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The Resilience of Electrical Support in UAV Swarms in Special Missions

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Abstract: Unmanned aerial vehicle (UAV) swarms serve as a dynamic platform for diverse missions, including communication relays, search and rescue operations, and environmental monitoring. The success of these operations crucially depends on the resilience of their electrical support systems, especially in terms of battery management. This paper examines the reliability of electrical support for UAV swarms engaged in missions that require prioritization into high and low categories. The paper proposes a dynamic resource allocation strategy that permits the flexible reassignment of drones across different-priority tasks, ensuring continuous operation while optimizing resource use. By leveraging the Markov chain theory, an analytical model for the evaluation of the resilience of the battery management system under different operational scenarios was developed. The paper quantitatively assesses the impact of different operational strategies and battery management approaches on the overall system resilience and mission efficacy. This approach aims to ensure uninterrupted service delivery for critical tasks while optimizing the overall utilization of available electrical resources. Through modeling and analytical evaluations, the paper quantifies the impact of various parameters and operating strategies on overall system resilience and mission availability, considering the utilization strategies of batteries and their reliability and maintenance metrics. The developed models and strategies can inform the development of robust battery management protocols, resource allocation algorithms, and mission planning frameworks, ultimately enhancing the operational availability and effectiveness of UAV swarms in critical special missions.

Keywords: UAV swarms; electrical support; resilience; reliability; Markov chain; priority-based mission

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1. Introduction

Unmanned Aerial Vehicles (UAVs), especially when deployed in swarms, have become integral to executing complex missions such as communication relays, search and rescue operations, and environmental monitoring. The effectiveness of these UAV swarms hinges significantly on the robustness of their electrical support systems, with a particular focus on battery management strategies crucial for sustained operations.

In the aftermath of natural disasters like earthquakes, floods, or hurricanes, terrestrial communication infrastructure may be damaged or destroyed. UAVs can be quickly deployed to act as temporary communication nodes, restoring critical communication links between rescue teams and between affected populations and the outside world [1]. They facilitate coordination, search and rescue operations, and the delivery of aid.

For areas lacking in infrastructure due to geographical challenges or economic constraints, drones can provide temporary or even long-term internet and telecommunications connectivity [2]. This is vital for remote education, health services, and economic development, allowing these areas access to information and communication technologies.

In complex and rapidly evolving battlefield environments, maintaining robust communication networks is vital for the success of operations [3,4]. UAVs can be deployed to establish secure and reliable communication links between various units, including ground troops, naval ships, and command centers, ensuring seamless information flow even in jamming or high-threat scenarios.

During large public events such as sports competitions, concerts, or festivals, existing cellular networks may become overwhelmed by the high demand [5]. UAVs can supplement these networks, enhancing capacity and coverage, ensuring attendees can communicate seamlessly and access online services.

For monitoring environmental changes, pollution levels, or wildlife in vast and inaccessible areas, UAVs equipped with sensors can collect and transmit data back to researchers or monitoring centers in real time [6]. This approach is less invasive, more flexible, and can cover larger areas more quickly than traditional methods.

UAVs can provide data collection in agriculture [7]. These data are transmitted in real time to farmers and agricultural experts, enabling them to make informed decisions regarding irrigation, fertilization, and pest control, thus optimizing resources and improving yields.

In scenarios where immediate medical communication is required (e.g., remote accident sites), UAVs can facilitate real-time video communication between onsite responders and medical professionals located elsewhere, providing guidance and support until emergency medical services arrive [8].

These examples illustrate the versatility and effectiveness of using UAVs as mobile communication nodes or sensors in various missions, significantly enhancing operational capabilities, efficiency, and safety in multiple domains.

The advent of UAVs has ushered in a new era of possibilities across various sectors, from emergency response to environmental monitoring. At the heart of UAV operations, especially in swarm deployments, lies the critical interplay between battery management and mission availability. Charging stations play a pivotal role in this dynamic, serving not only to maintain optimal depth of discharge (DoD) levels for battery longevity but also inadvertently impacting the availability of UAVs for mission tasks.

In the rapidly evolving landscape of UAV operations, ensuring uninterrupted mission capability is paramount. The use of backup drones emerges as a strategic solution to one of the most pressing challenges in UAV management [9].

As UAV swarms undertake increasingly complex missions, the performance and reliability of their battery systems have come under the spotlight. The DoD emerges as a pivotal factor influencing battery lifespan and, by extension, the operational efficiency of UAV swarms [10].

The DoD is a crucial parameter because it directly impacts the battery's lifecycle [11]. Frequent discharges to low levels before recharging can significantly shorten a battery's overall lifespan. In the context of UAV swarms, where operational demands can lead to varied and often substantial energy consumption, managing the DoD is essential for maintaining battery health and ensuring longevity.

Swarms deployed for extended missions or in areas where recharging facilities are scarce must optimize their battery usage to ensure continuous operation [12]. High DoD levels can degrade batteries more rapidly, necessitating more frequent replacements and potentially compromising the mission. Conversely, limiting the DoD to preserve battery life can reduce operational time and effectiveness. Therefore, UAV operators must strategically manage DoD to strike an optimal balance that maximizes both battery lifespan and mission efficacy [13].

Effective battery maintenance strategies are essential for mitigating the adverse effects of high DoD levels. One approach is the implementation of intelligent battery management systems within UAVs [14]. These systems can monitor battery health in real time, adjust power usage dynamically, and ensure that the DoD remains within a range that balances operational needs with longevity.

The strategic use of backup batteries and the development of advanced charging infrastructures are vital components of addressing DoD challenges in UAV swarms. Deploying backup drones with fully charged batteries can ensure uninterrupted mission continuation while primary units are being recharged or undergoing battery replacement. Furthermore, exploring innovative charging solutions such as solar-powered charging stations or in-flight wireless charging technologies can provide alternatives for extending mission durations without adversely affecting the DoD [15].

Utilizing swarms of drones to provide communication channels in special missions offers a versatile and dynamic approach to addressing complex operational needs. These UAV swarms can be categorized into two priority levels—high and lower—based on the criticality of their tasks [16]. High-priority drones are deployed for missions where uninterrupted communication is crucial, while lower-priority drones are used for tasks where temporary communication lapses are more tolerable [17]. The ability to replace high-priority drones with those from a lower-priority swarm ensures operational flexibility and resilience.

Current studies tend to explore aspects such as UAV redundancy, battery maintenance strategies, and priority-based drone allocation independently. This segmented approach, while insightful, falls short of fully capturing the complex interdependencies and real-world operational dynamics of UAV swarm deployments.

This paper seeks to bridge the gap in current research, offering a more integrated approach of how various operational factors interact to affect the performance of UAV swarms.

The purpose of this study was to develop and apply an integrated approach to analyze the effectiveness of UAV swarms in maintaining communication channel availability during special missions which will consider three critical aspects concurrently:

- The deployment of additional drones within the swarm to ensure the uninterrupted operation of communication channels, thereby enhancing the resilience of the communication network against individual UAV failures or battery depletion instances.
- The use of a specialized maintenance station to optimize the battery DoD levels. This is aimed at extending battery life and operational efficiency, ensuring that UAVs can perform their duties for longer and more reliably without frequent recharging interruptions.
- The strategic ability to replace high-priority drones or their batteries with those from a lower-priority swarm, ensuring that critical communication tasks are continually supported, even as specific drones are diverted for recharging or maintenance.

The resilience of these systems is paramount, as it directly impacts the UAVs' ability to maintain continuous operation under diverse and demanding conditions. Recognizing the critical nature of this resilience, the research aims to thoroughly investigate the reliability of electrical support in UAV swarms across missions that vary in priority from high to low. Each mission's success often relies on how effectively UAVs manage their battery resources and operational strategies to meet specific mission demands.

This paper introduces a dynamic resource allocation strategy that allows for the agile reassignment of UAVs between tasks of differing priorities, thereby ensuring that high-priority missions receive the necessary resources without compromising the overall mission effectiveness.

This approach not only helps in maintaining uninterrupted operations for critical tasks but also enhances the efficiency of resource utilization across the board. Through comprehensive modeling and analytical evaluations, the study provides a quantitative assessment of how various strategies and battery management practices influence the overall resilience and efficacy of UAV swarm missions.

The structure of this paper is as follows: Section 2 delineates the theoretical frameworks and methodologies employed in the study on the base of the Markov chain models used for evaluating the resilience of UAV swarms' battery management systems under different operational scenarios. Section 3 presents impact of various operational strategies and battery utilization techniques on the resilience and mission availability of UAV swarms. Section 4 serves to interpret the findings within the broader context of UAV swarm operations and give quantifiable insights into how these factors influence the service availability provided by UAV swarms in executing critical missions. Section 5 synthesizes the key insights and contributions of the study.

2. Materials and Methods

The deployment of UAV swarms, differentiated by mission priority levels, underscores a strategic approach to ensuring robust communication networks during special operations. However, the resilience of the electrical support systems—primarily battery life and recharging mechanisms—plays a critical role in sustaining operations and thereby determines the reliability of these UAV swarms. This paper delves into the resilience of electrical support for UAV swarms, examining the implications of priority differentiation on operational reliability during special missions.

UAV swarms are increasingly being utilized for missions with critical communication needs, such as disaster response coordination, military operations, and surveillance tasks. These missions are categorized into high and lower priorities, reflecting the urgency and importance of the communication services they provide. High-priority missions demand uninterrupted communication channels, necessitating a higher level of resilience in electrical support systems. In contrast, lower-priority missions may tolerate brief disruptions, allowing for more flexible battery management strategies.

The study's foundation lies in the application of reliability theory and Markov chain models to understand and predict the behavior of UAV swarm electrical support systems under varying operational conditions. Reliability theory, concerned with the probability of systems performing their intended function over a designated period, is particularly relevant for assessing high-priority UAV swarm operations, where failure can significantly impact mission outcomes. Markov chain models offer a mathematical framework for depicting the state transitions of UAVs within a swarm, focusing both on the recharging of batteries and their redundancy.

This study employs a mixed-methods approach, integrating simulation modeling with empirical analysis. Simulations based on Markov chain models enable the exploration of various scenarios, including battery performance under different operational loads, the effectiveness of recharging strategies, and the impact of reallocating UAVs between priority levels on system resilience. Empirical data from real-world UAV swarm operations provide a basis for validating the models and refining the analysis.

The model created for the analysis of the resilience of electrical support systems is critically affected by several factors:

- The effective management of battery charging and discharging cycles.
- The availability and accessibility of recharging stations.
- The strategic allocation of UAVs, allowing for the temporary reassignment of drones from lower- to high-priority missions.

By using reliability theory and Markov chain models, this study provides insights into resilience electrical support for UAV swarms, highlighting the significance of battery management, recharging infrastructure, and priority-based resource allocation.

The structure depicted in Figure 1 showcases a strategic framework for maintaining continuous UAV swarm operations during special missions, incorporating redundancy and energy management. It is divided into two main components based on mission priority, a high-priority mission (HPM) swarm and a low-priority mission (LPM) swarm, each with their own replacement fleet.

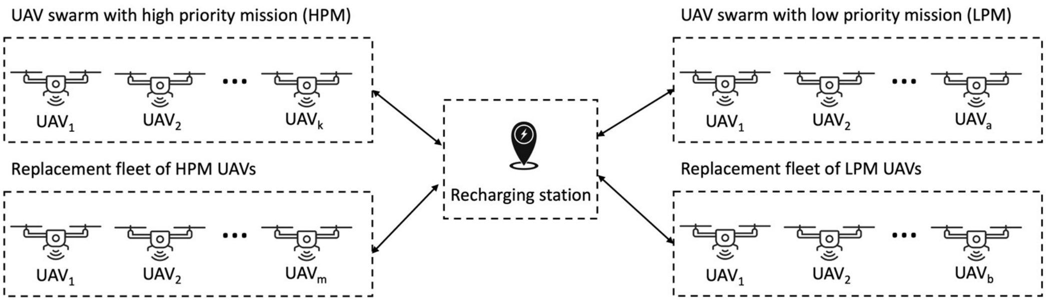

Figure 1. Framework for UAV swarm operations during special missions.

There is a primary fleet of UAVs with a HPM composed of a set with k number of UAVs; this group is tasked with critical mission objectives, where uninterrupted operation is essential.

An additional set of n UAVs is the replacement fleet and is on standby to replace any primary-fleet UAVs as their battery power is depleted or if they require maintenance. This ensures a seamless continuation of the mission without any loss of communication capabilities.

There is a primary fleet of UAVs with an LPM composed of a set with a number of UAVs, which is allocated for less critical tasks that can tolerate some level of interruption without significant consequences to the mission's overall outcome.

An additional set of b UAVs provides additional UAVs ready to step in when the primary UAVs need to recharge or undergo maintenance, ensuring the LPM tasks continue with minimal disruption.

Positioned centrally and strategically accessible to both swarms, the recharging station serves as the hub for replenishing UAV battery power. It plays a critical role in managing the depth of discharge for each UAV's battery, optimizing longevity and performance.

The high-priority UAVs can be supplemented by UAVs from the low-priority replacement fleet if the need arises, illustrating a flexible and dynamic resource allocation system.

The maintenance of batteries across both swarms ensures that the UAVs operate within their optimal DoD levels, reducing wear and extending battery life.

The redundancy and flexibility built into this system are intended to enhance the resilience and reliability of UAV swarms with high-priority operations, ensuring that essential services remain available and consistent throughout the durations of the special missions.

Evaluating the availability of a particular UAV to deliver a dedicated service (DS) within a HPM framework requires a focused examination of that UAV's service uptime. This scrutiny is pertinent to clients utilizing a specific UAV's service who are interested solely in its reliability and not the performance of other UAVs or functionalities within the LPM group. The assessment of the DS's reliability for the UAV within the HPM setup will utilize a modeling approach informed by Markov chain theories, as documented in references [18,19].

3. Results

Our exploration into the dynamics of battery management and strategic resource allocation, grounded in empirical evidence and simulation data, aims to uncover the pivotal factors influencing the robustness of UAV operations in mission-critical contexts.

The examination of DS availability for a UAV within the HPM cluster utilizes Markov models featuring Kolmogorov–Chapman equations for systems in steady states [19].

Table 1 lists the primary symbols employed in these models.

Table 1. Symbols utilized in the model.

Notations	Parameters
$p_i \to H_i$	Probability corresponding to the state
A	Availability of DS by UAV
$U = 1 - A$	Unavailability of DS by UAV
λ	Failure rate of service provided by UAV
μ	Repair rate of service provided by UAV
$\gamma = \lambda/\mu$	Dependability parameter
$\omega = \gamma/l$	Dependability parameter
λ_M	Maintenance flow rate
μ_M	Intensity of maintenance work
k	Main UAVs in HPM cluster
n	Redundant UAVs in HPM cluster
a	Main UAVs in LPM cluster
b	Redundant UAVs in HPM cluster
m	UAVs allocated in the LPM cluster for possible additional reservation of UAVs in the HPM cluster ($m \leq a + b$)
$N = k + n$	Total UAVs in HPM cluster
$1 \leq l \leq n$	Places for UAV repair

Let us build models for two main factors in the real use of a swarm of UAVs for critical missions, considering the following:

- The need to recharge the UAV batteries during the mission to maintain the specified depth of discharge levels.
- The possibility of the additional use of UAVs from a swarm of lower-priority functions for a swarm performing a critical function of a higher level.

3.1. Availability Model of Service Provided by UAV from HPM Cluster with Maintenance of Batteries

This system is represented by a Markov chain, with its state transition diagram illustrated in Figure 2.

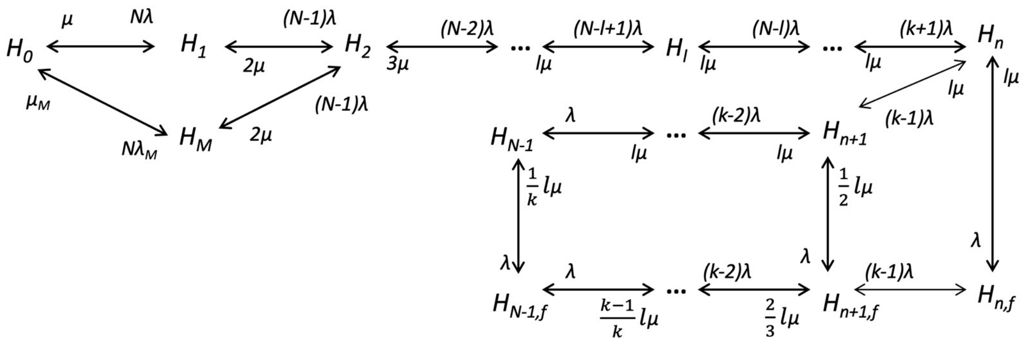

Figure 2. State transition graph of a Markov chain for HPM cluster with maintenance of batteries in autonomous mode.

The Markov model (Figure 2) is a tool used to determine the system's reliability. The symbols in this diagram represent the following: H_i indicates the system's state when there are i defective batteries yet a functioning battery is present in the dedicated service's area; $H_{i,f}$ signifies the state where there is an additional faulty battery, resulting in the absence of a functional battery in the dedicated service's workspace; H_M represents the state where all batteries are operational and one is undergoing maintenance.

By referring to the state transition diagram provided by the Markov model in Figure 2, we can formulate the Chapman–Kolmogorov equations as per standard methodology [19].

With these considerations, the formula for calculating the service availability of the dedicated UAV can be expressed as follows:

$$A = 1 - \sum_{i=n}^{N-1} h_{i,f} \tag{1}$$

We can calculate h_i as probabilities of the H_i states using the approach introduced in [20].

As outlined in [20], the initial graph (Figure 2)

$$H = H_S\ U\ H_R = \{H_M, H_v : v = 0,1,2\}\ U\ \{H_{ij}, H_{j,I} : i = 2, \ldots N-1; j = n, \ldots N-1\}$$

may be depicted using two analogous diagrams, S and R. The diagrams in Figures 3 and 4 consist of the following states:

$$S = \{S_0, S_M, S_1, S_2\};$$

$$R = \{R_{ij}, R_{jI} : i = 2, \ldots N-1; j = n, \ldots N-1\}$$

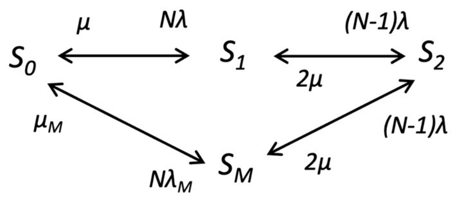

Figure 3. Markov chain diagram for S.

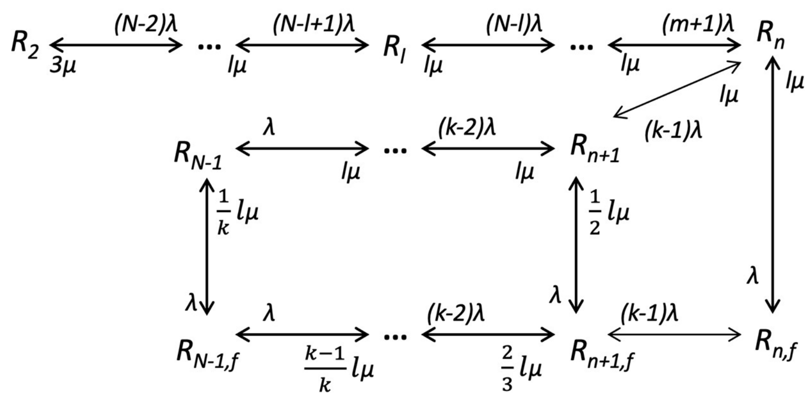

Figure 4. Markov chain diagram for R.

The collections of states in both R and S mirror the setup and attributes found in the analogous sections of the original graph:

The configurations and properties of graphs S and R are similar to the corresponding parts of the initial diagram:

$$R \equiv H_R; \quad S \equiv H_S$$

Figures 3 and 4 display diagrams of the S and R subsystems.

Following the methodology outlined in [20], we can derive the following:

$$h_i / h_2 = s_i / s_2 : \forall i \tag{2}$$

$$h_{\alpha\beta} / h_2 = r_{\alpha\beta} / r_2 : \forall \alpha, \beta \tag{3}$$

$$h_2 = r_2 s_2 / (r_2 + s_2 - r_2 s_2) \tag{4}$$

where $h_i, h_{\alpha\beta}, s_i, r_{\alpha\beta}$ are the probabilities of states $H_i, H_{\alpha\beta}, S_i, R_{\alpha\beta}$ corresponding to the relevant subgraphs.

As per standard conventions for Markov processes [19], the set of Chapman–Kolmogorov equations is structured as follows:

$$s_0'(t) = -N(\lambda + \lambda_M)s_0(t) + \mu s_1(t) + \mu_M s_M(t)$$

$$s_1' = N\lambda s_0(t) - [(N-1)\lambda + \mu]s_1(t) + 2\mu s_2(t)$$

$$s_2'(t) = (N-1)\lambda s_1(t) - 4\mu s_2(t) + (N-1)\lambda s_M(t)$$

$$s_M'(t) = N\lambda_M s_0(t) - [(N-1)\lambda + \mu_M]s_M(t) + 2\mu s_2(t)$$

Resolving this set of equations allows us to determine the probability s_2. The formula for s_2, when applied to systems of high reliability where λ is much less than μ, is given by:

$$s_2 = \frac{N(N-1)(\lambda + \lambda_M)\gamma}{a[(N-1)\gamma\mu + 2N\lambda_M + 2\mu_M]} \tag{5}$$

where $a = \begin{cases} 1, \ l = 1, \\ 2, \ 1 < l < n, \end{cases} \gamma = \lambda/\mu.$

For the diagram R, the probability r_2 can be borrowed from [21]:

$$\begin{aligned} r_2^{-1} = \quad & 1 + \tfrac{2}{N(N-1)} \sum_{i=3}^{l} \tbinom{i}{N} \gamma^{i-2} \\ & + \tfrac{2(N-2)!l^{l-2}\omega^{N-2}}{l!} \left\{ \sum_{i=m}^{N-l-1} \tfrac{1}{i!\omega^i} \right. \\ & \left. + \tfrac{1}{m} \left[\tfrac{1}{(m-1)!\omega^{m-1}} + \sum_{i=0}^{m-2} \tfrac{(m-i))}{i!\omega^i} \right] \right\} \end{aligned} \tag{6}$$

The initial probability h_2 from the graph shown in Figure 2 can be calculated by incorporating the formulas from expressions (5) and (6) into expression (4).

Based on expressions (2) and (3), the formula for the DS availability, as outlined in expression (1), is formulated as follows:

$$A_M = h_2 \left[\frac{1 - s_2}{s_2} + r_2^{-1} \sum_{i=2}^{N-2} r_i \right] \tag{7}$$

For the case under consideration, it can be determined that:

$$\sum_{i=0}^{N-1} r_i = r_2 \left\{ 1 + \frac{2}{N(N-1)} \sum_{i=3}^{l} \binom{i}{N} \gamma^{i-2} + 2(N-2)!l^{l-2}/l! \left[\sum_{i=l+1}^{n} \frac{\omega^{i-2}}{(N-i)!} + \sum_{i=n+1}^{N-1} \frac{\omega^{i-2}}{(N-i-1)!m} \right] \right\}$$

Therefore, by integrating Formula (4) through (6) into Equation (7), we can calculate the service availability of the dedicated UAV of the primary system depicted in Figure 2.

3.2. Availability Model of Service Provided by UAV from HPM Cluster with Maintenance of Batteries and Possibility of Using UAVs from LPM Cluster

The need for periodic recharging inherently reduces the number of UAVs available for active mission tasks at any given time. In scenarios requiring constant coverage or uninterrupted data flow—such as disaster response, border surveillance, or live event broadcasting—the temporary withdrawal of UAVs for charging can create gaps in coverage or delays in information relay. This challenge is exacerbated in large-scale operations or in environments where deploying additional charging stations is impractical due to logistical, environmental, or financial constraints.

Addressing the tension between battery maintenance and operational availability necessitates a multi-pronged approach.

One of them is incorporating redundancy within the UAV swarm, which can compensate for those temporarily sidelined by charging requirements, ensuring a constant operational presence.

There is an additional method for increasing stability in certain situations. Utilizing swarms of UAVs to provide communication channels in special missions offers a versatile and dynamic approach to addressing complex operational needs. These UAV swarms can be categorized into two priority levels—high and lower—based on the criticality of their tasks. High-priority UAVs are deployed for missions where uninterrupted communication is crucial, while lower-priority UAVs are used for tasks where temporary communication lapses are more tolerable. The ability to replace high-priority UAVs with those from a lower-priority swarm ensures operational flexibility and resilience.

In the last case, the system with high-priority UAVs has the Markov chain diagram shown in Figure 5.

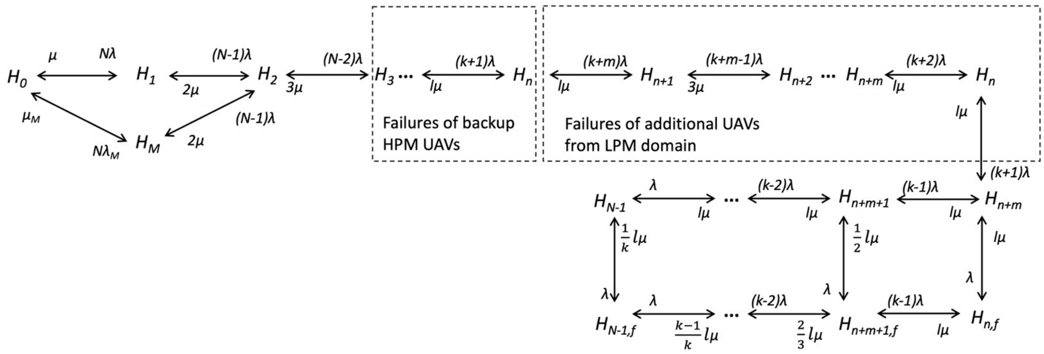

Figure 5. State transition graph for HPM with possibility of using UAVs from LPM cluster.

The states of this model include H_0—the starting state where all equipment is fully operational with no failures; H_i—a state where i UAVs have failed yet there remains a functional UAV for the dedicated service; and H_{if}—a state with $i + 1$ failed UAVs, leaving no operational UAV within the selected service.

The model assumes that in the absence of backup UAVs in a high-priority cluster, regardless of the reason for this (UAV failure or lack of properly charged batteries for them), m UAVs can be transferred from a cluster with a lower mission priority to a cluster with a higher priority. This work does not consider a strategy for selecting m БПЛА from the LPM cluster.

The availability of a dedicated service for the HPM cluster can be determined from the same expression (1).

In this case, to determine the DS availability provided by the higher-priority mission UAVs, we can use the previously applied approach of decomposing the Markov model into two components [20]. In this case, the graph presented in Figure 6 can be transformed into two graphs S and R (Figures 6 and 7), which are identical to the same parts of the original Markov chain transition graph (Figure 5).

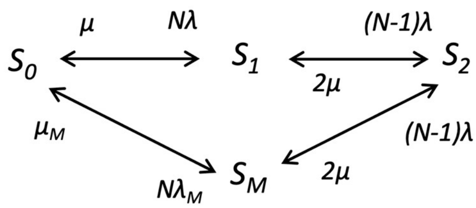

Figure 6. Markov chain for subsystem S.

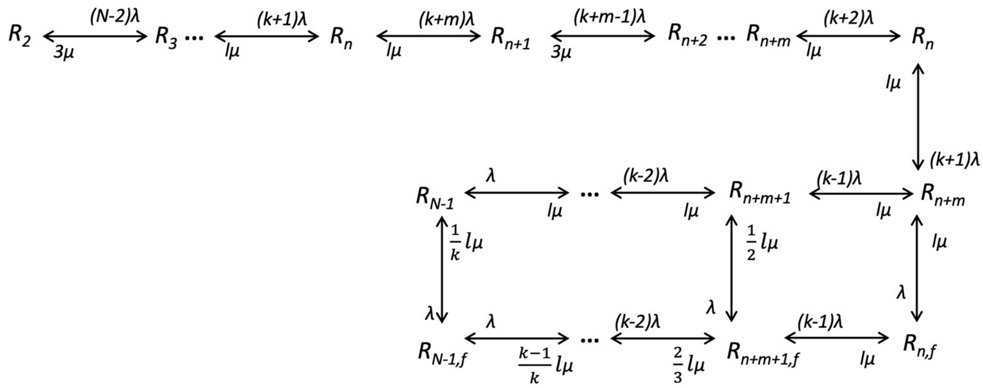

Figure 7. Markov chain for subsystem R.

By comparing the graphs presented in Figures 3 and 6, we can verify their complete identity. The graph in Figure 7 differs from the graph in Figure 4 by additional states $H_{n+1}, \ldots H_{n+m}$.

For the case under consideration, expressions (2)–(5) will still be valid. However, expression (6) will change due to changes in the corresponding graph (Figure 8). Let us define the expression for r_2 in accordance with the graph in Figure 8.

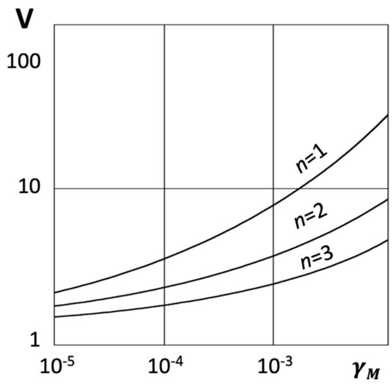

Figure 8. The availability reduction factor.

The Chapman–Kolmogorov equations for the diagram (Figure 7) can be formulated following established norms [19]. In this scenario, the steady-state probabilities are derived directly from the Markov Chain state transition diagram, in line with standard procedures:

$$r_i = C_N^i \gamma^i r_2, \quad 3 \leq i \leq l \tag{8}$$

$$r_i = \frac{N!}{(N-i)!} l^l \omega^i r_2, \quad l \quad \leq i \leq n \tag{9}$$

$$r_{n+i} = \frac{N!(m+k)!l^l}{(N-i)!(M+k-i)!l!l!} \omega^{n+i} r_2, \quad 1 \leq i \leq m-1 \tag{10}$$

$$r_{n+m+i} = \frac{N!l^l}{(k-i-1)!l!k} \omega^{n+m+i} r_2, \quad 0 \leq i \leq k-1 \tag{11}$$

$$r_{n+m+i,f} = \frac{N!(i+1)l^l}{(k-i-1)!l!k} \omega \gamma^{n+m+i+1} r_2, \quad 0 \leq i \leq k-1 \tag{12}$$

The normalizing condition is:

$$\sum_{\forall i} r_i(t) = 1 \tag{13}$$

The value of r_2 can be determined by substituting r_i, $\forall i$, and $r_{i,f}$, $\forall i$ from expressions (8)–(12) in the normalizing Equation (13):

$$r_2^{-1} = N!\left[\sum_{i=1}^{n}\frac{\gamma^i}{(N-i)!}+\sum_{i=1}^{m-1}\frac{(m+k)!}{(N-i)!(m+k-i)!}\gamma^{n+i}\right] + \sum_{i=0}^{k-1}\frac{N!}{(k-i-1)!k}\left[\gamma^{n+m+i}+(i+1)\gamma^{n+m+i+1}\right]$$

Substituting the resulting expressions for r_i, $\forall i$ into expression (7), we obtain the value that characterizes the service availability A_{MHL} in the HPM domain with k UAVs, n redundant UAVs in the HPM domain, and the opportunity for additional reservation by m UAVs from the LPM domain, maintaining the opportunity for battery charging at the recharging station:

$$A_{MHL} = h_2\left[\frac{1-s_2}{s_2}+r_2^{-1}\sum_{i=2}^{N-2} r_i\right] \tag{14}$$

4. Discussion

Simulations based on Markov chain models enable the exploration of various scenarios, including battery performance under different operational loads, the effectiveness of recharging strategies, and the impact of reallocating UAVs between priority levels on system resilience. Empirical data from real-world UAV swarm operations provide a basis for validating the models and refining the analysis.

At the heart of UAV operations, especially in swarm deployments, lies the critical interplay between battery management and mission availability. Charging stations play a pivotal role in this dynamic, serving not only to maintain optimal DoD levels for battery longevity but also inadvertently impacting the availability of UAVs for mission tasks.

Battery longevity and operational continuity are fundamental yet often conflicting requirements in UAV swarm operations. On one side, maintaining batteries within optimal DoD levels through regular charging can significantly extend their life cycle, reducing long-term costs and enhancing sustainability. Charging stations strategically deployed across the operational area facilitate this, enabling UAVs to recharge before their battery levels fall below a critical threshold. However, this necessary charging process introduces a period of unavailability for the UAV, during which it cannot perform its intended function, whether that be data collection, surveillance, or communication relay.

The impact of time loss on battery maintenance can be assessed by applying the availability reduction factor:

$$V = \frac{1-A}{1-A_M} \tag{15}$$

where A is the DS availability provided by the UAVs in the model before accounting for the impact of time loss on battery maintenance [21], and A_M indicates the availability in the model, considering the impact of maintenance time.

For instance, the availability reduction factor A_M is depicted in Figure 8 for $k = 10$ UAVs in an HPM cluster. It is shown as a function of the maintenance parameter $\gamma_M = \lambda_M/\mu_M$ for n redundant UAVs, each with a reliability parameter $\gamma = 10^{-4}$.

The deployment of UAV swarms, especially in contexts requiring differentiated priority levels, introduces complex challenges in maintaining uninterrupted communications for special missions. The resilience—or reliability—of the electrical support systems that power these UAVs is critical to mission success.

Let us determine the availability of some arbitrary selected dedicated service provided by UAVs from the HPM cluster with the described strategy of the possibility of borrowing UAVs from the LPM domain in the event of the failure of all backup UAVs in the HPM domain.

The reliability can be quantified using a two-stage strategy involving the reservation of the UAVs from the HPM cluster and comparing it against a strategy without such an opportunity to obtain the reliability improvement factor W. This factor is defined by the following formula:

$$W = \frac{1 - A_M}{1 - A_{MHL}} = \frac{U_M}{U_{MHL}} \quad (16)$$

where the value of A_{MHL} is calculated using the formula in expression (14). The availability A_M of the system, which includes a single level of backup redundancy and battery maintenance, is defined by expression (7).

In Figure 9, the reliability improvement factor W is graphically represented as a function of the number m of additional redundant UAVs from the LHM domain, considering the various reliability parameters of the UHV, denoted by γ.

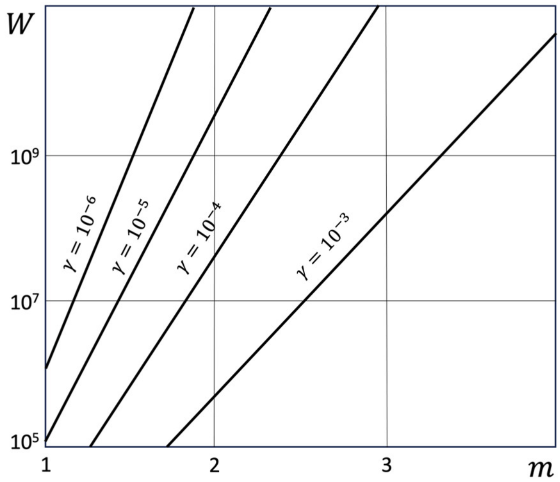

Figure 9. Dependability enhancement factor as a function of the number of extra redundant UAVs from the LHM sector.

The graph illustrates that the improvement in service reliability in the HPM cluster is substantial when there is an increase in the number of reserve elements M from the LPM cluster. Additionally, it shows that the reliability also significantly increases with the enhanced reliability of the UAVs themselves.

Figure 9 underscores the importance of both the quantity and quality of backup UAVs in the LPM cluster, ensuring the robust and reliable performance of the services provided by the UAV swarms.

This study underscores the importance of adaptive electrical support systems capable of meeting the diverse needs of UAV swarm operations. It highlights the necessity of incorporating priority considerations into battery management and recharging strategies to ensure that high-priority missions retain operational continuity. Furthermore, the research suggests that enhancing the resilience of electrical support systems contributes to the overall reliability and effectiveness of UAV swarms in fulfilling critical missions.

The study offers a comprehensive analysis of the resilience and reliability of electrical support systems, particularly battery management systems, in UAV swarms during special missions. However, like all research, it has its limitations:

- The primary methodological approach relies on Markov chain models, which, while powerful for analyzing stochastic processes, inherently assume that changes in state are memoryless. This assumption may not fully encapsulate the complexity of real-world UAV operations where past states can influence future conditions, especially under varying environmental influences and operational stresses, leading to potential gaps between the model predictions and actual outcomes.
- The paper discusses battery management and depth of discharge implications for UAV operations. However, it may not fully account for rapid advancements in battery technology, such as the development of more efficient or faster-charging batteries, which

could alter the dynamics considered in this study. These technological advancements could significantly impact the study's findings and recommendations.

- The operational dynamics of UAV swarms, including interactions with human operators and the physical environment, introduce complexities that are challenging to model accurately. The unpredictability of these interactions and their impact on system resilience might not be entirely captured in the study.
- The analysis simplifies some aspects of UAV swarm operations to make the problem tractable. For instance, interactions between UAVs and between UAVs and their control systems are modeled in a somewhat reduced form, which may not fully reflect the operational intricacies observed in dense, highly dynamic environments. These simplifications are necessary for analytical clarity but could lead to discrepancies between our predictions and actual field performance.
- The study does not extensively account for the potential impact of varying environmental conditions on UAV operations and battery performance. Factors such as extreme temperatures, precipitation, and varying geographical features that could affect UAV behavior are not deeply integrated into the models.
- While the findings provide valuable insights, the generalizability of these results to different types of missions, may require additional validation. The generalizability of our conclusions to other contexts, such as UAVs operating in non-communication-based missions, is not fully established and warrants further investigation.

The following future research directions could extend the study's findings, address its limitations, and explore new directions regarding the reliability of UAV swarm operations:

- The incorporation of machine learning algorithms with traditional Markov models will give us a better understanding of real-world dynamic operational environments and improve the accuracy of predictions.
- Through investigating the impact of emerging battery technologies and intelligent battery management systems on UAV swarm resilience, future research could focus on adaptive battery management systems that dynamically adjust to mission requirements and environmental conditions to optimize battery lifespan and performance.
- The integration of renewable energy sources, such as solar panels, into UAV design and operation could help in assessing the feasibility and efficiency of in-flight recharging, reduce the dependency on ground-based charging infrastructure, and enhance operational sustainability.
- Scalability and generalizability across mission types could be improved by tailoring battery management and resource allocation strategies to specific mission requirements and operational scales.

Future research directions can build upon this study, pushing the boundaries of UAV swarm capabilities, enhancing operational resilience, and addressing emerging challenges in autonomous system deployment.

5. Conclusions

This research provides a comprehensive analysis of the factors influencing the reliability and resilience of UAV swarms, with a particular emphasis on the critical role played by electrical support systems, especially battery management. By employing Markov chain models and leveraging empirical data, this study has elucidated the intricate dynamics of battery management and operational strategies that significantly influence mission success rates and overall system efficiency.

The key findings of this research highlight the importance of advanced battery management protocols and strategic resource allocation based on priority levels. The implementation of dynamic recharging strategies, as developed in models, enables continuous operational availability, which is vital for maintaining mission continuity in high-priority settings. These strategies are crucial for optimizing the deployment of UAV swarms, ensuring that missions requiring immediate response and sustained engagement are supported by robust and reliable electrical systems.

The adaptive and predictive resource allocation strategies proposed in the study enhance UAV swarm resilience and operational efficiency. These strategies equip UAV swarms to adapt to various and unpredictable operational scenarios, thereby improving both mission reliability and performance.

The study contributes to understanding and enhancing the resilience of electrical support in UAV swarms, laying the groundwork for future innovations in this rapidly evolving domain.

As UAV technologies progresses, the developed strategies form a foundational framework that will enhance the capability of UAV swarms to perform critical tasks in diverse settings, driving forward the capabilities of these systems in performing critical missions across diverse environments.

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