{k}. \tag{13}$$

Then the influence of local evaporation rate of pheromones is excluded and the amount of pheromones is determined according to equation (10).

Modeling the process of monitoring a group of unmanned aerial vehicles for object search

The accuracy of fault localization in the power supply system depends on the accuracy of determining the UAV's own coordinates. Taking into account the obtained information on the location of the UAV relative to other agents in the proposed inter-object navigation system significantly increases the accuracy of coordinate determination [25].

Modeling this navigation method was carried out with several restrictions:

- the proposed navigation system includes up to four UAVs or stationary sensors;
– the effect of electromagnetic radiation on the stability of the systems was not taken into account;
– the technical specifications of the proposed navigation system correspond to the values claimed by the equipment manufacturer.

In order to obtain reliable results, 100 experiments were conducted with different numbers of UAVs (from 1 to 4) in the navigation system. Their locations relative to each other were selected randomly.

The results of the modeling in Matlab using the Navigation Toolbox are presented in Table 1. In the columns of the table are reflected: **N_{uav}** – the number of UAV navigation systems; σ_{GPS} – the root mean square deviation (RMSD) of the measured position of the UAV from the true one; $\sigma_{Prop\,MIN}$ – RMSD of the measured position of the UAV from the true one at the minimum distance between the agents; $\sigma_{Prop\,MAX}$ – RMSD of the measured position of the UAV from the true one at the maximum distance between the agents.

Table 1. Accuracy of determining the UAV's own coordinates from the number of them in the navigation system's zone of action.

N_{uav}	σ_{GPS}, m	$\sigma_{Prop\,MIN}$, m	$\sigma_{Prop\,MAX}$, m
1	12,82	9,5923	10,7954
2	11,98	6,9251	7,8536
3	13,05	4,8961	6,0487
4	12,54	3,6528	5,2387

The analysis of the simulation results showed that with an increase in the number of sensors in the navigation system, the accuracy of determining the UAV's own coordinates increases.

The root mean square deviation of the measured position of the UAV from the true one at the minimum distance between the agents decreases. Thus, when using two agents, the RMSD of the measured position of the UAV from the true one at the minimum distance between them decreases by 1.39 times, three UAVs - by 1.96 times, four UAVs - by 2.63 times.

With the maximum distance between navigation system agents, the standard deviation of their coordinates decreases by 1.37, 1.78, and 2.06 times, respectively, for the same number of UAVs.

That is, as the number of UAVs in the navigation system increases, the accuracy of determining their coordinates increases. This allows for more accurate localization of faults in the power system.

It is obvious that the growth in the number of drones improves the efficiency of power line inspection. Additionally, the efficiency of inspection is influenced by the topology of the energy system itself, the degree of connectivity of the graph describing the power system, the ratio of the number of short and long sections of the network, and the overall length of the power transmission lines.

In general, it is difficult to estimate the efficiency of power line inspection. Therefore, for mathematical modeling, the representation of the power grid as a weighted graph is adequate. The specifics of its application have predetermined the characteristics of defining a weakly and strongly connected graph, which differs from the classical one.

We will call a graph weakly connected if the average number of arcs attached to one vertex is $\chi_{avg} \leq 3$.

Based on the results of modeling, the assessment of the efficiency of inspecting the main varieties of schemes is presented in Table 2. The data in the table are normalized, and the inspection time by one UAV is taken to be one unit.

Table 2. Inspection efficiency of the electrical network with different number of UAVs and graph connectivity degree.

Connectivity degree	**UAV used during inspection**			
	1	**2**	**4**	**8**
Strong	1	0,54	0,29	0,16
Weak	1	0,72	0,35	0,19

In a strongly connected network, increasing the number of UAVs used for inspection sharply reduces the inspection time. Thus, the second UAV used effectively reduces the inspection time by two; four UAVs reduce it by three times, and eight UAVs reduce it by 6.25 times.

For a weakly connected network, the observed dynamics are the same. Only at the initial stage is the reduction in inspection time less noticeable: for two UAVs it is reduced by 1.38 times; for four UAVs by 2.86 times; and for eight UAVs by 5.26 times.

The presence of 10 or more UAVs in the navigation system makes it possible to carry out an inspection equally efficiently for both highly and weakly connected power grids. The increase in the number of UAVs will only be determined by economic feasibility and the configuration of the power grid.

We introduce the ratio η - the number of short sections of the power grid to the total number of all sections (network topology): low ($\eta \leq 0,33$), medium ($0,33 < \eta \leq 0,66$), and high ($\eta > 0,66$).

During mathematical modeling, the following assumptions will be made:

1. A single sweep is carried out only by a multi-copter UAV.
2. In a multi-agent system, long sections of the power grid use aircraft-type UAVs, while short sections use multi-copter UAVs.
3. The cruising speed of the aircraft-type UAV is 2 times higher than speed of the multi-copter device.

The results of modeling the inspection efficiency of the power system with different network topologies and different numbers of UAVs involved are shown in Table 3. The data is normalized, and the inspection time of one UAV is taken as one unit.

Table 3. Inspection efficiency of the power grid with different ratios of the number of short sections to the total number of all sections of the energy system and different numbers of UAVs.

η	**UAV used during inspection**			
	1	**2**	**4**	**8**
Low	1	0,42	0,22	0,12
Average	1	0,56	0,28	0,15
High	1	0,67	0,36	0,21

The operational efficiency of inspecting the power grid is at a maximum when the low topology network is inspected. Increasing the number of UAVs used for monitoring leads to a significant reduction in inspection time. The topology of the power grid only significantly affects this indicator when 2-4 UAVs are used. Further increases in inspecting UAVs do not make a noticeable difference in the ratio of short segments of the power grid to the total number of all segments. The presence of more than 10 UAVs in the navigation system allows for equally efficient inspection of the power grids of different topologies.

Thus, from the analysis of the simulation results it follows:

- The proposed inter-object navigation approach increases the accuracy of inspecting power transmission lines from 27% to 73% depending on the number of UAVs in the operation area of the system.

- The use of a heterogeneous group of UAVs allows for the inspection of power grids to be increased by 2 to 8 times, depending on the number of drones used and the configuration of the power system itself. The inspection efficiency is greatly influenced by the ratio of the cruising speeds of different types of drones. An increase in this ratio results in a greater time gain in inspection when there is a large number of extended sections of the power system.

- The inspection efficiency of a power grid varies widely depending on the ratio of the number of short sections to the total number of sections of the power system and the number of UAVs. Inspection of a network with a low topology is carried out in the most efficient manner.

CONCLUSIONS

This article is devoted to the task of increasing the efficiency and accuracy of inspecting power transmission lines. The use of a unified computing and measuring platform has simplified the interaction between the proposed types of UAVs: a multicopter - on short sections with complex junctions and obstacles, and an unmanned aircraft with an airframe flight scheme - on long sections.

The increase in the efficiency of fault detection was achieved by simultaneous inspection of different parts of the network by several different types of UAVs. The use of inter-object navigation sensors of UAVs has increased the accuracy of determining the UAV's position in space and, accordingly, increased the accuracy of locating the site of the malfunction.

References

[1] Xie, X., Liu, Z., Xu, C., & Zhang, Y. (2017). A multiple sensors platform method for power line inspection based on a large unmanned helicopter. Sensors, 17(6), 1222.

[2] Katrasnik, J., Pernus, F., & Likar, B. (2009). A survey of mobile robots for distribution power line inspection. IEEE Liu, Y., Liu, Z., Shi, J., Wu, G., & Chen, C. (2019). Optimization of base location and patrol routes for unmanned aerial vehicles in border intelligence, surveillance, and reconnaissance. Journal of Advanced Transportation, 2019.

[3] Luque-Vega, L. F., Castillo-Toledo, B., Loukianov, A., & Gonzalez-Jimenez, L. E. (2014, April). Power line inspection via an unmanned aerial system based on the quadrotor helicopter. In MELECON 2014-2014 17th IEEE Mediterranean electrotechnical conference (pp. 393-397). IEEE.

[4] West, L. M., & Segerstrom, T. (2000, March). Commercial applications in aerial thermography: power line inspection, research, and environmental studies. In Thermosense XXII (Vol. 4020, pp. 382-387). International Society for Optics and Photonics.

[5] Jiang, S., Jiang, W., Huang, W., & Yang, L. (2017). UAV-based oblique photogrammetry for outdoor data acquisition and offsite visual inspection of transmission line. Remote Sensing, 9(3), 278.

[6] Deng, C., Wang, S., Huang, Z., Tan, Z., & Liu, J. (2014). Unmanned aerial vehicles for power line inspection: A cooperative way in platforms and communications. J. Commun, 9(9), 687-692.

[7] Jones, D. I., & Earp, G. K. (2001). Camera sightline pointing requirements for aerial inspection of overhead power lines. Electric Power Systems Research, 57(2), 73-82.

[8] Zhang, J., Liu, L., Wang, B., Chen, X., Wang, Q., & Zheng, T. (2012, August). High speed automatic power line detection and tracking for a UAV-based inspection. In 2012 International Conference on Industrial Control and Electronics Engineering (pp. 266-269). IEEE.

[9] Jiang, W., Wenkai, F., & Qianru, L. (2013, January). An integrated measure and location method based on airborne 2D laser scanning sensor for UAV's power line inspection. In 2013 Fifth International Conference on Measuring Technology and Mechatronics Automation (pp. 213-217). IEEE.

[10] Li, B., & Chen, C. (2018). Transmission line detection based on a hierarchical and contextual model for aerial images. Journal of Electronic Imaging, 27(4), pp. 43-54.

[11] Bhola, R., Krishna, N. H., Ramesh, K. N., Senthilnath, J., & Anand, G. (2018). Detection of the power lines in UAV remote sensed images using spectral-spatial methods. Journal of environmental management, 206, 1233-1242.

[12] Besada, J. A., Bergesio, L., Campaña, I., Vaquero-Melchor, D., López-Araquistain, J., Bernardos, A. M., & Casar, J. R. (2018). Drone mission definition and implementation for automated infrastructure inspection using airborne sensors. Sensors, 18(4), 1170.

[13] Debenest, P., Guarnieri M., Takita K., Fukushima, E. F. Hirose S., Tamura K. & Shiga F. (2008, May). Expliner-Robot for inspection of transmission lines. In 2008 IEEE International Conference on Robotics and Automation (pp. 3978-3984). IEEE.

[14] Katrasnik J., Pernus F., and Likar B., “New robot for power line inspection,” in Robotics, Automation and Mechatronics, 2008 IEEE Conference on. IEEE, 2008, pp. 1195–1200

[15] Golightly I. and Jones D., “Visual control of an unmanned aerial vehicle for power line inspection,” in Advanced Robotics, 2005. ICAR’05. Proceedings, 12th International Conference on. IEEE, 2005, pp. 288–295.

[16] Jones D., “Power line inspection-a UAV concept,” in Autonomous Systems, 2005. The IEE Forum on (Ref. No. 2005/11271). IET, 2005, pp. 8–15/

[17] Whitworth C., Duller A., Jones D., and Earp G., “Aerial video inspection of overhead power lines,” Power Engineering Journal, vol. 15, no. 1, pp. 25–32, 2001.

[18] Sun C., Jones R., Talbot H., Wu X., Cheong K., Beare R., Buckley M., and Berman M., “Measuring the distance of vegetation from powerlines using stereo vision,” ISPRS journal of

photogrammetry and remote sensing, vol. 60, no. 4, pp. 269–283, 2006.

[19] Williams M., Jones D., and Earp G., “Obstacle avoidance during aerial inspection of power lines,” Aircraft Engineering and Aerospace Technology, vol. 73, no. 5, pp. 472–479, 2001.

[20] Oberweger M., Wendel A., and Bischof H., “Visual recognition and fault detection for power line insulators.” 19th Computer Vision Winter Workshop, 2014.

[21] Li Z., Liu Y., Walker R., Hayward R., and Zhang J., “Towards automatic power line detection for a UAV surveillance system using pulse coupled neural filter and an improved Hough transform,” Machine Vision and Applications, vol. 21, no. 5, pp. 677–686, 2010.

[22] Golightly I., and Jones D., “Corner detection and matching for visual tracking during power line inspection,” Image and Vision Computing, vol. 21, no. 9, pp. 827–840, 2003.

[23] Sun C., Jones R., Talbot H., Wu X., Cheong K., Beare R., Buckley M., and Berman M., “Measuring the distance of vegetation from powerlines using stereo vision,” ISPRS journal of photogrammetry and remote sensing, vol. 60, no. 4, pp. 269–283, 2006.

[24] Australian electricity grid map. (2022). Retrieved from https://www.aemo.com.au/aemo/apps/visualisations/map.html (accsesed 01.02.2023)

[25] Fustii V.S., Tymochko O.I., Sytnyk Yu.B., Afanas′yev V.V., Tytarenko O.B., Stepanov H.S. Metod mizhob'yektovoyi navihatsiyi BPLA na osnovi kompleksnoyi obrobky informatsiyi vid klasychnykh ta al′ternatyvnykh system navihatsiyi. Nauka i tekhnika Povitryanykh Syl Zbroynykh Syl Ukrayiny. 2021. № 4(45). P. 65-74.

[26] Qin T., Li P., Shen S., “VINS-Mono: A robust and versatile monocular visual-inertial state estimator”. IEEE Trans. Robot. 34, 1004–1020 (2018).

[27] Meier L., Honegger D., Pollefeys M., “Px4: A node-based multithreaded open source robotics framework for deeply embedded platforms”. 2015 IEEE international conference on robotics and automation (ICRA) (IEEE, 2015), pp. 6235–6240.

[28] Keselman L., Iselin Woodfill J., Grunnet-Jepsen A., Bhowmik A., “Intel realsense stereoscopic depth cameras”, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (2017), pp. 1–10.

[29] ISO/IEC JTC 1/SC 31. Information technology – Real-time locating systems (RTLS) – Part 5: Chirp spread spectrum (CSS) at 2.4 GHz air interface. Official edition. 2010. URL: https://www.iso.org/standard/46534.html. (accsesed 01.02.2023)

[30] Ngoc Hung N., Kutluyıl D. Closed-Form Algebraic Solutions for Angle-of-Arrival Source Localization with Bayesian Priors. IEEE Transactions on Wireless Communications. 2019. V. 18, № 8. C. 3827–3842.

[31] State Estimation of Multiagent Systems under Impulsive Noise and Disturbances / L. R. G. Carrillo et al. IEEE Transactions on Control Systems Technology. 2015. Vol. 23, no. 1. P. 13–26.

[32] Curtright T.L., Fairlie D.B., Zachos C.K. Compact Formula for Rotations as Spin Matrix Polynomials. Symmetry, Integrability and Geometry: Methods and Applications, 2014 10, pp.1-15.

[33] Wei, L., Jian, Z., Chunzhi, W., & Hui, X. (2013). Kalman filter localization algorithm based on SDS-TWR Ranging. TELKOMNIKA Indonesian Journal of Electrical Engineering, 11(3), 1436-1448.

[34] Ilie, S., Bădică, C. Distributed Multi-agent System for Solving Traveling Salesman Problem Using Ant Colony Optimization. In: Essaaidi, M., Malgeri, M., Badica, C. (eds) Intelligent Distributed Computing IV. Studies in Computational Intelligence, vol 315. Springer, Berlin, Heidelberg. (2010).

About authors.

Tymochko Oleksandr, Doctor of Technical Sciences, Professor, Head of the Department, Flight Academy of the National Aviation University, area of scientific interests: Decision support systems, motion control, automation, E-mail: timochko.alex@gmail.com

Fustii Vadym
Adjunct, Kharkiv National Air Force University, area of research interests: UAV, decision support systems, E-mail: vadimfustie1995@gmail.com

Kolesnyk Anna, D. in Technical Sciences (PhD), Head of Department, Flight Academy of the National Aviation University, area of scientific interests: mathematical modeling. E-mail: annakol2603@ukr.net

Olizarenko Serhij, Doctor of Technical Sciences, Senior Researcher, Professor of the Department, Flight Academy of the National Aviation University, area of scientific interests: mathematical modeling, E-mail: solizarenko71@gmail.com

Kalashnyk Ganna, Doctor of Geological Sciences, Senior Researcher, Professor of the Department, Flight Academy of the National Aviation University, area of scientific interests: Decision support systems, E-mail: kalashnilga@ukr.net

Kulish Ruslan, Postgraduate student, Flight Academy of the National Aviation University, area of scientific interests: Decision support systems, motion control, E-mail: controllerskykrv@gmail.com

Tymoschuk Olena, Doctor of Technical Sciences, Professor, Director of the Institute of Water Transport of SUIT, area of scientific interests: navigation, E-mail: Mnielena7@gmail.com

Galinskyi Dmytro, Postgraduate student, Flight Academy of the National Aviation University area of scientific interests: navigation, UAV E-mail: Dmitronik70@i.ua