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Reliability Factors of Unmanned eVTOL¹ Vehicles

Unmanned eVTOL aircraft, also known as drones, require advanced reliability and maintainability metrics for safe and efficient fleet operations. Beyond basic measures, drone-specific metrics offer a more accurate assessment. Technologies enabling predictive maintenance, such as health management and digital twins, are key. In the future, AI and blockchain will further enhance the effectiveness of these systems, promoting the safer and broader adoption of drone technology.

Keywords: drone, eVTOL, smart city, reliability, urban air mobility, advanced air mobility

1. Introduction

The integration of eVTOL vehicles into UAM² systems raises complex risk factors. The aim of the analysis is to systematically explore and quantitatively estimate the most significant risk factors of unmanned eVTOL vehicles. Our analysis is based on the regulatory frameworks of the FAA³ and EASA.⁴ We utilise quantitative and qualitative risk analysis methods. Risk assessment is carried out according to the DAL⁵ and SWAL⁶ frameworks. Particular attention is paid to the airworthiness environment (FAA, EASA), the differences due to unmanned eVTOL vehicle architectures (multicopter, tilt-rotor, tilt-wing, lift and cruise, etc.), as well as simple reliability calculations that highlight the role of redundancy. The proposed metrics and methods can be used to support regulatory compliance, design trade-offs, and operational risk management.

2. Reliability concepts

2.1. Mean Time Between Failures (MTBF)

The MBTF is defined as the operating time between two consecutive failure events, i.e. the reliability indicator between failures within the expected operating time. As MTBF is defined

¹ Electric Vertical Take-Off and Landing.

² Urban Air Mobility.

³ Federal Aviation Administration.

⁴ European Union Aviation Safety Agency.

⁵ Design Assurance Level.

⁶ Software Assurance Level.

as the expected time between failures, it is considered to be one of the fundamental indicators of system reliability. This indicator assumes particular significance in the context of drones given the potentially disastrous consequences of failures occurring during air operations.

This safety indicator is often given in hours or the number of flight operations for drones. Complete reliability largely depends on the reliability of the subsystems (e.g. battery, motor, control electronics) [7].

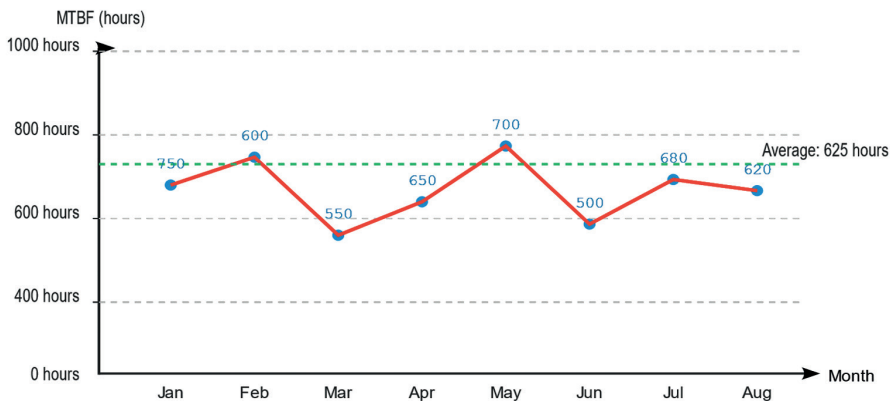


Figure 1.
Drone fleet MTBF analysis [the authors]

The chart (Figure 1) shows 8 monthly MTBF values, which illustrate the change in fleet performance.

It is important to note that an MTBF value of 50,000 hours does not mean that the device will definitely work for 50,000 hours. This is a statistical value that indicates how much the average time between failures is expected to be for high-volume devices.

Furthermore, it is not a warranty for a unique device, i.e. a particular device can fail much earlier or later than the MTBF value. The failure depends largely on the environment and usage. MTBF values generally refer to ideal or standardised conditions. In real, extreme conditions (high temperature, dust, or high loads), the time between actual failures can be significantly lower.

MTBF calculation:

$$MTBF = \frac{\text{Total Operating Time}}{\text{Number of Failures in a Given Period}} = \frac{\sum T_{op}}{N} \quad (1)$$

where: T_{op} – Cumulative error-free uptime for a given period

N – number of failures in the period.

For example:

A drone fleet consists of 10 drones that together completed 5,000 flight hours and 8 failures were recorded during this time.

$$MTBF = \frac{5000}{8} = 625 \text{ hours} \quad (2)$$

This indicates that, on average, a failure occurs in the fleet every 625 flight hours. The mean MTBF value of the fleet is 625 hours, which is considered to be an acceptable level. In the optimal month (January), an MTBF of 750 hours was achieved; conversely, in the sub-optimal month (June), only 500 hours were recorded. The variation (250 hours apart) indicates the potential for improvement. The mean of 500 hours per drone indicates that some drones likely had more and others had fewer error-free hours in operations.

2.2. Mean Time to Failure (MTTF)

MTTF is a standard reliability indicator defined in IEC 60050-192:2015 [3], the international standard. A product or system is expected Operational until the first failure. In the case of drones, it indicates how long a drone works on average without a component or the entire system failing. A higher MTTF means that the drone or one of its components (such as a battery, flight controller, or camera) is expected to continue to operate before it fails. This is vital for complex systems such as unmanned passenger drones. MTTF is usually used for parts such as a sensor, battery, or propeller, which are not repaired but replaced in the event of a malfunction, while MTBF refers to parts that can be repaired. MTTF helps determine the expected uptime of key drone components, allowing for proactive component replacement scheduling, reducing unexpected downtime and helping with maintenance planning. For commercial or industrial drones, a high MTTF means greater safety and lower costs over time, as it prevents sudden failures during operations. The IEC 60050-192:2015 [4] standard defines MTTF, while the DO-178C [9] and DO-254 [6] standards set out the reliability requirements for critical flight control systems.

Mathematical formula

$$MTTF = \frac{\text{All operation times}}{\text{Number of failures}} \quad (3)$$

where: *All operation times* – The combined operating time of all identical units during the measurement period.

Number of failures – Total number of units that failed in a given period

In integral form:

$$MTTF = \int_0^{\infty} R(t) dt = \int_0^{\infty} e^{-\lambda t} dt = \frac{1}{\lambda} \quad (4)$$

where: $R(t)$ – the reliability function, which specifies the probability of the system working at a point in time.

λ – the failure rate (failures/hour)

t – time

For practical calculation:

$$MTTF = \frac{\sum_{i=1}^n t_i}{n} \quad (5)$$

where: t_i – Operating time of i -th parts until failure

n – Number of parts tested.

MTTF is not a random value, but the result of a number of factors that affect the reliability and service life of your equipment. These factors can be classified into the following main groups, which we will discuss below.

2.2.1. Design and manufacturing features

2.2.1.1. Solid design

The frame structure and other components that respond well to loads and stresses, as well as reliable design, reduce the risk of failures. Careful planning for loads and stresses is not a luxury, but a basic requirement. Using modern tools (finite element analysis–FEM,⁷ CFD⁸), designers can accurately model the behaviour of the drone in different conditions, allowing you to design the optimal structure. Drone design is not based on the principle of “the stronger the better”, but on the principle of precisely calculated, proportional reinforcement in relation to the stress. This ensures that the drone represents a minimum weight and can safely withstand expected and unexpected loads throughout its lifetime.

2.2.1.2. Quality of the materials used

The material quality of drones directly determines not only performance, but also safety and service life. The ideal material is always the result of an optimised compromise between the specific requirements of the application, the budget and the production possibilities. The utilisation of durable, high-quality materials has been demonstrated to result in a longer service life and higher reliability.

2.2.1.3. Operating conditions

The operating conditions of drones determine their actual performance, reliability and economic efficiency. Successful operation depends not only on the quality of the drone, but also on understanding and adapting to environmental conditions. Even the best drone design can lead to failure if actual operating conditions are not taken into account at all stages of design, operation, and maintenance.

⁷ Finite Element Method.

⁸ Computational Fluid Dynamics.

2.2.1.4. Environmental impacts

Extreme temperatures can cause a significant reduction in the lifespan of motors and batteries. A humid or corrosive environment can cause electronics problems, oxidation, and structural damage. The following equation can be used to determine the actual failure rate in operation under specific environmental conditions:

$$\lambda_{eff} = \lambda_0 \prod_{i=1}^n k_i \quad (6)$$

where: λ_{eff} – (lambda effective): The actual operating failure rate (or equivalent parameter) under specific environmental conditions. This number indicates how often the drone (or its component) fails under real, non-ideal conditions.

k_i – Environmental factors (temperature, humidity, vibration).

2.2.1.5. Load profile

The MTTF value of drones depends significantly on the flight profile. Continuous or strong vibrations can lead to loosening of components, wear, breakage under heavy loads. Operations that constantly exceed the rated capacity accelerate the depreciation and failure of drones. Floating in a stationary position causes a 20-30% shorter service life, while stable cruising provides optimal operating conditions at the system level.

The value of MTTF is significantly affected by other factors, including:

- *Drone type:* Hobby or industrial (enterprise) drones;
- *Manufacturing accuracy:* Precise, standard-compliant manufacturing processes reduce the likelihood of early failures due to manufacturing errors.

Comprehensive knowledge and application of these factors allows you to improve reliability, optimise maintenance and extend service life.

MTTF is not an unpredictable figure, but a consequence of a number of factors. By knowing these factors, we can proactively improve the life of our equipment.

With the rapid expansion of drone technology, the reliability and operational readiness of fleets have become crucial both in industrial applications and in the control of critical infrastructure. The concept of Average Operating Time to Failure, although originally derived from general manufacturing, is also of paramount importance in the world of drones. This metric statistically expresses how long an unrepairable drone part or system can operate on average before a permanent failure occurs. In the case of drones, there are a number of such components, such as batteries, propellers, certain sensors or motor coils, which, in the event of a failure, are not repaired, but replaced. Knowing the value of MTTF allows fleet managers to make informed decisions about inventorying spare parts, compiling maintenance schedules, and estimating the expected life expectancy of drones.

Calculating MTTF is relatively simple: it is the total service life of all components of the same type divided by the number of failures that occurred during the observation period. Imagine being able to track the status of all the batteries in a fleet of 30 drones. If these batteries permanently fail 10 times over 15,000 charge cycles, the MTTF is 1,500 cycles. This data is extremely valuable, as it can predict the approximate number of flights after which the batteries will need replacing en masse. This allows you to prepare your battery budget and avoid stopping flight operations. However, it is important to distinguish MTTF from the related MTBF. While MTTF is specific to parts that need to be replaced, MTBF refers to systems that can be repaired. For example, a drone has batteries characterised by MTTF, but the flight control unit itself, which can be repaired, can be evaluated using an MTBF indicator.

The MTTF value is influenced by a number of factors that are specific to drones. Design quality and component materials are essential, but operating conditions often play a decisive role as well. For example, an agricultural drone operating in a dusty, humid environment with large temperature fluctuations will experience significantly faster component breakdown than a drone used for inventory surveys in an air-conditioned warehouse. The attitude and practice of the remote pilot or operator also make a significant difference, as rough handling, frequent hard landings, continuous use of maximum payload, or improper storage can all dramatically reduce component life expectancy. Therefore, fleet management involves not only maintaining the technology and managing the human factor, as well as ensuring compliance with operational protocols.

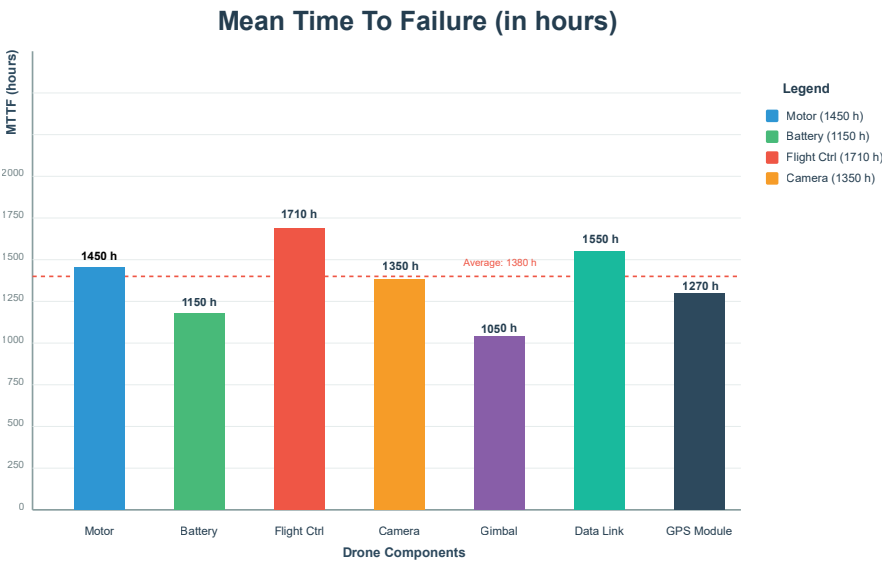


Figure 2.
MTTF analysis of drone components [the authors]

In this complex environment, modern drone fleet management (CMMS)⁹ software becomes an indispensable tool for improving MTTF values and increasing fleet reliability. These platforms offer much more than simple work order management. They facilitate predictive maintenance by continuously collecting and analysing data on the condition of each drone. For instance, built-in analysis software can detect an increase in a motor's vibration level or cells in a battery discharging faster than others. These signals, which occur before a malfunction, can trigger an alarm, enabling the technician to inspect and replace the problematic part during subsequent scheduled maintenance and preventing unexpected shutdowns.

The CMMS also becomes a central repository for all historical data, enabling in-depth analysis. It allows you to track whether the MTTF of parts purchased from a particular supplier is lower than average, or which component of a certain type of drone is the most likely to fail. This data-driven approach not only facilitates proactive maintenance, but also lays the foundation for purchasing decisions and long-term planning of fleet composition.

2.3. Bathtub Curve (BC)

In connection with the definition of MTTF, we must mention another important concept. This is the bathtub curve, which is a curve describing the development of the failure rate over time. The failure rate of drone components usually follows the famous BC, which consists of three characteristic stages:

- *Early failures* (manufacturing defects) – decreasing failure rate;
- *Accidental failures* (normal lifetime) – low, constant on;
- *Wear failures* – increasing failure rate.

2.3.1. Stage of early failures

This stage is characterised by low MTBF values, i.e. frequent failures. According to calculations [1] 20–30% of new drones (prototypes) can fail during the first 50 flights. In such cases, the common causes are manufacturing errors, software errors and component compatibility problems.

2.3.2. Stage of accidental failures

This section is characterised by a stable, high MTBF value. The average MTBF of commercial drones at this stage is 500–1,000 flight hours [2]. Reliability prevails under the intended conditions of use.

⁹ Computerised Maintenance Management System.

2.3.3. Wear failures stage

At this stage, the MTBF is constantly decreasing. The service life of drone components is 300–500 charge cycles for batteries, 1,000–2,000 flight hours for motors, and fatigue cracks and fractures due to vibration can occur in structural elements. The MTBF value can be increased by up to 60% through the implementation of redundant GPS,¹⁰ IMU¹¹ and computer systems.

Other factors that increase reliability include *predictive maintenance*, which can be used to predict failures based on sensor data, and early¹² detection of the third stage of the bathtub curve using AI-powered analytics.

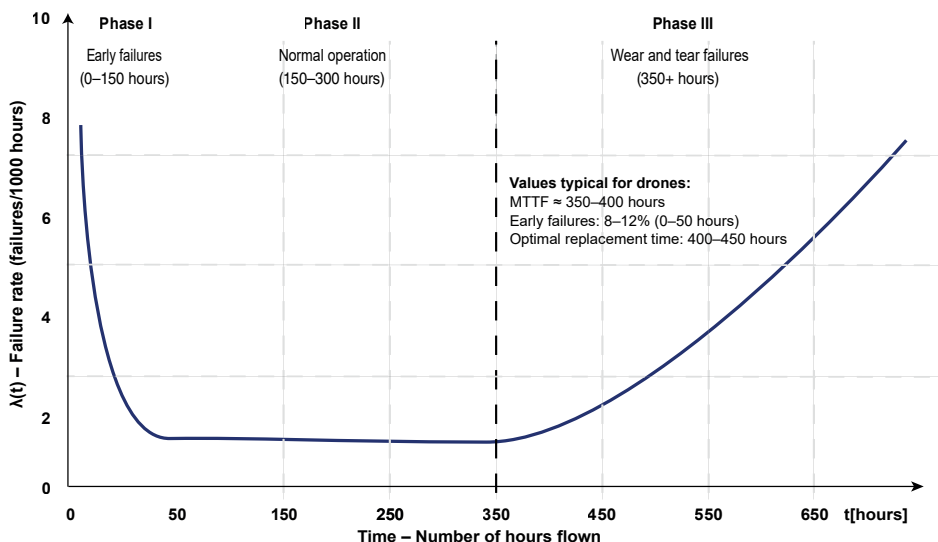


Figure 3.
Tub curve in the reliability of drones [the authors]

The following parameters are to be observed in relation to the stage:

$\beta < 1$ ($\beta \approx 0.5$) – early failures

$\beta = 1$ – normal operation (exponential distribution)

$\beta > 1$ ($\beta \approx 3.0$) – wear failures

Mathematical model: The three-parameter Weibull distribution is defined by the following equation:

$$\lambda(t) = f(t)/R(t) \quad (7)$$

¹⁰ Global Positioning System.

¹¹ Inertial Measurement Unit.

¹² Artificial Intelligence.

Table 1.
Explanation of the tub curve [the authors]

$\lambda(t)$	0–10 bugs/1000 hours	Failure rate
t	0–650 hours	Flight time
β	0.5, 1.0, 3.0	Weibull Shape Parameter
MTTF	~400 hours	Expected failure time

2.3.4. System reliability

In the case of serial switching, the MTTF of the entire drone system is as follows:

$$MTTF_{\text{system}} = \frac{1}{\sum_{i=1}^n x \lambda_i} \quad (8)$$

where: i – Index or ordinal number that runs from 1 to n .

For example:

$i = 1 \rightarrow$ battery

$i = 2 \rightarrow$ motor

$i = 3 \rightarrow$ flight controller

$i = 4 \rightarrow$ communication system

the failure rate of each (i)-th component. Unit of Failures/Hour or 1/Hour

Calculation:

$$\lambda_i = \frac{1}{MTTF_i} \quad (9)$$

n – total number of system components.

For example: If a drone consists of 4 critical components (battery, motor, flight controller, communication system), then $n = 4$.

2.3.5. Practical examples

An MTTF value of 150 hours means that an average of 63 out of 100 drones will fail in 150 operating hours (assuming an exponential distribution).

Let's say a drone consists of 3 critical components in series (Table 2):

Table 2.
MTTF calculation specific data [the authors]

Component	Index (i)	MTTF $_i$ (hours)	$\lambda_i = 1/MTTF_i$ (1/hour)
Battery	1	200	0.00500
Engine	2	500	0.00200
Flight controller	3	1,000	0.00100

Calculation step by step:

$n = 3$ (there are 3 components)

Summary $i = 1$ to 3:

$$\sum_{i=1}^3 \lambda_i = \lambda_1 + \lambda_2 + \lambda_3 = 0.00500 + 0.00200 + 0.00100 = 0.00800 \quad (10)$$

System MTTF calculation:

$$MTTF_{system} = 10.00800 = 125 \text{ hours} \quad (11)$$

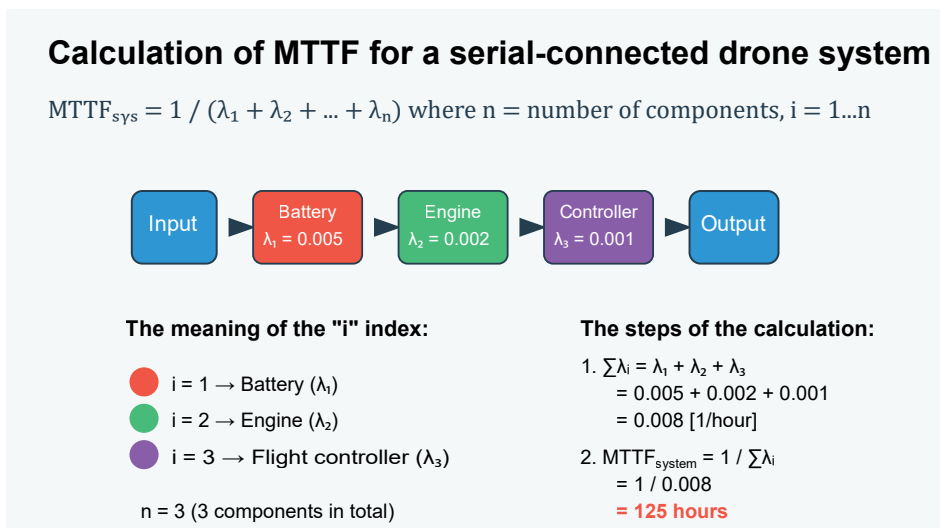


Figure 4.
Calculation of serial drone systems [the authors]

2.4. Mean Time to Repair (MTTR)

The MTTR shows the average time between when a failure occurred and when the repair is completed. For drones, this includes diagnostics, component replacement time, and testing.

$$MTTR = \frac{\sum \text{Repair time}}{\text{Repair time}} = \frac{\sum T_{repair}}{N} \quad (12)$$

where: T_{repair} – Repair time
 N – Number of repairs.

The repair time for the above 8 malfunctions is: 2, 3, 1, 4, 2, 3, 5, 2 hours.

$$MTTR = \frac{2+3+1+4+2+3+5+2}{8} = \frac{22}{8} = 2.75 \text{ hours.} \quad (13)$$

2.5. Mean Cycles Between Failures (MCBF)

The MCBF is the number of cycles between failures. In the case of drones, a cycle is usually a series of take-offs, flight missions and landings.

$$MCBF = \frac{\text{All flight cycles}}{\text{Number of failure}} = \frac{C_{\text{total}}}{N} \quad (14)$$

where: C_{total} – Number of failure
 N – Number of failure.

Example:

If the 10 drones in the previous example performed a total of 2,500 flight cycles and 8 failures occurred:

$$MCBF = \frac{2500}{8} = 312.5 \text{ cycle.} \quad (15)$$

2.6. Degradation Rate (DR)

DR shows the rate of performance degradation over time. In the case of drones, this can be, for example, a decrease in battery capacity or a decrease in motor efficiency.

$$DR = \frac{P_{\text{initial}} - P_{\text{final}}}{T_{\text{operation}}} \quad (16)$$

where:

P_{initial} – initial performance
 P_{final} – end-state performance
 $T_{\text{operation}}$ – Operation time.

Example:

The battery capacity of a drone drops from 10,000 mAh to 8,500 mAh after 200 cycles.

$$DR = \frac{10,000 - 8,500}{200} = 7.5 \text{ mAh/cycle} \quad (17)$$

2.7. Failure Mode and Effects Analysis (FMEA)

FMEA is a system-wide method for identifying, prioritising, and preventing potential failures that helps you assess their risk and determine the necessary corrective actions. The parameters

underlying the calculation, which need to be analysed as failure modes in drones, are the following:

- Battery Failure – $RPN^{13} = \text{Severity} \times \text{Occurrence} \times \text{Detection}$
- Engine Failure – RPN Evaluation
- Loss of communication link – RPN calculation
- Navigation error – RPN value

2.8. Risk Priority Number rating

The primary purpose of RPN classification is to *rank sources*. The above categories are a good starting point, but they should be adapted to the needs of the organisation.

The *most important rule* is to focus on the items with the highest risk first, especially those that endanger life safety and have serious consequences.

2.8.1. General RPN classification categories and operational boundaries

The goal of risk management is to focus resources on managing the items with the highest risk. Therefore, RPN values are usually classified into 3-4 categories.

Category I

High risk: Immediate intervention is required.

RPN Range: For example, above 100 (common threshold), or even above 125/150, or for any very high severity ($S = 9$ or 10) error, regardless of the total RPN. These are unacceptable risks. The product/process must not leave the design/development phase, or production must stop.

Mandatory measures: It requires an immediate and prioritised solution. Changes in planning/process are necessary to reduce the risk (first of all, reduction of severity and then incidence). The activity must be completed before work can continue.

Category II

Medium risk: Planned repair required.

RPN Range: For example, between 30 and 100. This is the most common "warning" zone. The risk may be acceptable in the short term, but it must be reduced in the long term. Indicates that repairs are needed to increase reliability, quality, or safety.

¹³ Risk Priority Number.

Mandatory measures: Planning and implementing corrective actions with a set deadline. Responsible persons should look for cost-effective solutions (e.g. process optimisation, better control methods to improve detection), and the effectiveness of measures should be monitored.

Category III

Low risk: Accepted/To Watch.

RPN Range: For example, under 30. The risk is currently acceptable. These error modes usually do not require specific action, or the measure is not cost-effective.

Proposed actions: They should be treated as part of routine process control. Further mitigation of risk may be considered if there is an easy way to do so. It should be reviewed regularly, especially if the product, process, or environment changes.

Table 3.
RPN risk levels [the authors]

Risk Level	RPN Range	Severity (S) Criteria	Mandatory Operations
HIGH	> 100 or S = 9–10	Catastrophic, dangerous to security	IMMEDIATE INTERVENTION The product/process cannot be started/continued. Changes need to be made to the plan/process
MEDIUM	30–100	Significant, reduces performance, causes operational risk	PLANNED IMPROVEMENT Development and implementation of a deadline-bound action plan. Impact assessment
LOW	< 30	Minor, unnoticeable, or causes slight disadvantage	ACCEPTABLE/MONITOR NEEDED Routine process control Recommended to review when updating FMEA

Calculation of RPN value:

$$RPN = S \times O \times D \quad (18)$$

where: S – Severity (scale 1–10)
O – Occurrence (scale 1–10)
D – Detectability (scale 1–10).

Calculation example of a drone battery system:

Let us examine the lithium-polymer battery of a drone, where we have identified the following modes of failure.

Failure mode: Battery overheating in flight

Impact: Interruption of drone power supply, crash, fire hazard

Causes: Overload, faulty charger, extreme values of ambient temperatures

Rating:

1. Severity (S) = 9
 - failure can cause significant property damage (e.g. destruction of the drone);
 - it poses a safety risk (e.g. crash and fire);
 - it has a high severity value, as personal injury may occur.
2. Prevalence (O) = 3
 - modern batteries have proper load management;
 - it rarely occurs with proper maintenance;
 - the incidence is low but not negligible.
3. Detection (D) = 2
 - the drone has temperature sensors in its system;
 - early warning is given to the operator;
 - failure is easy and early to detect.

2.8.2. RPN calculation example for a battery

$$RPN = S \times O \times D = 9 \times 3 \times 2 = 54 \quad (19)$$

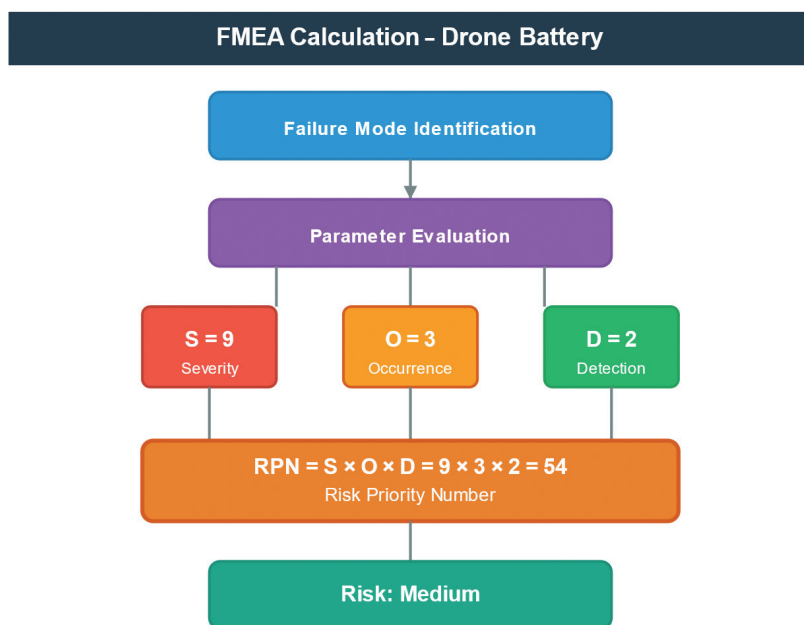


Figure 5.
FMEA calculation for batteries [the authors]

Based on the above calculations, the RPN is 54, which indicates medium risk. Although the severity is high, the low incidence and good detectability reduce the overall risk value. In the event of such failure modes, it is recommended to strengthen preventive measures, such as regular testing of the temperature monitoring system and periodic replacement of batteries. It is important to note that it is a mistake to focus only on RPN! Analysing the unique values of S-O-D is much more important.

For example: An $S = 10$, $O = 2$, $D = 3$ ($RPN = 60$) is actually much more dangerous than an $S = 5$, $O = 6$, $D = 4$ ($RPN = 120$) because it has serious consequences, even if it is rarer. Therefore, items with a high severity rating should always take priority.

The FMEA calculation helps prioritise risks so that limited resources can be focused on the items with the highest risk [12]. In the case of the drone, in addition to the battery system, it is also important to examine the motors, control system and communication system to obtain a comprehensive risk assessment.

2.9. Overall Equipment Effectiveness (OEE)

OEE is a comprehensive performance indicator that evaluates, for example, the efficiency of drone fleets based on three key factors:

- availability;
- performance;
- quality.

From a mathematical perspective, the following equation is applicable:

$$OEE = A \times P \times Q \quad (20)$$

where: A – availability
 P – the performance factor
 Q – the quality factor

Availability (A)

Measures system availability, and can be calculated from traditional reliability indicators.

$$A = MTBF / (MTBF + MTTR) \quad (21)$$

If a drone fleet has an MTBF value of 200 hours and an MTTR value of 6 hours, the following calculation can be made:

$$A = 200 / (200 + 6) \approx 0.971 = 97.1\%. \quad (22)$$

Performance factor (P)

This term refers to the discrepancy between the actual performance and the ideal cycle time. In the event of a drone possessing a nominal speed of 50 km/h, yet, in practice, operating at an average speed of 46 km/h, the following equation can be utilised:

$$P = 46 / 50 = 0.92 = 92\%. \quad (23)$$

Quality factor (Q)

It expresses the proportion of flawless products (or successful tasks). If the drone fleet performed 98 out of 100 operations without errors, then the following conclusions can be drawn:

$$Q = 98 / 100 = 0.98 = 98\%. \quad (24)$$

The product of these three components gives the OEE value:

$$OEE = 0.971 \times 0.92 \times 0.98 \approx 0.875 = 87.5\%. \quad (25)$$

This means that a civilian drone fleet uses 87.5% of its potential capacity to create real value. The remaining 12.5% loss consists of: availability losses (2.9%), performance losses (8%) and quality losses (2%).

An OEE of 100% is an ideal case that can only be achieved if all drones are always available, operating at rated speeds, and performing all tasks flawlessly [13].



Figure 6.
Analysis of the Efficiency of the Entire Drone Fleet (OEE) [the authors]

2.10. Technology and design risks

The majority of modern multirotor and higher payload drones use lithium-ion / lithium-polymer (Li-ion / LiPo) technology. These have a high energy density but are susceptible to high discharge/load ratios, high or low temperatures, physical damage, and improper BMS¹⁴ application. Reliability is determined by several factors, which are as follows:

¹⁴ Battery Management System.

- capacity fade;
- increase in internal resistance;
- cell consistency;
- BMS errors;
- temperature rise to a critical level.

It is important to take into account the concept that defines the use of batteries, which is known as thermal runaway. Thermal runaway is a feedback-based, self-excitatory heating process in lithium-ion (and other types) batteries that can lead to the complete, often irreversible destruction of the cell. Since thermal runaway is a dangerous, self-excitatory process, internal overheating can trigger a chemical chain reaction. This reaction can lead to rapid heat release, the release of gases, and eventually a fire or explosion. For Li-ion batteries, the TR¹⁵ probability of 1×10^{-7} /hour/cell [5], [10] for a 1000-cell configuration.

2.10.1. Risk

The initial and final phases of flight are particularly challenging, because take-off and landing, as well as hover phases, require short but very high power drawdowns, which can lead to high loads, heating and rapid aging of the battery. In the absence of thermal control, increased loads can cause catastrophic battery failure.

3. Predictive Maintenance (PdM)

PdM primarily reduces the probability of technical failure in the field of flight safety; at the same time, it itself requires cybersecurity protection, because if diagnostic data or models can be manipulated, maintenance decisions may also become incorrect.

Therefore, PdM should not be treated as a standalone algorithm. From a scientific and engineering perspective, PdM becomes a genuine safety mitigation only when it is integrated into the complete system of risk assessment, operation, maintenance, cybersecurity, and compliance. EASA's SORA methodology also applies risk-based thinking. It treats operational risk, mitigations, personnel training, technical requirements, and operational procedures as an integrated whole [14].

3.1. *The role of PdM in the drone safety threat model*

PdM mainly addresses technical risks originating from degradation. These are failures that do not necessarily occur suddenly, but appear as measurable deterioration in condition. Examples include motor bearing wear, ESC overheating, an increase in battery internal resistance, propeller microcracks, IMU drift, or structural fatigue.

¹⁵ Thermal Runaway.

Several studies on multirotor multicopters emphasise that vibration data are particularly valuable for estimating the condition of the propulsion system, because motor, rotor, or propeller faults often appear first as deviations in the frequency domain, before visible physical damage can be observed [8]. The task of PdM is therefore not only to determine whether a component is functioning, but also to estimate how long it may continue to operate at an acceptable level of risk.

The role of PdM differs across various drone safety risks. In the case of motor failure, the system may monitor vibration and current anomalies; in the case of battery failure, it may monitor capacity loss, cell-voltage deviation, internal resistance, and temperature trends; in the case of propeller failure, spectral vibration changes; and in the case of sensor failure, drift and inconsistency. GNSS spoofing or radio jamming, however, belongs more to the security category, which PdM can support only indirectly through anomaly-detection tools.

Predictive maintenance alone does not constitute safety evidence. The fact that a model predicts motor failure or battery degradation does not yet prove that the overall drone operation has become safer. This requires a security justification; that is a structured security argument that demonstrates which hazards the given technology reduces, under what conditions, and based on what evidence [15].

The role of PdM within a safety case can be described using the following logic:

hazard → failure mode → PdM indicator → decision threshold → evidence

For example:

loss of control → motor bearing wear → increase in vibration spectrum → RUL < 5 hours
→ flight prohibition

In this example, loss of control is the hazardous system state, motor bearing wear is the failure mode, the increase in the vibration spectrum is the condition indicator detected by PdM, and RUL < 5 hours is the decision threshold below which the drone may no longer be permitted to fly.

The previously described FMEA is suitable, for example, for analysing motor bearing wear, ESC overheating, battery cell weakening, propeller cracking, or IMU drift. FMEA fits well with PdM because both start from the condition of individual components [15].

4. Conclusion

A complex system of drone reliability and maintainability metrics is essential for the efficient and safe operation of modern drone fleets. In addition to the basic MTBF and MTTR indicators, drone-specific metrics (MTBF, MCBF, DR) provide a more accurate picture of the real operational reliability of drones. Advanced technologies like PdM and digital twin [8] enable predictive maintenance and proactive improvements in reliability. The integration of artificial intelligence and blockchain technology in the future [11] will further increase the accuracy and usability of drone reliability metrics, which will contribute to a safer and more economical use of drone technology in both civilian and military areas.

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A pilóta nélküli eVTOL légi járművek megbízhatósági mutatói

A személyzet nélküli eVTOL légi járművek, vagy más néven drónok, megbízhatósági és karbantarthatósági mutatóinak fejlett rendszere elengedhetetlen a biztonságos és hatékony üzemeltetéshez. Az alapvető mérőszámok mellett a drónra jellemző metrikák pontosabb képet adnak. A prediktív karbantartást lehetővé tevő technológiák, mint az állapotfelügyelet és a digitális iker, kulcsfontosságúak. A jövőben a mesterséges intelligencia tovább fogja javítani ezek hatékonyságát, elősegítve a drónok szélesebb körű, biztonságos alkalmazását.

Kulcsszavak: drón, eVTOL, megbízhatóság, smart city, nagyvárosi légi mobilitás, fejlett légi mobilitás

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