

Reliability Analysis of Anti-Drone Laser Systems: A Probabilistic Approach

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This research paper addresses the need for effective countermeasures against drones, particularly focusing on Anti-Drone Systems (ADS) incorporating laser technology. The study proposes a mathematical model for reliability assessment in safeguarding military assets and civilian populations from drone threats. By considering factors such as the number of lasers, laser failure, and laser strike misses, the paper presents a comprehensive model for evaluating system reliability. Numerical illustrations demonstrate the impact of varying parameters on system reliability. The proposed reliability measure serves as a valuable tool for evaluating and enhancing existing ADS. The research contributes to a gap in the literature by providing insights into the reliability analysis of ADS and offers a foundation for future research in this area.

Keywords: Anti-drone systems; laser systems; probabilistic model; reliability; drones.

1. Introduction

Unmanned Aerial Vehicles (UAVs) which are nowadays commonly known as drones are becoming an integral part of our lives due to their widespread deployment in various applications. In the recent times, the activities and usage of drones have increased manifolds. Drones are deployed for military purposes, surveillance purposes.^{1–3} These advanced aerial platforms are deployed for various military

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purposes, including reconnaissance, surveillance, and targeted strikes. Given their agility, autonomy, and potential for carrying lethal payloads, drones pose significant challenges to defensive strategies.^{4,5}

Envisioning a future where swarms of UAVs/drones fill the skies akin to flocks of birds is increasingly plausible, given the myriad applications they offer. Developing effective countermeasures and defense mechanisms against UAVs is imperative to safeguarding military assets, critical infrastructure, and civilian populations from potential threats and attacks.⁶ With the introduction of drones to civilian, drones are now gaining attention as a threat of safety and security, which leverages the emergence of the anti-drone or anti-UAV (or counter-drone) technologies.⁷ Anti-UAV systems are designed to defend against drone accidents and needed to be advanced to cope with future UAV flight systems.⁸

There are various types of anti-drone systems (ADSs) currently in use, including radio frequency jammers, electromagnetic pulse devices, and kinetic interceptors. Each of these systems offers unique advantages depending on the threat scenario. However, laser-based ADSs have gained significant attention due to their precision, speed of engagement, and ability to neutralize targets with minimal collateral damage. These systems can effectively disable or destroy drones without the need for physical projectiles, making them both efficient and cost-effective over time. Even among such ADSs, the ones incorporated with laser technology are most effective in countering drones.⁹ While building such a crucial system can be complex, one has to make sure that the performance of such a system cannot be compromised. This paper provides a reliability analysis for measuring the performance of such a system.

To destroy or disable a drone, ADSs often rely on various mechanisms such as kinetic strikes, radio jamming, or electromagnetic pulses. Among these, laser-based ADSs have gained prominence due to their ability to deliver precision strikes with minimal collateral damage. These systems use directed energy technology to focus high-energy laser beams on aerial threats, effectively neutralizing them without the need for conventional ammunition. For this purpose, an ADS may incorporate multiple lasers working in coordination to ensure reliable interception and destruction of drones.¹⁰

Laser ADSs come in a variety of configurations, including fiber lasers, solid-state lasers, and chemical lasers, each with its own advantages in terms of power output, beam quality, and operational constraints. Despite this variety, all share the goal of providing fast, accurate, and scalable defense solutions. In this work, we specifically focus on high-energy solid-state laser systems, which are among the most promising due to their compactness, efficiency, and integration potential with modern sensor and control systems. Liao and Xie¹¹ developed a laser-integrated ADS that combines advanced laser technology with sensors, tracking mechanisms, and command-and-control interfaces, offering a comprehensive and responsive solution to drone threats. High-energy laser weapons are particularly effective in this role, offering the ability to precisely engage targets while minimizing unintended

damage — something traditional kinetic systems struggle with Ref. 9. Additionally, Lyu and Zhan’s global overview of high-energy laser weapon technologies¹² highlights the growing military interest in these systems, exploring their strategic and tactical roles. Other studies, such as Ref. 13, delve into technical performance limitations including laser types, beam control, atmospheric interference, and targeting accuracy, which are critical factors in real-world deployment.

Successfully destroying a drone may require multiple successful laser hits, rather than a single strike.¹⁴ To model this, a k -out-of- $n(G)$ redundancy framework is used, which effectively enhances the reliability of such complex systems. Xing *et al.*¹⁵ explored the reliability assessment of k -out-of- $n(G)$ phased mission systems under imperfect fault coverage, and a similar scenario is incorporated into our proposed model, which is discussed in detail later in this paper. The number of lasers in an ADS is a configurable parameter in the model, reflecting the system’s design flexibility. Given that ADSs use high-energy laser systems, a cool-down period is required after a specific operational duration to prevent overheating and maintain performance.¹⁶ Additionally, laser failures are considered likely during an engagement, with each laser failing independently of the others. It is also assumed that repair or recovery of failed lasers is not feasible during an active attack. Kalita *et al.*¹⁷ studied the reliability of ADS from the stochastic modeling perspective and obtained the numerical results. The literature contains some pioneer work on the reliability of such types of systems using various methodologies.^{18–22}

1.1. Contribution

This study considers a general ADS equipped with a laser-based interception mechanism. Note that the proposed methodology can be applied to other types of ADS also. In the modeled scenario, multiple drones are assumed to approach a protected area, prompting the ADS to initiate its neutralization process. Specifically, the paper focuses on a worst-case scenario in which all drones attack simultaneously. While this assumption simplifies the analysis, it also presents a disadvantage for the defense system, as real-world scenarios would more likely involve staggered drone arrivals. Simultaneous attacks, though less practical in reality, pose a more challenging condition for the defense system and therefore serve as a conservative estimate of system performance. For the sake of modeling, laser strikes are assumed to require a constant amount of time per engagement.

Numerical illustrations in this study highlight how variations in system parameters influence overall reliability, defined as the probability of successfully neutralizing all incoming threats. The impact of number of lasers in the ADS on the reliability is also analyzed. An optimal number of ADS has been obtained through the analysis to increase the reliability of the mission. The findings can be applied to evaluate the reliability of existing ADSs deployed globally. By incorporating system-specific parameters into the proposed reliability framework, practitioners can estimate system performance under different configurations. In the authors’

view, there has been limited research on the reliability assessment of laser-based ADSs. The insights gained from this study could support strategic decisions related to system upgrades and operational improvements.

This work is arranged into five sections. In Sec. 2, a model for the calculation of reliability has been introduced. Section 3 describes the underlying probabilistic model and calculation of the reliability measure. In Sec. 4, numerical illustrations are provided to demonstrate the impact of varying multiple parameters on the performance of the system. Finally, the underlying model is concluded with insight for future works in Sec. 5.

2. Model Description

The model consists of multiple ADS. Each system is built on laser technology. A particular system consists of multiple lasers. The laser is employed to strike down a drone.²³ A high-energy laser is required for this task. An ADSs lasers target the same drone for a strike. After some consecutive strikes, the laser requires a cool-down time due to its high energy.¹⁶ As a result, ADS enters a cool-down state after some strikes. It is assumed that ADS works independently of each other, that is, the different ADSs do not coordinate their actions with each other.

Drones are anticipated to operate cohesively in swarms rather than sporadically appearing over time. Our model accommodates the presence of a variable number of drones within these swarms. In such scenarios, where an ADS confronts drones, it typically aims at vulnerable and critical components of the drones, such as rotors or engines, during its strikes. However, due to various factors such as atmospheric attenuation, weather conditions (temperature, humidity, and pressure),²⁴ Fast Steering Mirror (beam jitters),²⁵ and Signal-to-Noise ratio (SNR) the precision of these strikes may not always be optimal. Consequently, a single drone may require multiple strikes before being successfully neutralized.

The ADS is assisted by RADAR or LIDAR²⁶ with a detection range over 2 kilometers.²⁷ However, engagement by the ADS commences when a hostile drone enters the critical region or, equivalently, reaches the critical distance (R_c), defined as the distance at which a foreign entity poses a potential threat to the protected entity, and hence, the ADS will engage. This distance is influenced by the capabilities of the ADS and the extent of protection required for the entity. In practice, the detection range is higher than the critical distance. Once a drone has reached the critical distance, it takes a finite amount of time, called critical time (t_c), to reach the protected entity. All drones must be struck down before t_c . Figure 1 depicts the possible engagement scenarios between the drone and ADS. Figure 2 depicts the engagement from the drone's perspective.

$$t_c = \frac{R_c - R_{\min}}{V_d}, \quad (1)$$

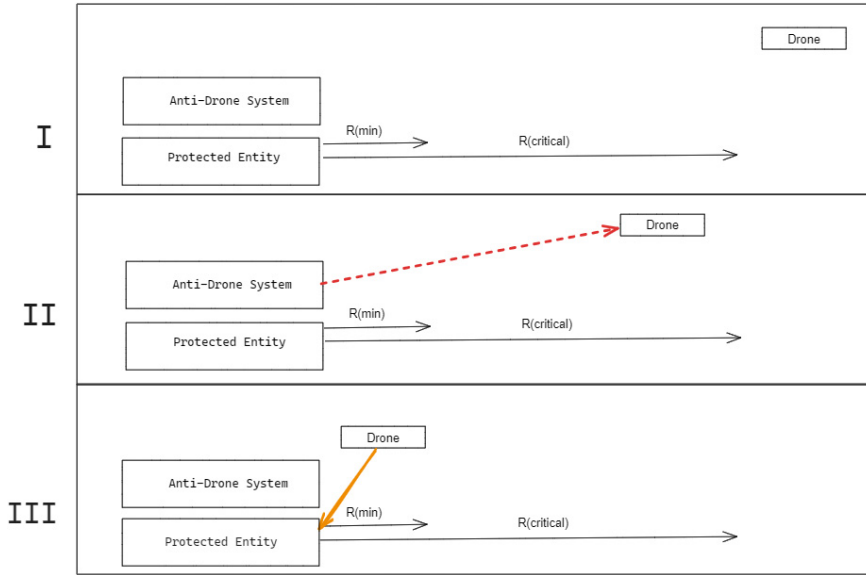


Fig. 1. I: Drone has been detected but has not encroached critical region. ADS does not engage. II: Drone enters critical region where it is posed as a threat by the ADS. ADS engages. III: Drone is at a distance $R_{\min}$ from the protected entity and has initiated harm.

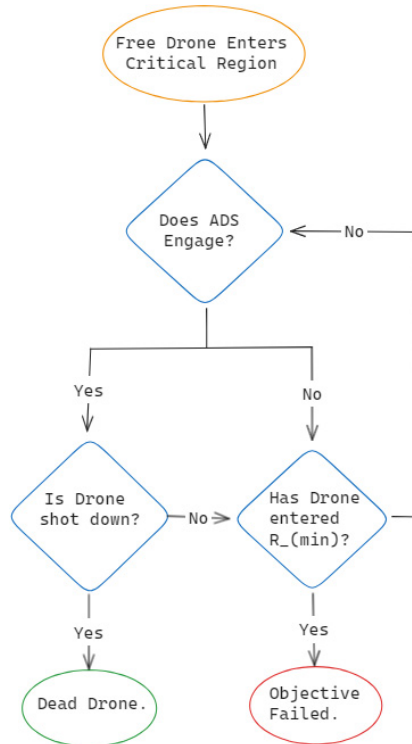


Fig. 2. Flow chart for drone.

where V_d is drone velocity, and $R_{\min}$ is the minimum distance for drone to induce harm to the protected entity. For calculation purposes, this paper considers the protected entity to be damaged, if a drone gets closer than $R_{\min}$. During the period when a drone transitions between the detection zone and the critical region, precision speed detectors can be utilized to estimate the velocity of the drones accurately. Meanwhile, the maximum permissible range within which the drone can pose a threat is determined. Drones typically fall into two categories: reconnaissance and military/combat types.⁷ By categorizing the drones, estimation of the minimum distance for potential harm, denoted as $R_{\min}$, to the protected entity is done.

Objective: The multiple ADSs objective is to prevent all drones from reaching $R_{\min}$. The reliability of the model serves as a metric for evaluating the effectiveness of the multiple ADS in thwarting missions involving multiple drones.

Assumptions: The model described in this paper assumes the following:

- (1) All drones are statistically identical, that is, the parameters for all drones, such as their velocity, structure materials, etc., are the same.
- (2) There are two ways in which a laser may fail.
 - (a) **Internal System Fault:** There are several components that make up a laser system. Some of the components are a voltage regulator, a laser diode, focusing lenses, and a water cooling system. The mentioned components are critical for a laser to work. Failure in any of these components results in the malfunction of the laser, with the probability of failure increasing with laser usage. The probability of failure of a laser, denoted as $f(k)$, is represented as a function dependent on the count (k) of strikes conducted by the laser previously.
 - (b) **External System Fault:** A strike on the drone is influenced by various external factors that are independent of the ADS. These factors include atmospheric attenuation (more pronounced in rainy weather and less in clear skies) and beam jitters, among others. These are accounted for as external system faults. A strike may fail with a fixed probability m_f , and thereafter, the drone requires another strike, if not struck down by other lasers.
- (3) A laser may fail internally only after a strike has occurred.
- (4) **Arrival of Drones:** The model assumes a scenario wherein a constant number of drones (n_d) is present in the environment initially.
- (5) **Strike Pattern:** For an ADS, its lasers target the same drone for a single strike. Each ADS operates independently, meaning different systems do not coordinate their actions.
- (6) All ADS are statistically identical. Each ADS delivers α strikes before entering the cool-down state, during which the ADS is rendered inactive.

3. Probabilistic Model

This section presents the formulation of a probabilistic model to quantify the reliability of the system under consideration. To facilitate a clear and systematic analysis, we first introduce a set of notations that define the key elements of the scenario. Using these notations, we define the probability of transitions between system states, which is computed through a dedicated algorithm outlined later in the section. These transition probabilities form the foundation for the reliability computation. Subsequently, we derive a recursive relation to express the reliability of the system, supported by a clear explanation of the base cases.

Notations: We define the following terms for use in our model.

- (1) n_s : Number of ADSs.
- (2) n_d : Number of drones introduced in the environment.
- (3) l : Initial number of nonfaulty lasers in an ADS. It is a known constant value.
- (4) S : Strike time of a nonfaulty laser for a drone. S is assumed to be a constant value.
- (5) α : The number of strikes a laser provides before requiring cool down.
- (6) C : Cool down period of an ADS. C is assumed to be a constant value.
- (7) $f(k)$: The probability of an internal system fault occurring for a laser after k strikes have been conducted.
- (8) r : The required number of successful strikes for a drone to be completely shot down.
- (9) q_0 : The number of available strikes for each of the lasers before the drone enters the critical region. So, if a drone is targeted by an ADS that has 3 working lasers and since, all of the lasers of an ADS attack the same drone at a time, in one attempt of the ADS, it fires 3 strikes to the drone. Figure 3 illustrates the formulation of q_0 . It depends on t_c , S and C as follows:

$$q_0 = \underbrace{\alpha \times \left\lfloor \frac{t_c}{\alpha S + C} \right\rfloor}_{\text{Term 1}} + \underbrace{\min \left\{ \left\lfloor \frac{t_c \bmod (\alpha S + C)}{S} \right\rfloor, \alpha \right\}}_{\text{Term 2}}. \quad (2)$$

Reliability Notation: We define the following terms for reliability measure calculation:

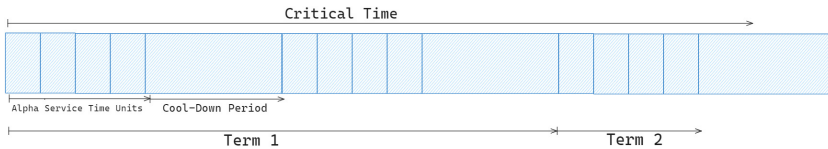


Fig. 3. Dividing total available time into possible strike units. Chosen $\alpha = 4$ for the above illustration.

- (1) r_i : The number of remaining successful strikes required by the i th drone for complete destruction. Observe that $r_i \leq r$.
- (2) $\mathbf{R}$: It denotes the state of drones with respect to the number of strikes required to destroy each drone. $R = \{r_i\}_{i=1}^{n_d}$
- (3) l_j : The number of nonfaulty lasers in the j th ADS. Observe that $l_j \leq l$.
- (4) $\mathbf{L}$: It denotes the state of multiple ADS with respect to the number of nonfaulty lasers remaining in each ADS. $L = \{l_j\}_{j=1}^{n_s}$
- (5) $\mathbf{Z}_{\mathbf{L}, \mathbf{R}}^{(q)}$: Probability of success when the system is in a state defined by $L = \{l_1, l_2, \dots, l_{n_s}\}$ and $R = \{r_1, r_2, \dots, r_{n_d}\}$ with a maximum of q strikes available for each ADS.
- (6) $\mathbf{Z}_{\mathbf{L}_0, \mathbf{R}_0}^{(q_0)}$: Initially, all lasers are functioning, and no drone has been struck. Therefore, $L_0 = \{l, l, \dots, l\}$ and $R_0 = \{r, r, \dots, r\}$. This is the reliability measure.

Probability of Transition: We define the probability of a state transition after a single strike, where the system state is characterized by the status of all lasers across the ADS units and the condition of each drone in terms of the number of strikes required for its neutralization.

The model assumes that all system failures occur only at the end of a strike. So, the transition from $R \rightarrow R'$ does not depend on the number of laser failures during that strike unit. Hence, it is independent of L' . Similarly, the transition from $L \rightarrow L'$ does not depend on the number of successful strikes during that strike unit. Hence, it is independent of R' .

$$\begin{aligned} P(\{L, R, q\} \rightarrow \{L', R', q-1\}) \\ = P(R \rightarrow R' | L, q) \cdot P(L \rightarrow L' | R, q). \end{aligned} \quad (3)$$

The state of lasers in ADS do not depend on the success of a strike. This implies the transition from L to L' does not depend on R and R' .

$$P(L \rightarrow L' | R, q) = P(L \rightarrow L' | q). \quad (4)$$

However, it depends on q as internal fault probability is contingent on the number of strikes conducted by the laser previously. Laser failure in ADS is independent of each other, and hence, the transition from l_j to l'_j is independent of j .

$$P(L \rightarrow L' | q) = \prod_{j=1}^{n_s} P(l_j \rightarrow l'_j | q). \quad (5)$$

The transition from $l_j \rightarrow l'_j$ follows a Binomial Distribution with failure probability $f(q_p)$, where $q_p = q_0 - q + 1$ represents the number of strikes conducted so far. Note that the calculations are performed for a new system, i.e., unused in the past. This can be modified to reflect the current state of an ADS by introducing the true

count of strikes performed previously as a parameter in f .

$$P(l_j \rightarrow l'_j | q) = \binom{l_j}{l'_j} (1 - f(q_p))^{l'_j} (f(q_p))^{(l_j - l'_j)}. \quad (6)$$

Finally, we obtain the following expression:

$$P(L \rightarrow L' | R, q) = \prod_{j=1}^{n_s} \binom{l_j}{l'_j} \times (1 - f(q_p))^{\sum_{j=1}^{n_s} l'_j} (f(q_p))^{\sum_{j=1}^{n_s} (l_j - l'_j)}. \quad (7)$$

Since lasers cannot fail during a strike, the transition from $R \rightarrow R'$ depends only on L . This study assumes no communication between different ADS. During each strike, there are multiple assignments possible, where each working ADS can target any harmful drone. For $R \rightarrow R'$, this paper assumes each such assignment is equally likely. Denote K as the set of all possible assignments. $|K|$ represents the cardinality of set K .

$$P(R \rightarrow R' | L, q) = \frac{1}{|K|} \sum_{k \in K} P(R \rightarrow R' | k). \quad (8)$$

For a given assignment, given are r_i , r'_i , and k_i where k_i is the total number of lasers targeting the i^{th} drone $\forall i \in \{1, \dots, n_d\}$. Note, given an assignment, the number of successful strikes received by a drone is independent of each other.

$$P(R \rightarrow R' | k) = \prod_{i=1}^{n_d} P(r_i \rightarrow r'_i | k_i). \quad (9)$$

The transition probability from r_i to r'_i varies depending on whether r_i is zero or nonzero. If r'_i is nonzero, then the transition follows a binomial distribution with failure probability m_f . However, in the case, the drone is neutralized, i.e., $r'_i = 0$, more than r_i successful strikes also yield the same result, and hence, we sum over all such possibilities. The probability of transition $P(r_i \rightarrow r'_i | k_i)$ can be calculated as follows:

$$\begin{cases} \binom{k_i}{r_i - r'_i} (1 - m_f)^{r_i - r'_i} (m_f)^{k_i - r_i + r'_i}, & \text{if } r'_i \neq 0 \\ \sum_{x=0}^{k_i - r_i} \binom{k_i}{r_i + x} (1 - m_f)^{r_i + x} (m_f)^{k_i - r_i - x}, & \text{o.w.} \end{cases} \quad (10)$$

Here, an algorithm for finding all possible assignments is presented:

- (1) Each ADS selects a drone from the available set, i.e., $\forall j \in \{1, \dots, n_s\}$ choose $i \in \{1, \dots, n_d\}$ such that r_i is nonzero.
- (2) Choose all such possible selections. Let a selection be represented by $\{d_1, d_2, \dots, d_{n_s}\}$. Create a list of length n_d denoting the number of lasers targeting i th drone, represented by $K = \{k_1, k_2, \dots, k_{n_d}\}$ where k_i is calculated

as sum of all nonfaulty lasers in j th ADS, where $d_j = i$.

$$k_i = \sum_{j \mid d_j=i} l_j. \quad (11)$$

Reliability Measure Calculation: It is the probability that the objective has been achieved, that is, all drones are shot down within available strike units, q_0 .

• **Recursive Relation:**

$$Z_{L,R}^{(q)} = \sum_{\{L',R'\}} Z_{L',R'}^{(q-1)} \times P(\{L, R, q\} \rightarrow \{L', R', q-1\}) \quad (12)$$

$$L = \{l_j\}_{j=1}^{n_s}, \quad R = \{r_i\}_{i=1}^{n_d},$$

$$L' = \{l'_j\}_{j=1}^{n_s}, \quad R' = \{r'_i\}_{i=1}^{n_d}.$$

Consider an instance when each ADS has a maximum of q strikes left. After one strike, the maximum leftover strikes go to $q-1$. After this strike, the number of working lasers in the j th ADS, may remain the same or decrease. As a result $l'_j \leq l_j \forall j \in \{1, \dots, n_s\}$. Alternatively, one can say that going from a state $L \rightarrow L'$, where $\exists j$ such that $l'_j > l_j$ is not possible.

Similarly, after a strike, the number of remaining successful strikes required by the i th drone for complete destruction may remain the same or decrease. As a result $r'_i \leq r_i \forall i \in \{1, \dots, n_d\}$. Alternatively, one can say that going from a state $R \rightarrow R'$, where $\exists i$ such that $r'_i > r_i$ is not possible.

Therefore,

$$L' \in \{\{l'_j\}_{j=1}^{n_s} \mid l'_j \in \{0, 1, \dots, l_j\}\},$$

$$R' \in \{\{r'_i\}_{i=1}^{n_d} \mid r'_i \in \{0, 1, \dots, r_i\}\}.$$

- **Base Case:** Observing the recurrence relation, the number of maximum available strikes is decreased by one at each step. When this value reaches 0, no more strikes are possible. The only way the objective is achieved is if all drones are neutralized. $r_i = 0$ represents i th drone is neutralized. So, $r_i = 0 \forall i \in \{1, \dots, n_d\}$ implies the objective is achieved, and hence, the probability of success at this moment is 1. Consequently, if any drone needs more strikes to be neutralized, the objective fails, and hence, the probability of success is 0.

$$Z_{L,R}^{(0)} = \begin{cases} 0 & \text{if } \sum_{i=1}^{n_d} r_i > 0 \\ 1 & \text{otherwise.} \end{cases} \quad (13)$$

4. Numerical Illustration

This paper has considered the following parameters as constants for numerical analyses. The strike time of a laser is 15s. Each laser can shoot four times before the cool-down period, which is considered 240s.

f : This probability is contingent on the number of laser strikes observed thus far. The candidate function for f must follow the two properties as outlined as follows:

- The function f must approach unity as the number of strikes tends toward infinity.
- f must be an increasing function, i.e., $f'(k)$ must be nonnegative.

It is also desired that f exhibit a minimal value before ADS is used. This paper uses the parameterized sigmoid function for this purpose.

$$f(k; a, b) = \frac{1}{1 + a \cdot e^{-b \cdot k}}. \quad (14)$$

Figure 4 represents the parameterized sigmoid function and its derivative graph. The parameters for f are chosen as follows:

- (1) a : It controls f at $k = 0$. $f(0)$ is chosen to be 0.001 for this work, which yields $a = 999$.
- (2) b : It controls the rate at which f increases. After careful observation, note that the derivative of the parameterized sigmoid function has a maxima at $k = \frac{\ln(a)}{b}$. At this k , $f(k) = 0.5$. This study selects $k = 1400$ strikes, where the probability of laser failure reaches 50%, implying $b \approx 0.005$.

4.1. Single ADS ($n_s = 1$)

In this section, the reliability of the system is analyzed when the number of ADSs, $n_s = 1$. In the beginning, this section diagrammatically represents the scenario of a single drone as a state transition diagram. Later, the effect of varying different parameters is shown to analyze changes in the reliability of the system.

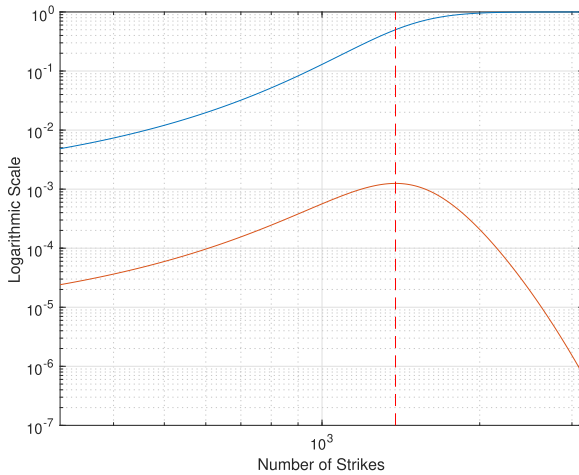


Fig. 4. (Color online) Parameterized sigmoid function, $f(k)$ (blue), $f'(k)$ (red), dotted line at $k = \frac{\ln(a)}{b}$.

4.1.1. State transition diagram

The number of drones is 1, and this drone takes two successful strikes to be completely neutralized. The ADS has two lasers, and a laser strike may miss with a probability of 0.05. The total time available for the ADS to achieve its objective is 30s. Parameters $n_d = 1$; $l = 2$; $m_f = 0.05$; $t_c = 30$ s; $r = 2$.

With the parameters described above, the model initially resides in state $\{q, L, R\} = \{2, [2], [2]\}$. Following the first strike, the model transitions to any of the nine possible states as shown in Fig. 5, each with corresponding probabilities as specified. Upon the second strike, the model converges to its base case, returning either 0 or 1 depending on the number of remaining drones in the environment. The resulting reliability is 0.9995.

4.1.2. Varying number of lasers (l)

The number of drones is 1, and this drone takes three successful strikes to be completely neutralized. A laser strike may miss with a probability of 0.1. The total time available for the ADS to achieve its objective is 60s. Parameters: $n_d = 1$; $m_f = 0.1$; $t_c = 60$ s; $r = 3$.

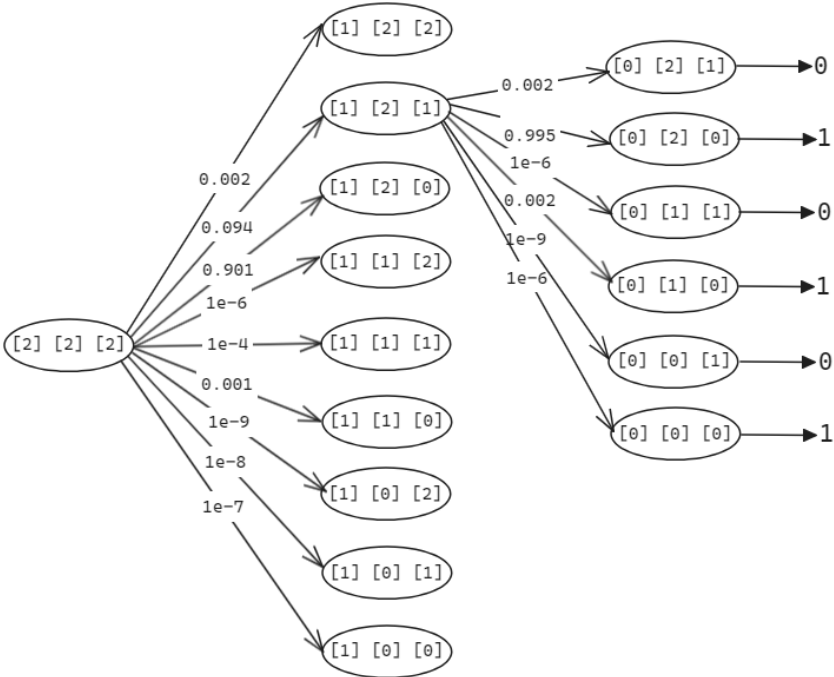


Fig. 5. State Transition Diagram. A state is characterized by $\{q, [L], [R]\}$.

Table 1. Changes in reliability as l increase.

l	Reliability	Successive Difference	Order of Difference
2	0.9999549285	—	—
3	0.9999999787	+0.0000450502	10^{-5}
4	0.9999999999	+0.0000000212	10^{-8}
5	0.9999999999	0	—
6	0.9999999999	0	—

Table 1 illustrates the reliability values across different values of l in an ADS. As expected, reliability increases as the number of lasers increases in the ADS. Moreover, the initial change in reliability is notably more pronounced, after which it approaches saturation.

4.1.3. Varying strike failure probability (m_f)

The number of drones is 1, and this drone takes three successful strikes to be completely neutralized. There are three lasers in the ADS. The total time available for the ADS to achieve its objective is 60s. Parameters: $n_d = 1$; $l = 3$; $t_c = 60$ s; $r = 3$.

Table 2 illustrates the variation in reliability as the probability of a strike miss, m_f , is varied. The reliability of the system decreases with an increase in the probability of strike failure. Furthermore, as the value of m_f increases, the magnitude of change in reliability amplifies.

 Table 2. Changes in reliability as m_f increase.

m_f	Reliability	Successive Difference	Order of Difference
0.10	0.999999978	—	—
0.15	0.999999525	−0.000000453	10^{-7}
0.20	0.999994188	−0.000005337	10^{-6}
0.25	0.999956831	−0.000037356	10^{-5}
0.30	0.999775577	−0.000181253	10^{-4}
0.35	0.999104582	−0.000670995	10^{-4}
0.40	0.997083569	−0.002021013	10^{-3}
0.45	0.991913671	−0.005169897	10^{-3}
0.50	0.980350440	−0.011563231	10^{-2}

 Table 3. Changes in reliability as n_d increase.

n_d	Reliability	Successive Difference	Order of Difference
1	0.9999999999	—	—
2	0.9999967945	−0.0000032054	10^{-6}
3	0.9914972613	−0.0084995332	10^{-3}
4	0.8027873615	−0.1887098998	10^{-1}

4.1.4. Varying number of drones (n_d)

Each drone takes three successful strikes to be completely neutralized. A laser strike may miss with a probability of 0.1. The ADS has four lasers. The total time available for the ADS to achieve its objective is 60 s. Parameters: $l = 4$; $m_f = 0.1$; $t_c = 60$ s; $r = 3$. The reliability of the system declines with an increase in the number of drones, as is shown in Table 3. Furthermore, as the value of n_d is increased, the magnitude of decrease in reliability intensifies.

4.1.5. Varying the number of lasers (l) for different m_f

The number of drones is 1, and the drone takes three successful strikes to be completely neutralized. The total time available for the ADS to achieve its objective is 60 s. Parameters: $n_d = 1$; $t_c = 60$ s; $r = 3$.

Table 4 represents the change in reliability values as l varies in the ADS along a row for different values of m_f . Figure 6 shows the reliability as a plot where different curves indicate different values of m_f . For different m_f , reliability increases with decreasing m_f and increasing l . The above analysis can be used to design certain protocols. For instance, when due to external factors, the probability of miss of a

Table 4. Changes in reliability for l versus m_f .

$l \setminus m_f$	0.1	0.2	0.3	0.4	0.5	0.6
2	0.999955	0.998614	0.988245	0.949298	0.854185	0.683193
3	0.999999	0.999994	0.999776	0.997084	0.980350	0.915746
4	0.999999	0.999999	0.999997	0.999866	0.997848	0.981380
5	0.999999	0.999999	0.999999	0.999994	0.999791	0.996312
6	0.999999	0.999999	0.999999	0.999999	0.999981	0.999320

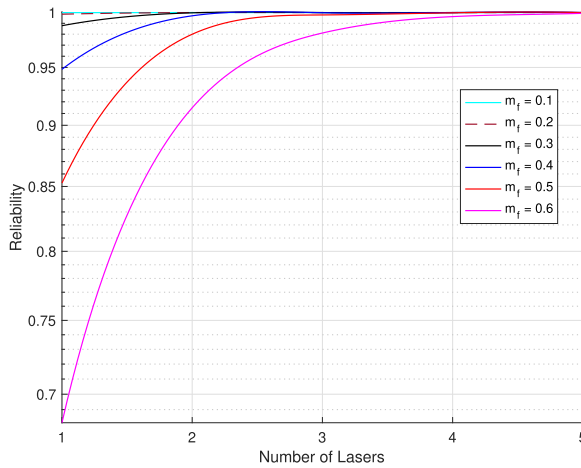


Fig. 6. Plot of reliability against number of lasers (l) in an ADS with different values of m_f .

laser strike is estimated to be 40%, to achieve a reliability of at least 0.99999, this model recommends at least 5 lasers per ADS be active.

4.1.6. Reliability change with increasing usage of ADS

For previous analysis, it is assumed that the initial number of strikes (before the current mission) for an ADS is zero. Here, the study varies this parameter q_p , which denotes the number of strikes previously conducted by the ADS. Note q_p affects the internal failure probability, and it is assumed that all other parameters are held constant. The number of drones is 1, and this drone takes three successful strikes to be completely neutralized. The ADS has three active lasers. The total time available for the ADS to achieve its objective is 60 s. Parameters: $n_d = 1$; $l = 3$; $r = 3$; $t_c = 60$ s.

Figure 7 illustrates the change in reliability as the ADS is used more, i.e., the number of previous strikes by this ADS is increased. As usage of ADS increases, the probability that ADS fails after a strike also increases, decreasing the reliability. Increasing the probability of strike miss yields a more drastic change in reliability with an increasing number of previous strikes.

4.2. Multiple ADSs ($n_s \geq 1$)

The number of drones varies, and each drone takes three successful strikes to be completely neutralized. The ADS has three active lasers. A laser strike may miss with a probability of 0.1. The total time available for the ADS to achieve its objective is 60 s. Parameters: $l = 3$; $r = 3$; $m_f = 0.1$; $t_c = 60$ s.

As shown in Fig. 8, the reliability of the system demonstrates a positive correlation with the number of ADSs. However, in scenarios where the number of

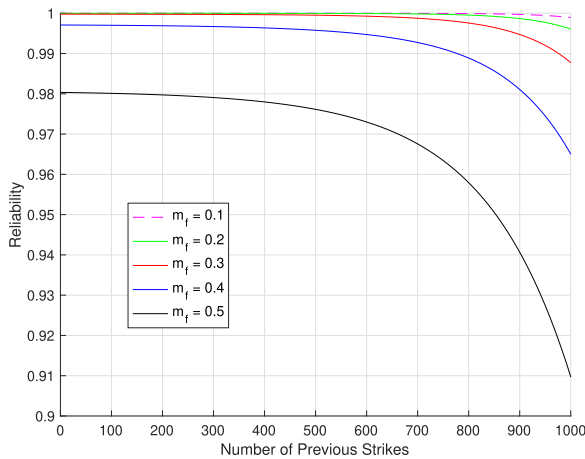


Fig. 7. Plot of reliability against number of previous strikes in an ADS with different values of m_f .

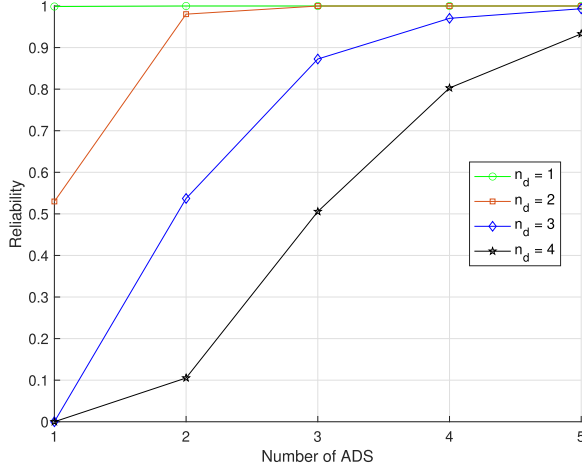


Fig. 8. Plot of reliability against different numbers of ADS with different values of n_d .

drone significantly exceeds the number of ADS, the system's reliability approaches zero. Moreover, with a substantial increase in the number of ADSs, the reliability saturates at a value of 1.

4.3. Varying critical time

Critical time is a crucial parameter for determining the maximum number of available strike units for ADS. As critical time increases, available strike units may also increase, leading to higher reliability values.

This illustration considers a single ADS where the number of active laser units is 3, with each strike taking 10s. Note that the strike time is different for this particular analysis. The probability of a strike miss is 0.1. The number of drones is 1, and each drone takes three successful strikes to be completely neutralized. The critical region extends up to 750m from the ADS. Parameters: $n_s = 1$; $n_d = 1$; $l = 3$; $r = 3$; $m_f = 0.1$; $R_c = 750$ m; $S = 10$ s.

4.3.1. Varying $R_{\min}$

The range of $R_{\min}$ is $[0, R_c]$. This value is dependent on the capability of the drone. For a drone, according to the capability of the harming mechanism associated with the drone, $R_{\min}$ will lie from 0 to R_c . V_d is chosen as 60 km/hr (16.67 m/s) for this case analysis.

Table 5 shows the range of $R_{\min}$ for a particular desired q_0 and the corresponding scenario's reliability. This table also illustrates that as $R_{\min}$ moves away from the critical region (R_c), q_0 increases. Note that for the same q_0 , the reliability remains the same, but the $R_{\min}$ has a range of possible values. It is observed that the system is more reliable when the system has more available strike units.

Table 5. Changes in reliability for different $R_{\min}$.

q_0	$R_{\min}$ (in m)	Reliability
0	(583.33, 750.00]	0
1	(416.66, 583.33]	0.729
2	(250.00, 416.66]	0.998708
3	(83.333, 250.00]	0.999996
4	(0, 83.333]	0.999999

 Table 6. Changes in reliability for different V_d .

q_0	V_d (in m/s)	Reliability
0	(75, ∞]	0
1	(37.5, 75]	0.729
2	(25, 37.5]	0.998708
3	(18.75, 25]	0.999996
4	(15, 18.75]	0.999999
4*	[13.88, 15]	0.999999

Note: *Represents cool-down may start during this mission.

4.3.2. Varying the velocity of drone (V_d)

The typical range of velocity of small and medium-sized drones lies from 13.88 m/s to 41.66 m/s.¹⁴ The value of $R_{\min}$ is chosen as 0 for this case analysis.

Table 6 shows the range of V_d for a particular desired q_0 and the corresponding scenario's reliability (similar to Table 5). This table also illustrates that as the drone's velocity decreases, the drone takes longer to reach $R_{\min}$, thereby giving more time to ADS to engage, and so, q_0 increases. Note that the reliability remains the same for the same q_0 , but the drone's velocity can be from a range of possible values.

4.4. Alternate f for internal system fault

The numerical illustrations in previous sections employ a parameterized sigmoid function denoted as f . While f is utilized in the analysis, it's important to note that alternative functions can be considered, provided they adhere to the two fundamental properties mentioned above. Another example of such a function is

$$f(k; a, b) = \frac{k + a}{k + b}. \quad (15)$$

The parameters of the above function are described as follows:

- The probability of failure before the first strike is given by $f(0) = a/b$.
- The derivative of $f(k)$ is given by $f'(k) = -\frac{a-b}{(k+b)^2}$. This implies the difference between a and b governs the rate at which the function increases. Since the derivative is required to be nonnegative, $a \leq b$.
- As previous analysis, this paper chooses $f(0) = 0.001$, and the number of strikes to reach a failure probability of 0.5 should be 1400. This yields $a = 1.4$, $b = 1400$.

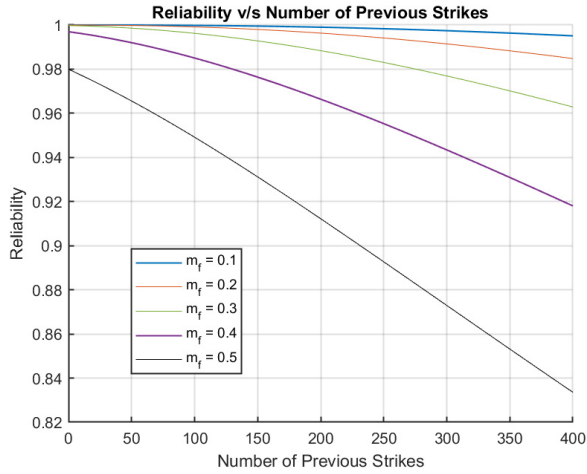


Fig. 9. Plot of reliability against the number of previous strikes in an ADS with different values of m_f .

The key difference between these two functions of f employed here is that the first function grows more rapidly with the number of strikes, relative to the second function. This difference provides valuable insights into the rate at which laser failure occurs with successive strikes. This finding is reflected in the results, where the reliability demonstrates a more linear trend in the second scenario than the first. This underscores the profound impact of failure rate order on overall system reliability, as illustrated in Figs. 7 and 9.

For this analysis, the following parameters are considered. There is one ADS. The number of drones is 1, which takes three successful strikes to neutralize completely. The total time available for the ADS to achieve its objective is 60 s.

4.4.1. Varying the number of lasers (l) for different m_f

Table 7 represents the change in reliability values as l varies in the ADS along a row for different values of m_f . For different m_f , reliability increases with decreasing m_f and increasing l .

Table 7. Changes in reliability for l versus m_f .

$l \setminus m_f$	0.1	0.2	0.3	0.4	0.5	0.6
2	0.999934	0.998468	0.987782	0.948350	0.852769	0.681585
3	0.999999	0.999993	0.999757	0.996973	0.979959	0.914845
4	0.999999	0.999999	0.999996	0.999858	0.997782	0.981068
5	0.999999	0.999999	0.999999	0.999994	0.999782	0.996227
6	0.999999	0.999999	0.999999	0.999999	0.999980	0.999300

4.4.2. Reliability change with increasing usage of ADS

There are three lasers in the ADS.

Figure 9 illustrates the change in reliability as the ADS is used more, i.e., the number of previous strikes by this ADS is increased. This is a similar illustration as Fig. 7. As usage of ADS increases, the probability that ADS fails after a strike also increases, decreasing the reliability.

4.5. Simulations v/s Probabilistic Model

This section provides a comparative analysis between the probabilistic model and simulated data of an ADS. The simulations are conducted based on the assumptions outlined during the construction of the model. As shown in Fig. 10, the success rate converges to the theoretical reliability as the number of simulations is increased.

Parameters: $n_s = 2$, $n_d = 5$, $l = 4$, $r = 3$, $m_f = 0.2$ and $t_c = 60$ s.

The theoretical probability is obtained using the proposed model with the substitution of these parameters and it comes out to be 0.914079577446248.

5. Conclusions and Future Works

This study conducts a reliability analysis for ADS integrating laser technology. It introduces a probabilistic model aimed at assessing the reliability of these systems against drone threats. By considering factors such as the number of lasers, instances of laser failure, and occurrences of laser strike misses, a comprehensive model for evaluating system reliability is proposed. Numerical illustrations are employed to depict the influence of varying parameters on system reliability. The analytical results obtained are validated through comparison with simulated outcomes.

Building on the proposed model, we consider a scenario with a single ADS, as observed and intended in the baseline configuration. The analysis reveals that

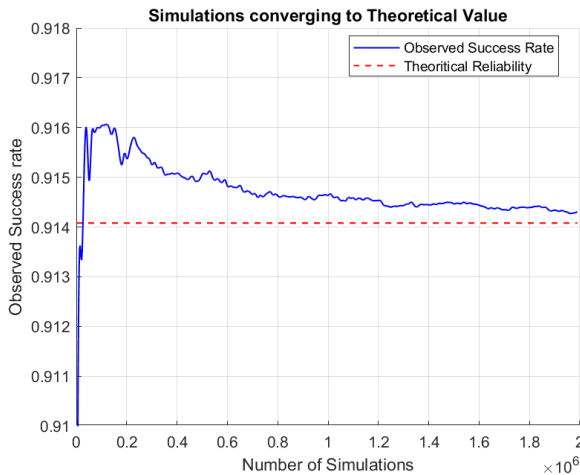


Fig. 10. Plot showing convergence of simulated success rates to theoretical reliability measure.

reliability increases with the number of lasers integrated into the ADS. However, the marginal improvement in reliability diminishes beyond a certain point, indicating the presence of an optimal laser count — contingent on other system parameters — beyond which additional lasers yield negligible benefits. Furthermore, as the probability of a failed strike (e.g., due to beam divergence or target evasion) increases, system reliability declines. Notably, this degradation is nonlinear, with the absolute drop in reliability intensifying, thereby highlighting the critical impact of external environmental factors such as atmospheric attenuation and beam jitter. Additionally, when the number of drones per ADS increases, overall system reliability decreases due to time constraints and a nonzero probability of failing to neutralize every target. This introduces a practical upper limit on the number of drones an ADS can engage effectively, which can be estimated using our model. Moreover, acknowledging the mechanical nature of ADS, system performance is observed to degrade nonlinearly with usage — as demonstrated in Fig. 7. This degradation is incorporated into the model to determine the optimal maintenance and repair intervals. For systems deploying multiple ADS units, the model identifies an optimal number of units beyond which additional deployment does not significantly enhance reliability, thereby offering guidance on cost-effective system scaling. Finally, drone speed emerges as a key variable, with increased speed correlating with reduced interception reliability. Nevertheless, given specifications of state-of-the-art drones, the model can be leveraged to configure ADS parameters to meet desired reliability thresholds.

Future work on this topic may involve enhancing the robustness and incorporating the stochastic nature of laser strike time, possibly through the utilization of machine learning techniques for parameter estimation. Additionally, efforts could be directed towards enhancing the model to encompass a broader range of environmental factors, enabling a more comprehensive analysis of the system. Conducting a comparative analysis of various ADS under specified conditions could offer valuable insights into their performance. Moreover, expanding the sensitivity analysis would provide a deeper examination of the dynamics within the system. Furthermore, incorporating additional metrics such as Mean Time Between Failures (MTBF), Mean Time To Failure (MTTF), and survivability could enhance the evaluation criteria. It will provide a more holistic assessment of the system's effectiveness an ADS.

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