Statistical simulation of failures of the systems and structures of helicopters in Nigeria

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Abstract

To avoid severe loss of lives and finances in civil aviation, both manufacturers and operators must guarantee high levels of reliability and flight safety. Various activities including but not limited to maintenance processes ensure that the operational reliability requirements of aircraft are strictly maintained. Maintenance processes can be improved using probability theory and mathematical statistics, so this paper focuses on developing statistically simulated models of failures of structural systems of helicopters in Nigeria using the Monte Carlo technique. The origin dataset for performing computation was the statistics of failures of the helicopter systems and structures. The simulation model determines the probability distribution of operating time between failures for systems and structures of helicopters.

Keywords

Statistical data processing, reliability, reliability-centered maintenance, condition-based maintenance, Monte-Carlo simulation method

1. Introduction

The global commercial helicopter market is forecast to have an average year growth rate of 2% from 2020–2025 [1]. In Nigeria, the commercial helicopter sector contributes to the economy by providing search and rescue services (SAR) and transportation to the offshore oil and gas industry. Current trends across industries especially aviation shows increasing importance of cost effective and accurate maintenance with the end goal of reducing downtime and enhancing reliability. Reliability is defined as probability that a device will serviceably perform its function for the time interval of the designated mission under specified conditions of use. Reliability index can be denoted by: mean time to failure (MTTF), mean time between failures (MTBF), mean time to repair (MTTR) and hazard or failure rate [2, 3].

Maintenance costs make up a significant portion of operational costs. The costs for maintenance contain both direct and indirect expenditures. Direct expenditures are incurred from materials, means, resources of spare parts, unavailability, personnel, technical data etc. while indirect expenditures are incurred from administrative staff needed to carry out maintenance programs, overhead cost and additional costs due to downtime [3]. There are 2 main types of maintenance:

1. the corrective maintenance which is implemented after the complete breakdown or system failure;
2. the preventive maintenance which can be realized based on predetermined intervals with the goal of reducing the likelihood of failure or degradation.

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In aviation, a continuous airworthiness maintenance program consists of maintenance and inspection actions an operator uses to comply with maintenance needs. A continuous airworthiness maintenance program outlines procedure for scheduled and unscheduled maintenance, aircraft inspections, repairs and overhauls of engines etc. [2].

According to [2] the concept of modern day aircraft maintenance schedule started in the 1960s by the Federal Aviation Administration and was put together by the Air Transport Association (ATA) Maintenance Steering Group (MSG). Prior to this, aircraft maintenance was based on preventive maintenance which required expensive restoration and replacement of components. Over time, MSG has evolved into MSG-2 and MSG-3. MSG and MSG-2 processes follow a bottom-up approach while MSG-3 follows a top-down approach and was built based on the framework of MSG-2. In a top-down approach, consequences of component failure and how aircraft operations are affected is the focus. Application of reliability-centered maintenance (RCM) also known as MSG-2 was introduced to the aviation industry in 1974 by United Airlines and the United States Department of Defense and it has been successfully implemented in offshore oil industry and nuclear power. According to regulatory documents, RCM is defined as methods to detect and chose failure control strategies with the goal of obtaining required safety, availability, and economy of operation efficiently and effectively [4]. This is carried out based on:

- Analysis of statistical data on reliability during system's operation,
- Main elements of preventive maintenance approach, repair process, and removal actions.

The RCM plans for future activities associated with maintenance process using result current technical state monitoring.

Different complicated distributions can be used to describe the model of wear out. At the stage of normal operations, the most common probability distribution used is exponential. The probability of equipment operation without failure and availability coefficient for this case is determined according to formulas:

$$P_{eo}(t) = e^{-\lambda t}, \tag{1}$$

$$C_a = \frac{MTBF}{MTBF+MTTR} = \frac{\rho}{\lambda+\rho}, \tag{2}$$

$$MTBF = \frac{1}{\lambda}, \tag{3}$$

$$MTTR = \frac{1}{\rho}, \tag{4}$$

$$MTBF = \int_0^\infty P_{eo}(t)dt, \tag{5}$$

where $P_{eo}(t)$ is probability of equipment operation without failure at time *t;* λ is failure rate; C_a is availability coefficient; ρ is repair rate

There are four paths of RCM:

- condition-based maintenance (CBM) which involves monitoring the state of basic elements to obtain a maintenance schedule,
- Run-to-Failure approach,
- Time-Directed Maintenance,
- indirect solutions.

The RCM requires 2 basic actions:

1. identification of a part or line replaceable unit;
2. failure occurrence phenomenon understanding that can be observed in this unit.

Reliability mathematical models characterize part failure condition indicators that allow implementation of CBM [5].

The statistical simulation can be implemented to estimate and analyze maintainability of a system. This paper considers a Monte Carlo simulation process for the component failures of helicopters in

Nigeria. Data for a 4-year operational period was gotten from seven of those helicopters and a reliability analysis to determine the statistical characteristics of parameters.

2. Literature review and the statement of the problem

In [6], the authors discusses a Markov-based reliability model for optimizing redundancy and minimum equipment list to ensure flight safety and reduce operational cost. Using an induction system of an elevator [4] developed an optimized CBM system that combined both RCM and data fusion strategies to improve accuracy of maintenance. Wessels [7] proposed that time to failure reliability models are meaningless because time does not cause part failure – stress based reliability models are meaningful.

The paper [8] presented a hybrid RCM and proposed maintenance decision tree to increase the efficiency of operation process. This model gives ability to risk optimization and reducing the costs related to reliability. Paper [9], presents a CBM+RE prototype which carries out maintenance only when there's evidence of need. The authors of [10] presented various case studies on common utilized solutions in different areas and how manufacturers follow maintenance practices – IBM's general solution is called MAXIMO and it can monitor the maintenance process for systems of helicopters and aircraft.

An evidenced by the literature review sufficient attention is being paid to the synthesis of RCM approaches. However, the insufficient attention is paid to the mathematical models building to determine both the characteristic state of reliability of component parts and operational processes of aircraft. Review of the literature [11 – 30] shows that the actual tasks during the operation of aviation equipment are: 1) analysis of the processes of deterioration of the technical state of systems and 2) minimization of maintenance costs to ensure acceptable risk of failure of aviation equipment. The paper [11] discusses a new model for reliability, which can gain the efficiency of electronics operation for wind turbines. Their work highlighted a need to develop reliability models for the structural systems of aircraft. Therefore, this paper deals with statistical simulation models of the failures of basic components of helicopters.

3. Preliminary analysis of the reliability for helicopter systems

The purpose of this statistical simulation is to obtain the model of failures for systems and structures of helicopters in Nigeria. The information about quantity of failures for different the systems shown in Table 1 is used as initial data, the observation time $T_{\text{obs}} = 29116$ flight hours. As shown in Table 1, the landing gear is the most susceptible to failure and in-flight, the navigation equipment was the most susceptible to failure therefore for the 4-year period analyzed, the landing gear was the overall least reliable system and in-flight the navigation equipment was least reliable. The overall failure rate of any arbitrary component of the helicopter is $\lambda = 0.058$ hours^{-1} and this indicates that failures on the average occur after 17 flight hours.

The most used probability distribution to describe time between failures is the exponential type therefore this paper proposes an exponential law for possible failures in helicopters in Nigeria. For the model, an analysis of M = 1000 failures of helicopter components will be carried out and we assume that one sufficiently small interval of time does not contain more than one failure. To obtain information which helicopter component failed, we calculated the specific number of failures for each system. This value is generally a conditional probability of a given component failure if any arbitrary component of the helicopter fails. It is determined by the formula below

$$p_i = \frac{n_i}{N}, \tag{6}$$

where $N = \sum_i n_i$ – total number of observed failures, $i \in [1; 32]$.

For the first step of simulation, we determine the operating time between failures t_k in hours. An example of probability density function (PDF) for system failures of the helicopters is shown in

Figure 1. For the second step, we determined which component failed and for this, we generated random values x_k with total volume 10000. Obtained values are described by uniform PDF at the interval [0; 1].Each generated number is compared to a threshold system and in this case, we previously calculated 33 single threshold values using the formula (we consider $p_0 = 0$) below

$$V_j = \sum_{i=0}^{j} p_i \quad (7)$$

,

Next is the decision algorithm for the component failure. If the value of the generated number x_k falls in the interval $[V_j;\ V_{j+1}]$, we consider that $j+1$ helicopter component has failed. As a result of 10,000 repetitions of the decision algorithm, $\vec{T_i}$ failure vectors are formed for each helicopter component. In the third stage of the simulation, the characteristics of the random vectors for each component of the helicopter are evaluated.

Table 1

Failures quantity for helicopter systems

ATA Chapter Number	Observed Failures, n_i	In-Flight Failures
21	11	3
22	104	49
23	39	12
24	57	20
25	27	2
26	15	
28	9	3
29	46	3
30	14	4
31	31	18
32	211	16
33	76	16
34	173	91
39	9	2
45	17	1
51	70	3
52	53	7
53	165	21
55	13	
56	4	
65	192	8
66	37	4
67	76	12
71	24	2
72	20	6
73	48	16
74	1	
75	54	18
76	5	1
77	8	6
78	4	
79	48	1
80	15	3
Total	1676	348

Figure 1: The PDF for observed time of failures for helicopter systems

4. Analysis of the resulting failure models of helicopter component

4.1. ATA chapter 21

The PDF for observed time between failures of the air conditioning system (ATA 21) obtained during simulation is shown in Figure 2.

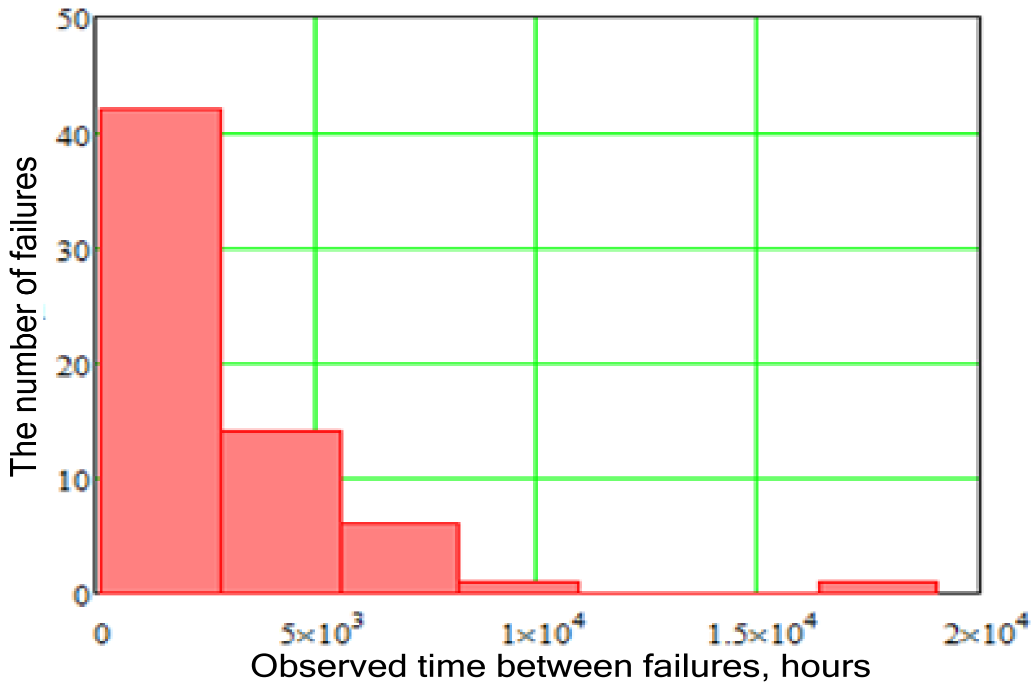

Figure 2: The PDF for observed time of failures for ATA chapter 21

For a single simulation as shown in Figure 2, 64 failures were observed in the air conditioning system. The probability of failure of this system $p_1^* = 0.0064$ and the initial data $p_1 = 0.006563$. The resulting MTBF for the air conditioning system is 2,705 hours and the standard deviation is 2,886 hours.

4.2. ATA chapter 22

The PDF for operating time between failures for the auto flight component (ATA 22) is shown in Figure 3. For a single simulation as shown in Figure 3, 607 failures were observed in the auto flight system – the probability of the failure of this system $p_2^* = 0.0607$ and the initial data $p_2 = 0.062$. The resulting average MTBF for the auto flight system is 285 hours and the standard deviation is 292 hours.

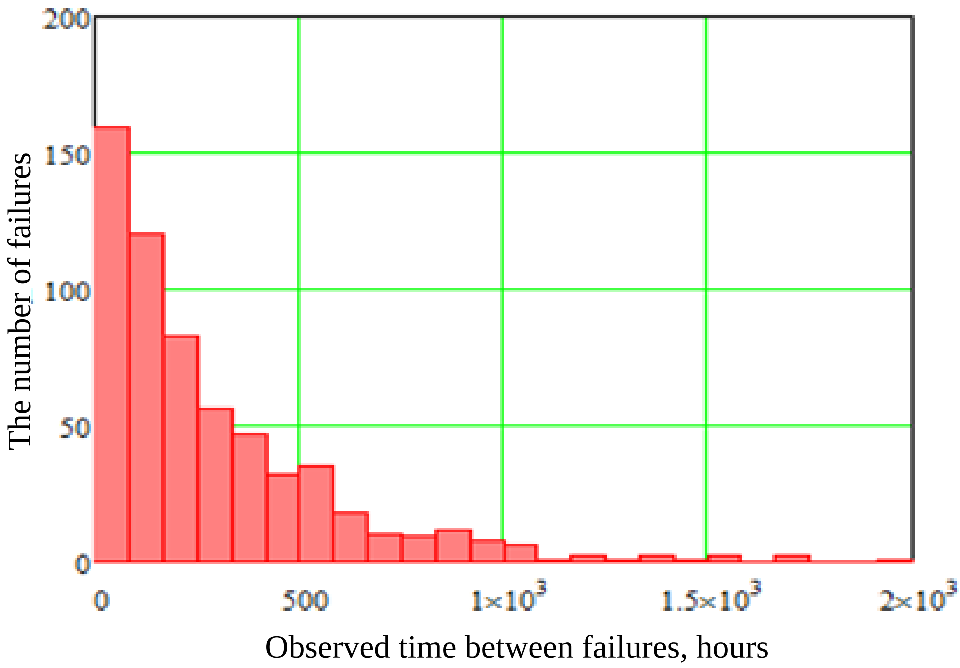

Figure 3: The PDF for observed time of failures for ATA chapter 22

4.3. ATA chapter 23

The PDF for operating time between failures for the communication equipment (ATA 23) is presented in Figure 4. According to Figure 4, for a single simulation, 236 failures were observed in the communication system. The probability of the failure of this system $p_3^* = 0.0236$ and the initial data $p_3 = 0.023$. The resulting average MTBF for the communication system is 732 hours and the standard deviation is 698 hours.

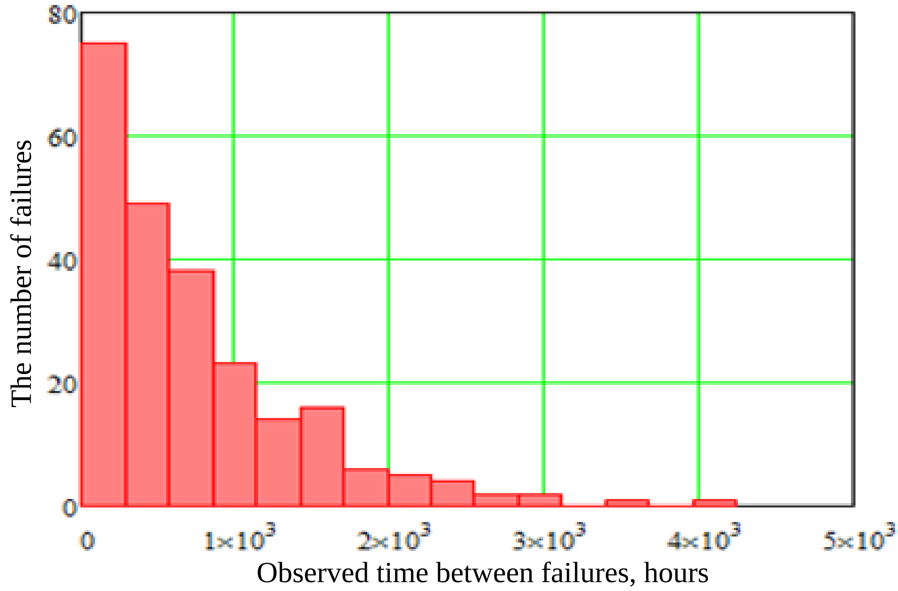

Figure 4: The PDF for observed time of failures for ATA chapter 23

4.4. ATA chapter 24

The PDF for operating time of failures for the electrical power component (ATA 24) is shown in Figure 5.

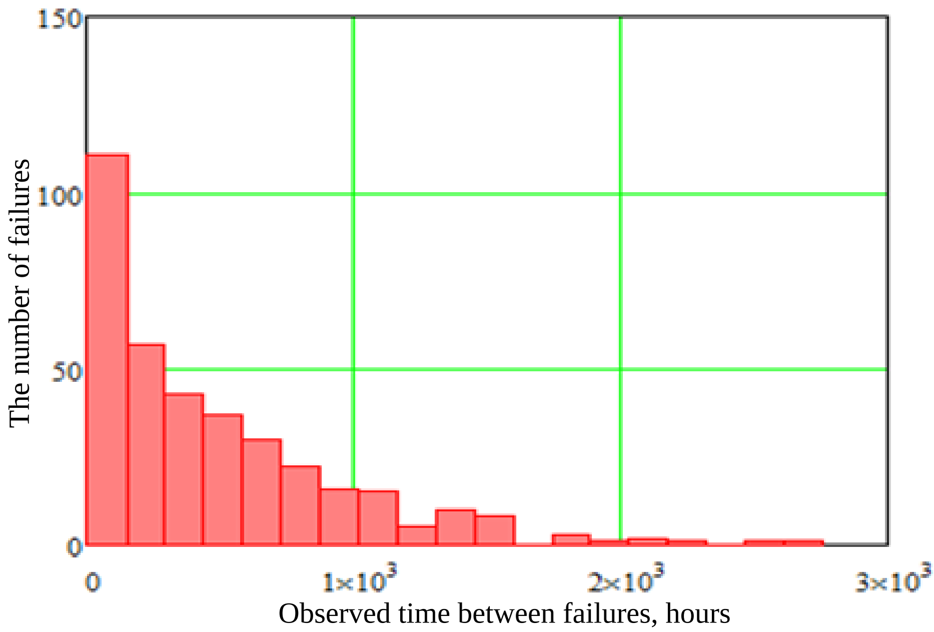

Figure 5: The PDF for observed time of failures for ATA chapter 24

For a single simulation as shown in Figure 5, 362 failures were observed in the electrical power system. The probability of the failure of this system $p_4^* = 0.0362$ and the source data $p_4 = 0.034$. The resulting average MTBF for the electrical power system is 475 hours and the standard deviation is 469 hours.

Similarly, failure statistics of other helicopter components can be calculated.

4.5. Algorithm for statistical simulation

In general, the algorithm for statistical simulation is shown in Figure 6.

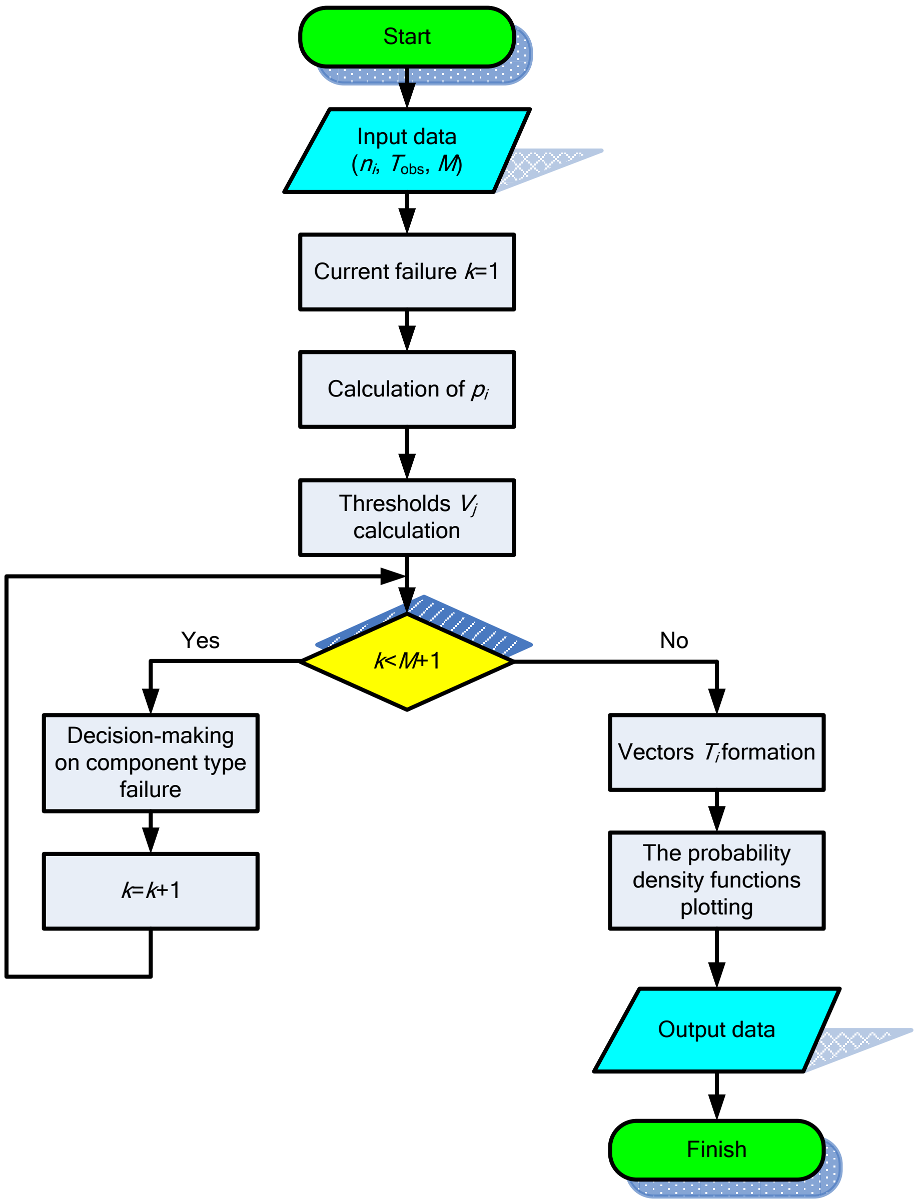

Figure 6: Structural diagram of the simulation

The statistical simulation models of the failure of helicopter components can be used to improve the maintenance processes and the risk assessment of in-flight incidents.

5. Conclusion

The paper discusses the Monte Carlo simulation model for generating possible failures of systems and structures of helicopters in Nigeria. The model was used to obtain the PDFs of the systems as well as calculation of other parameters.

The proposed model can be utilized for optimization of the current maintenance process thereby reducing cost of operations and increasing the level of flight safety. The optimization is possible because of possibility of effective preventing failures using the results of simulation.

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