A Stochastic Continues-Time Model of the Drone Fleet: Research of Survivability and Choice of Parameters

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Abstract: - The main tasks that drone fleet can perform for radiation and safety monitoring are formulated. Perturbing factors that can cause operability failures are presented. An approach to the drone fleet survivability assessment based on a stochastic continues-time model is proposed. The input data are the number of the drones, the drone fleet redundancy coefficient, the drone stability and restoration rate, the limit deviation from the norms of the drone fleet recovery, the drone fleet operational availability coefficient, the probability of the drone failure-free operation, time needed for performing the required tasks by the drone fleet survivability rate on the drone stability, the number of the drones, time needed for performing the required tasks, the number of the drones needed for performing the required tasks by the drone fleet survivability rate on the drone stability, the number of the drones, time needed for performing the required tasks, the number of the drones needed for performing the required tasks by the drone fleet are analysed. The recommendations to choice of the parameters for drone fleet are described.

Key-Words: - drone fleet; nuclear power plant; perturbing factors; survivability rate; monitoring time; mathematical expectation; stability

1 Introduction

After the Fukushima accident, a drone fleet is actively used for nuclear power plants (NPPs) monitoring because airborne surveys are the most time effective way to quickly gather radiation data over large areas due to the high operational speed and lack of obstacles at the altitudes at which the surveys are conducted.

Besides, drones are applied to support physical security functions during operation in pre- and post-accident time.

The main tasks that separated drones and drone fleet can perform for radiation monitoring of NPPs are the following [1-4]:

- investigate nuclear and radiation accidents areas on emergency;
- detect radioactive contamination sources and radioactive plume movement; examine nuclear energy facilities for corresponding to the standards;
- monitor ground and air radioactive ecological pollution;
- scientific research according with station and national plans;
- serve as an instrument for initial assessment of radiation situation when using as a part of mobile radiation monitoring labs;

• perform other tasks requiring urgent detection of x-rays and gamma emission sources.

According to [5, 6], drone fleet can be divided by the role and equipment into: repeaters, observers (equipped with a TV camera) and additional sensors (they can be located in drones or be dropped down in certain places).

The paper [7] presents an approach to research integrated drone-based systems for post emergency monitoring of NPPs as systems with a multi-level degradation. The approach covers Reliability Block Diagrams of the systems, systems' degradation levels, conditions which determine the levels and formulae for calculating the reliability functions of the systems on these levels.

2 Problem Formulation

Carrying out the monitoring tasks, drones of a drone fleet can be affected by various perturbing factors that cause operability failures. There are a lot of reasons of failures described in particular in [8].

- Horizontal and vertical wind gusts during open-air flights, resulting in a big deviation from the flight path and the desired orientation.
- Deviations of forces and moments acting on the UAV from their pre-calculated values.
- Regress of inertia characteristics after the cargo release.
- Damage to the aerodynamic surfaces and the housing due to collision with obstacles.
- Critical states caused by a transition from the hover mode to the horizontal flight, and vice versa, leading to controllability breakdown.
- Collisions with other UAVs resulting in flight path changes.

Also note that drones can break down due to electronics failures that are about 25% of all drones failures. These failures can occur from electro-static discharge, electrical overstress from a power surge, vibration causing connector and solder joint issues, along with thermal fatigue of interconnects due to material properties such as coefficient of thermal expansion.

The listed perturbing factors and causes of electronics failures point to the need to ensure needed level of drone fleet survivability at NPP monitoring. Drone fleet survivability is quantified ability of a drone fleet to continue to function during and after a natural or man-made disturbance.

The aim of the paper is to present an approach to the drone fleet survivability assessment based on stochastic continues-time model, considering the proposed recoverable drone fleet as an associative multi-state system. Using the model research of survivability and recommendations to choice of the drone fleet parameters are formulated.

3 Problem Solution

3.1 Methodology and mathematical model

If a drone fleet consists of identical drones performing the same task (for example, fleet collects some information from monitoring stations), one can be considered as an associative system (A-system) [9].

In this case, the drone fleet ability state depends on the number of its drones. If after exposure to perturbing factors the number of the drones in operational state meets the requirement, the drone fleet will be able to continue being in ability state. To take into account the drone fleet degradation process, the drone fleet damage D is used.

The drone fleet is able to perform the required task if:

$$D \leq D_p$$
, (1)

where D_p is the drone fleet permissible damage.

 D_p is regarded as a criterion to determine the ability states during the process of identifying the drone fleet states. D_p is the permissible number of the failed drones to continue performing the required tasks by the drone fleet.

If drone fleet survivability is ensured not only by redundant drones, but also by carrying out the measures aimed at recovering failed drones, it is necessary to take into account the drone fleet residual damage D_r .

This damage is calculated by the following formula:

$$D_r = D - D_c, \qquad (2)$$

where D_c is the drone fleet prevented damage as a result of recovery.

With regard to (1) drone fleet survivability rate can be calculated as the probability that drone fleet residual damage does not exceed the permissible value D_p :

$$G = \int_{0}^{D_p} f(D_r) dD_r.$$
 (3)

If we equate the value of the drone fleet prevented damage to zero ($D_c = 0$) than the model (1) can be modified into the model of unrecoverable drone fleet (4):

$$G = \int_{0}^{D_p} f(D) dD.$$
 (4)

Consider the opportunity to evaluate the drone fleet survivability based on the model (3). Assume the following limitations and assumptions for the drone fleet.

- The recoverable drone fleet consists of *n* drones and each of the drones has stability *q*.
- Both the drone fleet residual damage D_r and the drone fleet prevented damage D_c have a normal distribution and there is no correlation between them.
- Resources of drones recovery is characterized by restoration rate μ, drones per hour (*dr/h*).
- The drone fleet is able to perform the required task, if during time τ drone fleet has n_r drones and by the end of performing the required task the number of the redundant drones is $k_r n_r$, where k_r is the drone fleet redundancy coefficient.

Let introduce the following parameters needed for evaluating the drone fleet survivability:

- *n* is the number of the drones;
- *n_r* is the number of the drones needed for performing the required tasks;
- k_r is the drone fleet redundancy coefficient;
- q is the drone stability; μ is the drone fleet restoration rate, dr/h;
- $\Delta \mu$ is the limit deviation from the norms of the drone fleet recovery, %;
- Ad is the error limit in evaluating the value of the drone fleet damage, %;
- K_A is the drone fleet operational availability coefficient showing what part of the drone is not under maintenance (repair) and can be used for performing the required tasks;
- *p* is the probability of the drone failure-free operation;

• τ is time needed for performing the required tasks by the drone fleet.

3.2 The algorithm of evaluating

The algorithm of evaluating the drone fleet survivability rate includes the following steps.

1. Calculation of the mathematical expectation of the drone fleet damage

$$D_i = n_i (1 - q_i). \tag{5}$$

2. Calculation of the limit deviation in evaluating the drone fleet damage

$$\Delta D_p = \frac{\Delta d}{100} D. \tag{6}$$

3. Calculation of the mathematical expectation of the residual fleet damage

$$D_r = D - D_c = D - \mu \tau. \tag{7}$$

4. Calculation of the permissible drone fleet damage

$$D_{p} = K_{A}n - n_{r} - n_{r \setminus}(1 + k_{r})(1 - p) - k_{r}n_{r}.$$
 (8)

5. Calculation of the dispersion of the residual drone fleet damage

$$\delta_{D_r} = \sqrt{\left(\frac{\Delta D}{3}\right)^2 + \left(\frac{\Delta \mu}{100}\mu\frac{\tau}{3}\right)^2} . \tag{9}$$

6. Calculation of the drone fleet survivability rate

$$G = F\left(\frac{D_p - D_r}{\delta_{D_r}}\right) + F\left(\frac{D_r}{\delta_{D_r}}\right),\tag{10}$$

where both $F\left(\frac{D_p - D_r}{\delta_{D_r}}\right)$ and $F\left(\frac{D_r}{\delta_{D_r}}\right)$ are

Laplace functions.

3.3 Results of model research

Using the proposed algorithm of evaluating the drone fleet survivability rate, some dependencies were obtained (see Fig. 1 for the input data presented in Table 1, Fig. 2 for the input data presented in Table 2, Fig. 3 for the input data presented in Table 3, Fig. 4 for the input data presented in Table 4).

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15



7 8 9 6 Fig. 4. Dependencies of the drone fleet survivability rate on the number of the drones needed for performing the required tasks

3.4 Discussion and recommendations

We can make the following conclusions based on the analysis of the proposed dependencies:

- 1. To improve the drone fleet survivability, we should increase the value one of the following parameters: drone fleet restoration rate, the drone stability, the number of the drones, time needed for performing the required tasks by the drone fleet. The drone fleet survivability also can be improved by decreasing the number of the drones needed for performing the required tasks.
- 2. For the input data presented in Table 1 the maximum value of drone fleet survivability rate is achieved when $\mu = 0.03$ and q = 0.7(Fig. 1).
- 3. For the input data presented in Table 2 the maximum value of drone fleet survivability rate is achieved when n = 17 and q = 0.7(Fig. 2).

0.1

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- 4. Increasing the value of the drone fleet restoration rate from 0.1 to 0.3 (Fig. 1) makes it possible to increase the value of drone fleet survivability rate: 5.9 times when q = 0.55, 2.7 times when q = 0.6, 1.5 times when q = 0.65 and 1.01 times when q = 0.7.
- 5. Increasing the value of the number of the drones from 14 to 17 (Fig. 2) makes it possible to increase the value of drone fleet survivability rate: 9.9 times when q = 0.55, 3.7 times when q = 0.6, 1.5 times when q = 0.65 and 1.1 times when q = 0.7.
- 6. Increasing the value of time needed for performing the required tasks by the drone fleet from 16 to 28 (Fig. 3) leads to an increase in the value of drone fleet survivability rate by: 22 per cent when $\mu = 0.03$, 34 per cent when $\mu = 0.02$ and 29 per cent when $\mu = 0.01$.
- 7. Increasing the value of time needed for performing the required tasks by the drone fleet from 16 to 28 (Fig. 3) leads to an increase in the value of drone fleet survivability rate by: 22 per cent when $\mu = 0.03$, 34 per cent when $\mu = 0.02$ and 29 per cent when $\mu = 0.01$.
- 8. Increasing the value of the number of the drones needed for performing the required tasks from 6 to 9 (Fig. 4) significantly reduces value of drone fleet survivability rate in comparison with previous results. For example, this value is 0.013 only when n = 21 drones.

4 Conclusion

An approach and the algorithm to the drone fleet survivability assessment based on a stochastic continues-time model have been proposed.

According to the algorithm, the following parameters should be calculated: the mathematical expectation of the drone fleet damage, the limit deviation in evaluating the drone fleet damage, the mathematical expectation of the residual fleet damage, the permissible drone fleet damage, the dispersion of the residual drone fleet damage, the drone fleet survivability rate.

Using the algorithm makes it possible to determine the ways for improving the recoverable drone fleet survivability, taking into account perturbing factors. To improve the drone fleet survivability, we should increase the value one of the following parameters: drone fleet restoration rate, the drone stability, the number of the drones, time needed for performing the required tasks by the drone fleet.

The drone fleet survivability also can be improved by decreasing the number of the drones needed for performing the required tasks.

Future work will include an approach to the drone fleet survivability assessment based on Lanchester's modified deterministic model.

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