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Petri Net–Based Analysis of UAV Networks Availability Issues in Conditions of Adversary Counteraction

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Abstract

The article proposes Petri net-based models that make it possible to simulate scenarios that reflect the real operating conditions of unmanned aerial vehicles (UAVs) in the presence of hostile factors. The modeling takes into account cyber-physical aspects of UAV availability and attacks aimed at disrupting this availability, including by means of enemy electronic warfare (EW) systems. The factor of natural obstacles is also considered, in particular terrain-induced obstacles that interfere with communication between operational UAVs and the relay node.

A set of basic places and transitions is proposed and implemented as a software model. The study uses both ordinary and colored Petri nets. In the ordinary Petri net, the state corresponds to the signal level of the device, and the simulation is carried out to track precisely this characteristic for each UAV in the network. Interference leads to degradation of the state, which can be improved by introducing additional relay devices into the line of sight of the current UAV, reducing the distance between the current UAV and the relay, or deliberately searching for an exit from the EW coverage area.

The colored Petri net is intended for more general tasks, which include counting the active devices in the network, assessing the impact of interference on changes in the network structure, and evaluating mission success. Simulation based on this model was implemented in a Python software application, with visualization performed using the graph-oriented library Graphviz. To account for specific conditions such as terrain and changes in device parameters, an additional module was developed that extracts data from open terrain map datasets.

Keywords: Internet of drones, cybersecurity, cyber-physical attacks, Petri nets, availability

Introduction

Nowadays, UAVs perform a wide range of functions and missions, including monitoring, cargo delivery, coordination of robotic devices, and others [1]. UAVs can also be actively employed to carry out various tasks in combat environments. Regardless of the application domain, it is necessary to take into account additional factors affecting UAV availability that may arise as a result of adversary actions [2].

The study presented in this article is driven by the need to improve the mathematical and computational tools for planning successful missions involving UAV networks. The relevance of this problem stems from the fact that existing UAV network simulation frameworks do not take into account factors that can affect device availability under critical conditions, in particular radio signal interference of both artificial and natural origin.

The problem addressed in this work is the development of mathematical and software tools for modeling the state of devices in a UAV network, taking into account terrain conditions and enemy electronic warfare (EW) systems.

1. State of art and paper objectives

In [3] A. Fedorova, V. Beliautsou and A. Zimmermann consider the problem of UAV-based monitoring under limited battery charge. The Petri net–based model takes into account altitude, speed, flight range, and maneuvering along the route. However, the modeling is carried out for favorable conditions, without considering possible availability disruptions.

The work [4] by D. Xu, P. Borse, K. Altenburg, and K. Nygard uses Petri nets to model reconnaissance processes, taking into account such factors as following a predefined route, maintaining the distance between neighboring devices, entering orbit around a patrolled object, and decision-making based on a Markov process. Interfering actions are considered there in the context of possible physical destruction as a result of enemy strikes.

The work [5] by W. Shi, Z. He, C. Gu, N. Ran, and Z. Ma demonstrates the use of Petri net–based models to solve performance optimization problems for flexible manufacturing systems (FMSs) under limited resources, in particular sensors and devices. This suggests that the Petri net formalism is promising for optimal planning problems; however, it does not account for a number of adverse factors that may arise in industrial scenarios in terms of availability loss.

The authors of [6] (P. Gonçalves, J. Sobral, L. A. Ferreira) consider the use of UAVs in both civil and military domains. The paper presents a Petri net-based model for the UAV safety assessment process, taking into account the recommendations of STANAG 4671 UAV Airworthiness Requirements Specification (USAR) [7].

In the study [8] by Xiaodong Wang, Yangming Guo, Nan Lu, and Pei He, the Petri net formalism is applied to the problem of modeling a UAV cluster, taking into account weather conditions, the surrounding environment, and onboard equipment. A spatio-temporal Petri net model is constructed, within which the process of executing an attack mission and coordinating the devices in the cluster is described.

In the work [9] drone swarm control issues are considered. The authors give attention to the high level Petri nets (HLPN), and propose transitions TakingOff, TakeOffToEnroute, and others, but the issues of cyberphysical problems, which lead to the device take off the route, was not revealed.

The work [10] investigates the evaluation of availability and reliability of drone systems using stochastic Petri nets (SPNs). The model takes into account factors such as battery discharge time, device failure rates, and the number of repairs. Critical system components and overall system performance are considered. Thus, the study focuses on technical threats arising from objective factors rather than subjective ones, such as deliberate adversary actions.

The analysis of existing research in the field of UAV network modeling shows a strong interest in using Petri nets as a convenient and promising mathematical formalism. However, current studies do not take into account a number of factors that occur in real-world conditions, in particular: signal degradation with increasing distance from the control center and the resulting loss of availability; the impact of terrain elevation on signal loss and availability disruption; and the influence of enemy EW devices aimed at jamming the signal or spreading malware, which leads to device unavailability.

Therefore, it is reasonable to address the problem of analyzing device availability in UAV networks on the basis of Petri nets, taking into account adversary actions aimed at creating availability disruptions. The objectives of research are:

- Classic Petri net (for specific device) development, which takes into account adversary influences, such as jamming.
- Colored Petri net development (for group of devices), which takes into account electronic counteraction means (ECM) influence, and influence of landscape, signal degradation and other cyber-physical factors.
- Background simulation program models development, which process real landscape data and take into account drones position.

2. Methodology

Electronic Warfare (EW) Disruption Petri net models allow for modeling signal loss. The stochastic transition of a system from a "Connected" state to a "Jammed" state can be represented. This simulates the sudden removal of "Signal" tokens, forcing the system into specific reactive sub-nets.

Petri net allows the visualization of relay search algorithms. The model captures the logic flow where the system enters a "Scanning" state.

Petri nets enable the definition of fallback mode rules. Deterministic logic can be created where the absence of a control token (command link) automatically enables "Return-to-Home" or "Loiter" transitions, ensuring failsafe operations without operator input.

Our approach represents combination in one model several transitions: “connected” to “jammed” transitions, relay search, landscape-caused denial of service, and others, which are applicable in hostile conditions.

Simulation based on this model was implemented in a Python software application, with visualization performed using the graph-oriented library Graphviz. For computer experiments, software was created in Python

[11], the models were visualized using the Graphvis library [12].

The behavioral pattern of the devices modeled in the work most closely corresponds to multirotor UAVs, however, it is not tied to a specific model. All input data is entered by the user, so the developed software can be adapted to the desired types of unmanned aerial vehicle models.

Signal power degradation with the distance from control device (or center) is showed as follows [13]:

$$\frac{S_r}{S_t} = k\left(\frac{\lambda}{d}\right)^2,$$

where S_r is the signal strength at the receiver side, S_t is the signal strength at the transmitter side, k is a constant, λ is a constant, d is the distance between the current UAV and control device (center).

The signal values lead to the signal levels, which are assumed to be discrete. In following models we use contrinuous values of signal power in the background simulation, and discrete levels in Petri net implementation.

As the input landscape data the [14] open map dataset was used. It was previously pre-processed [15] to be applicable for the simulation needs.

The tokens that describe the state of one network device are signal levels. Three tokens mean the highest level, one – the critical (weakest) level. To model the network behavior, such a model should be applied to each UAV. The starting signal level corresponds to three markers that denote conditional signal levels. Transitions from one state to another are shown by rectangles.

Among them are:

1. Decrease/increase of the signal level with increase/decrease of the distance to the control center;
2. Decrease of the distance to the control center according to the control signal of the control center;
3. The influence of the terrain (taken into account using a topological height map and the location of the device), thus taking into account that the device must be in the “line-of-sight” with the drone-“hub”, or the control center. We can use open maps [13] for landscape simulation.
4. Signal amplification if a drone-hub appears in the “line-of-sight” within the radius of action of this device, which relays the center’s signals;
5. The impact of powerful electronic warfare means that completely disrupt the functionality of the UAV;
6. The impact of less powerful electronic warfare means that disorient the UAV for a while, however, after leaving the EW zone, the UAV’s functionality is restored.

3. Proposed solutions

3.1. One device state Petri net

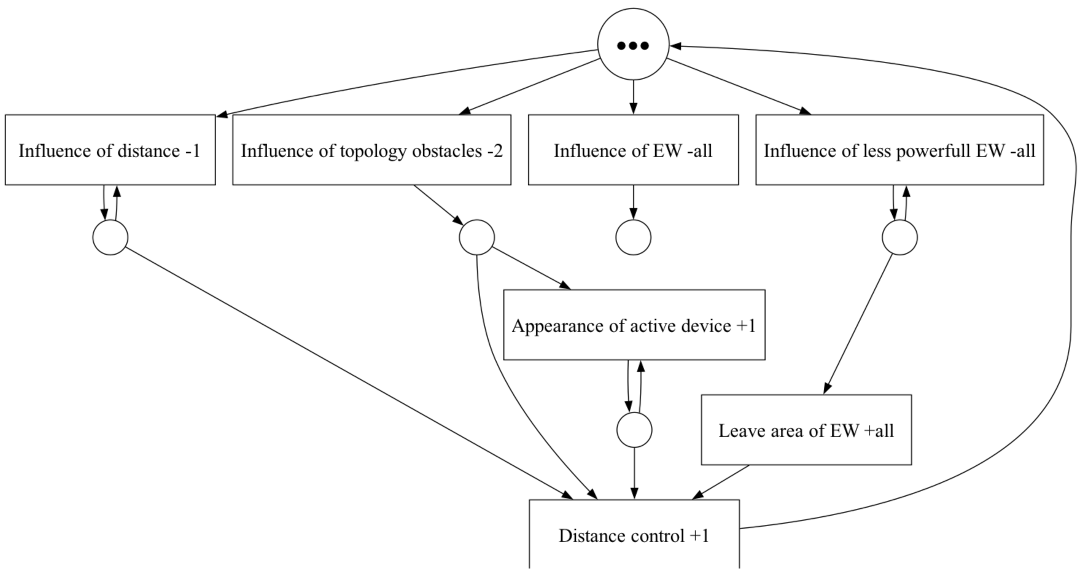

Figure 1: Influence of the factors on signal level value of specific device

Model structure is represented in Fig.1.

Let $Q(D,t) \in \{0,1,2,3\}$ be current level of signal on the specific device (number of tokens in the place); $d(Q,H,t)$ be distance from drone D to nearest hub H in the time t; $O(D,t) \in \{0,1\}$ be indicator of landscape obstacles presence; $E(D,t) \in \{1,2\}$ be level of ECM impact, where: 1 – weak impact, 2 – strong impact.

Places represent signal level $Q(D,t)$, which is represented by tokens (dots in the Fig.1).

Transitions T1-T7 determine factors, which influence on the signal quality.

Scenario of simulation can be described by following transitions implementation:

T1 (Influence of distance):

$$if\ d(Q,H,t+\Delta t) > max\ d(Q,H,t)\ then\ Q(D,t+\Delta t) = Q(D,t) - 1$$

$$if\ Q(D,t+\Delta t) < 0\ then\ Q(D,t+\Delta t) = 0.$$

T2 (Influence of landscape):

$$if\ O(D,t) = 1\ then\ Q(D,t+\Delta t) = Q(D,t) - 2;$$

$$if\ Q(D,t+\Delta t) < 0\ then\ Q(D,t+\Delta t) = 0.$$

T3 (Strong ECM impact):

$$Q(D,t+\Delta t) = Q(D,t) - 3;$$

T4 (Weak ECM impact)

$$Q(D,t+\Delta t) = Q(D,t) - 2;$$

$$if\ Q(D,t+\Delta t) < 0\ then\ Q(D,t+\Delta t) = 0.$$

T5 (Active retranslator impact):

$$if\ Q(t) \neq 3\ then\ Q(D,t+\Delta t) = Q(D,t) + 1;$$

T6 (Exit from ECM zone):

$$if\ E(D,t) = 0\ then\ Q(D,t+\Delta t) = Q(Dstored,t).$$

T7 (Restoration of distance to control center):

$$if\ max\ d(Q,H,t) < max\ d(Q,H,t)\ then\ Q(D,t+\Delta t) = Q(D,t) + 1.$$

3.2. Colored Petri net for group of devices

Let $Q(D,t) \in \{0,1,2,3\}$ be current level of signal on the specific device (number of tokens in the place); $d(Q,H,t)$ be distance from drone D to nearest hub H in the time t; $O(D,t) \in \{0,1\}$ be indicator of landscape obstacles presence; $E(D,t) \in \{1,2\}$ be level of ECM impact, where: 1 – weak impact, 2 – strong impact.

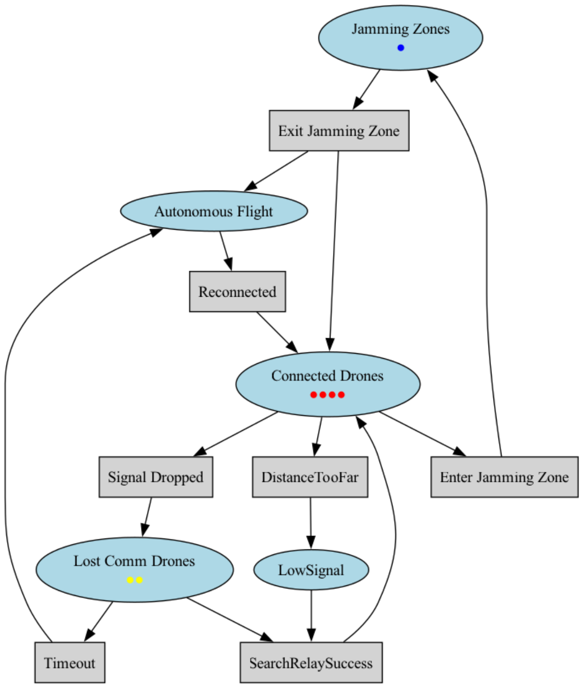

Figure 2: Colored Petri Net

Table 1 illustrates the quantitative results of the Colored Petri Net simulation, tracking the distribution of signal levels (S) across the drone swarm over discrete simulation steps (Steps 0–5). The signal levels range from 3 (Highest/Strongest Signal) to 0 (Critical/Lost Signal).

Initial State (Step 0): At the beginning of the simulation, the entire swarm (76 devices) is in an ideal state, with all devices possessing Signal Level 3 (Strongest). This indicates a fully connected network before mission execution or adversary impact begins.

Degradation Phase (Steps 1–2): As the mission progresses and drones move away from the control center or encounter terrain obstacles.

By Step 1, a significant portion of the swarm loses top-tier connectivity. Only 11 devices remain at Level 3, while the majority (65 devices) drop to Level 1 (Critical). This sharp decline likely corresponds to the firing of Transition T1 (Influence of Distance) or T2 (Influence of Landscape) as the swarm traverses the map.

By Step 2, the network attempts to stabilize, but degradation continues. We see the first appearance of Level 0 (Lost Signal) devices (28 devices), indicating that a substantial part of the swarm has entered a "Dead" or "Jammed" state, possibly due to entering an EW zone (Transitions T3/T4).

Recovery and Fluctuation are represented by steps 3–4. The system demonstrates dynamic behavior where devices fluctuations.

Step 3 shows a redistribution where 39 devices regain some connectivity to reach Level 2 (Moderate), likely due to the successful activation of Transition T7 (Restoration of distance) or T6 (Exit from ECM zone). However, the number of disconnects (Level 0) peaks at 34 devices.

Step 4 shows a critical point where 50 devices. The majority of the swarm have lost signal (Level 0). This suggests the swarm has reached the farthest point of the mission trajectory (as seen in Figure 4) or the center of a jamming zone.

Table 1
Devices with level S by steps

S	Step 0	Step 1	Step 2	Step 3	Step 4	Step 5
0	0	0	28	34	50	0
1	0	65	24	3	0	0
2	0	0	17	39	26	76
3	76	11	7	0	0	0

Mission Conclusion or Reset (Step 5): In the final step recorded, 76 devices return to Level 2. This uniform recovery suggests the swarm has either exited the hostile area and re-established a mesh link or triggered a "Return-to-Home" fallback protocol (Transition T7), bringing them back within effective communication range.

The Table 1 data show a clear transition from a stable state (Step 0) to a highly degraded state (Step 4), followed by a recovery phase (Step 5), validating the logical correctness of the Petri net's recovery and fallback transitions.

3.3. Background simulation

Python-based environment that processes real-world elevation maps was developed. This module calculates the physical validity of transitions (T1, T2) by checking the drone's coordinates against the terrain data, bridging the gap between abstract mathematical modeling and physical reality.

Background simulation is critical because the Petri net is an abstract logical model that requires real-world physical data (terrain, distance, coordinates) to trigger its transitions accurately.

Figure 3 demonstrates the terrain-based background simulation used to verify the "Line-of-Sight" (LoS) conditions for a single UAV. The visual represents a topological height map generated from open datasets, where color gradients indicate elevation changes.

This module calculates the input parameters for Transition T2 (Influence of landscape). The red marker represents a UAV's specific geospatial coordinate. The software checks if the terrain elevation at this point obstructs the signal path to the control center. If an obstacle is detected ($O(D,t) = 1$), the background simulation forces the Petri net to fire transition T2, reducing the signal level (Q) by 2 discrete units, effectively moving the drone token to a "Low Signal" or "Disconnected" place.

Figure 4 visualizes the dynamic flight path of a UAV group over the terrain. The red loop indicates the predefined mission coordinates overlaying the elevation heatmap.

This simulation runs continuously to feed data into the Colored Petri Net (CPN). It calculates the variable d (distance) and landscape factors for every step of the mission. As the UAVs move along the red trajectory, the simulation updates the distance to the hub ($d(Q,H,t)$) in real-time.

When the drone reaches the far end of the loop, the distance exceeds the threshold ($d > max\_d$), triggering Transition T1, which degrades the signal quality token.

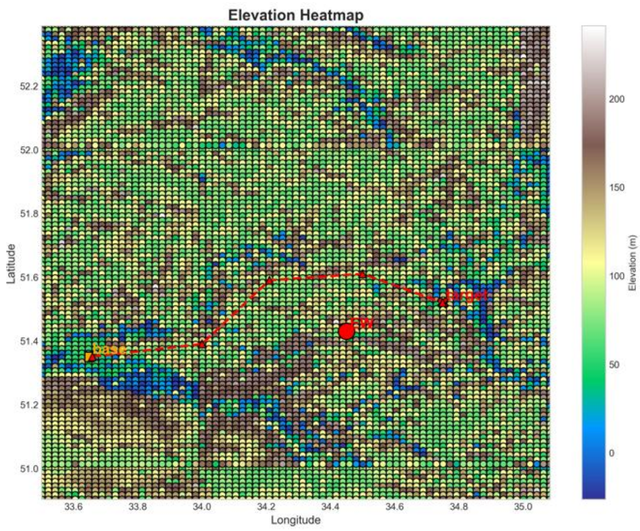

Figure 3: Background simulation of the single device

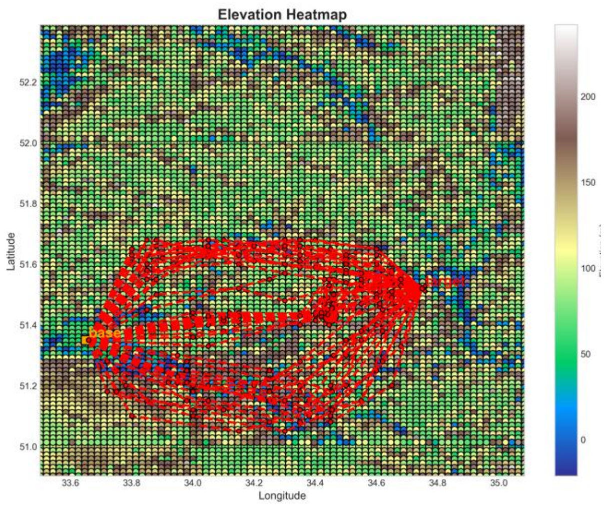

Figure 4: Background simulation of group of devices with specific mission

As the drone loops back closer to the center, the simulation triggers Transition T7, restoring the signal level token. The experiments quantitatively confirm the model's ability to capture the volatility of UAV availability.

4. Discussion

Dynamics of Swarm Availability The simulation results presented in Table 1 reveal the non-linear nature of network availability during a mission. At the initial stage (Step 0), the swarm exhibits 100% availability with maximum signal strength ($S = 3$). However, the rapid degradation observed in Steps 1 and 2, where the majority of devices drop to critical signal levels ($S = 1$) or complete disconnection ($S = 0$) confirms the model's sensitivity to distance and environmental interference. Specifically, the peak of unavailability at Step 4, where 50 devices lost connection ($S = 0$) , likely corresponds to the swarm traversing the "Jamming Zones" or "Line-of-Sight" shadows identified in the background simulation (Figure 4). This validation proves that the Petri net transitions T1 (Influence of distance) and T3/T4 (ECM impact) are correctly triggering based on the physical input data.

Resilience and Recovery Mechanisms A key finding is the swarm's recovery capability observed in Step 5, where the device states largely homogenize at Signal Level 2. This indicates the successful activation of the "Fallback" and "Relay Search" logic modeled in the CPN. The transition from a highly fragmented state (Step 4) back to a stable connected state demonstrates that the deterministic logic for autonomous behavior, such as searching for a relay or exiting an EW zone, effectively mitigates permanent system failure. This confirms that the model can be used not just for failure prediction, but for verifying the safety properties of autonomous recovery algorithms. The Role of Hybrid Modeling The integration of the Python-based background simulation (Figures 3 and 4) was critical for calculating the transitions that the abstract Petri net cannot determine on its own. By pre-processing open terrain maps to generate the $O(D, t)$ (obstacle indicator) variable, the model effectively bridges the gap between theoretical state-machine logic and physical reality. This addresses the gap in current research noted in the introduction, where terrain elevation impacts on signal loss are frequently overlooked.

Practical Implications The proposed method allows mission planners to identify "deadlock" states and regions of high unavailability prior to deployment. By analyzing the simulation steps where tokens accumulate in the "Lost Comm Drones" place, operators can adjust flight trajectories to avoid terrain shadows or known interference zones, thereby maximizing the probability of mission success.

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Conclusions

The study successfully developed and implemented a mathematical modeling approach for analyzing the availability of Unmanned Aerial Vehicle (UAV) networks in hostile environments. By leveraging the formalism of Petri nets, the research addressed the critical gap in existing frameworks, which often overlook external adversarial factors such as Electronic Warfare (EW) and complex terrain obstacles.

In summary, the proposed software and mathematical tools provide a robust foundation for mission planning. They enable operators to predict "dead zones" and reliability bottlenecks caused by adversary counteraction, ultimately enhancing the survivability and effectiveness of UAV networks in combat conditions. Future work may focus on optimizing the computational efficiency of the background simulation for larger swarms and integrating more complex adversary attack vectors.

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