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Proceeding Paper

Minimization of High Maintenance Cost and Hazard Emissions Related to Aviation Engines: An Implementation of Functions Optimizations by Using Genetic Algorithm for Better Performance †

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Abstract: This research paper explores the relationship between different functionalities of aircraft and investigates the impact of increased air travel on carbon dioxide, nitrous oxide, water vapor, and hydrocarbon emissions. These emissions contribute to both local airport pollution and global atmospheric pollution, posing significant environmental challenges. The study aims to minimize the high maintenance costs associated with aviation engines and to reduce the hazardous emissions from aircraft engines in order to protect the environment. A genetic algorithm is employed for multi-objective optimization, generating a set of desirable solutions applicable in real-world scenarios. The results demonstrate the effectiveness and simplicity of the genetic algorithm in iteratively searching for optimal solutions. This research provides valuable insights for the research community and paves the way for further investigations into these critical issues.

Keywords: aircraft functionalities; genetic algorithm; atmospheric pollution

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1. Introduction

The rapid growth of worldwide commercial aviation, coupled with increasing environmental awareness, has brought attention to the significant issue of airplane emissions. In particular, the European Union Emissions Trading Scheme has imposed penalties on airlines exceeding carbon emission limits, highlighting the urgency of addressing emissions. Apart from the environmental impact, pollutant emissions also have the potential to escalate future aircraft operating expenses. Aircraft engines emit a range of gases, including CO_2, nitrogen oxide, water vapor, hydrocarbons (HC), and smoke, affecting the environment in two primary areas: local airport pollution [1] and greenhouse effects in the atmosphere [2–5].

Previous studies have primarily focused on pollution in the vicinity of airfields, and the International Civil Aviation Organization (ICAO) has set caps on emissions during normal landing and takeoff cycles at sea level. However, there is growing recognition of the greenhouse gases produced during cruise flights, with water vapor, CO_2, and NOx [6–9] being the main contributors. Limiting emissions, such as HC, NOx, smoke [10], and others, during landing and takeoff cycles is crucial, as per the guidelines of the ICAO. The indirect greenhouse impact of NOx [11,12] is complex, as its transfer to the stratosphere can contribute to ozone depletion, while its presence in the upper troposphere may impact stratospheric ozone and methane production. The influence of water, particularly through contrails and cirrus formations, varies with the flying altitude, further complicating the relationship between low altitudes and the aircraft's greenhouse effect.

In addition to environmental concerns, affordability has become a significant factor in commercial airplane design. Aircraft and engine manufacturers, as well as airlines, strive to reduce expenses, particularly the direct operating cost (DOC), to maintain a competitive edge. Previous studies have explored the environmental impact and lowest possible Direct Operating Costs (DOC) of long-range airplanes during cruise flights by adjusting the thrust-to-weight and weight-to-wing-area ratios [13]. However, climate impact models are less commonly used for comparing different designs.

This research aims to address two key objectives: firstly, to minimize the high maintenance costs associated with aviation engines, and secondly, to reduce carbon emissions to protect the environment while ensuring engine quality, reliability, and adherence to maintenance schedules. To achieve these objectives, a genetic algorithm will be employed for multi-objective optimization, generating a set of practical and desirable solutions which are applicable in real-world environments.

2. Literature Review

M Airplane engine maintenance involves three core processes: Hard Time (HT), On Condition (OC), and Condition Monitoring (CM). HT establishes regular intervals for maintenance tasks, while OC evaluates the engine's condition through quantitative data analysis and prompts maintenance when parameters exceed the limits or indicate imminent failure. CM [14] focuses on monitoring fleet airworthiness and maintenance performance, collecting data throughout the component's life cycle and allowing for predictive maintenance. These processes are supported by a comprehensive dependability program that assesses their efficacy and recommends adjustments to maintenance intervals or procedures.

Cost is a crucial factor in engine maintenance [15] and directly impacts the direct operating cost (DOC) of an aircraft [16]. Engine performance, design, reliability, fuel costs, acquisition, and maintenance expenses collectively contribute to the DOC, with maintenance accounting for a significant portion. Engine maintenance costs can be categorized as on-aircraft and off-aircraft. On-aircraft maintenance covers routine inspections and services, while off-aircraft maintenance, or shop visits (SVs), involve more extensive and time-consuming repairs or overhauls to be conducted in an engine shop. Off-aircraft maintenance tends to be substantially more expensive than on-aircraft maintenance, making cost management a critical aspect of engine maintenance.

Time, referring to maintenance time and material procurement lead time, is another important consideration [17,18]. Maintenance time represents the duration required to complete specific engine maintenance tasks requested by the client [19]. The material procurement lead time encompasses the time between issuing an order and receiving the requested materials. Delays in transportation, customs clearance, and other factors can extend the lead time. Prolonged engine repair and parts acquisition result in increased aircraft downtime, leading to higher costs for the client. Therefore, efficient time management plays a significant role in aviation engine maintenance.

Reliability refers to a system's ability to perform its intended function satisfactorily over a specific period and under specified conditions. In the case of aviation engines, reliability encompasses various factors, including the engine's reparability after damage. It can be quantified using the equation $R(t) = e^{-\lambda \mathrm{t}}$, where R(t) represents the possibility of the equipment functioning as expected over time t; e is the mathematical constant, approximately equal to 2.7182818; λ is the failure rate (1/MTBF); and t is the indicated operation time [18].

Figure 1 illustrates the relationship between increased mean time between failures (MTBF) and improved reliability. Lower maintenance downtime contributes to higher reliability, which is influenced by factors such as part procurement, lead time, and repair time. Frequent failures requiring regular maintenance or repairs indicate low reliability. Increased reliability can be achieved through well-equipped facilities, qualified staff, appropriate tools, and an inventory of spare components and replacement parts. Dependability plays a crucial role in engine maintenance.

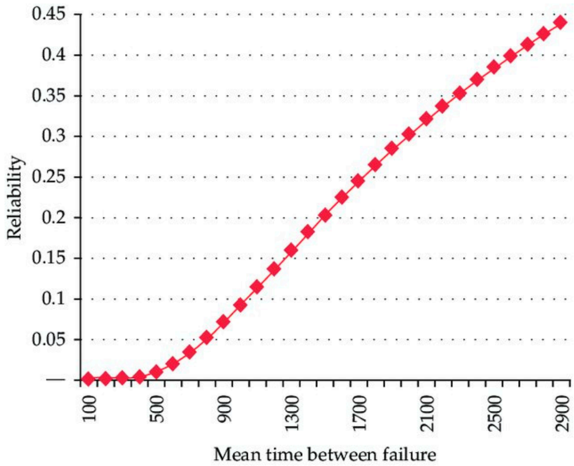

Figure 1. Improved reliability for MTBF.

Emissions: Global warming has become a major concern due to the unregulated emission of harmful gases by various industries. CO_2 emissions are the primary contributor to global warming. In 2019, global flights produced 915 million tons of CO_2, accounting for 2% of human-caused CO_2 emissions and 12% of total CO_2 emissions from all modes of transportation. Long-haul flights, especially those over 1500 km, contribute significantly to aviation CO_2 emissions.

In addition to CO_2, aircraft emissions also include water vapor, which accounts for 30% of the exhaust. Water vapor has a modest direct impact on global warming, but it indirectly contributes through the formation of contrails. Contrails are formed when water vapor freezes and forms ice crystals in the cold ambient temperature, leading to the creation of contrail-induced clouds. These contrails trap infrared rays and have a warming effect three times greater than CO_2 emissions. The overall impact of contrails surpasses the warming effect of all CO_2 emissions released by aircraft since commercial flying began.

Considering the carbon footprint is essential when deciding whether to repair, lease, or purchase a part, as it involves transportation from various locations worldwide. Furthermore, the carbon emissions associated with repaired and new parts may differ significantly.

Other criteria, such as maintainability, availability, and flexibility/replaceability, can also be categorized under the aforementioned maintenance considerations. However, for this study, the key parameters chosen were engine maintenance costs, aircraft downtimes, quality, and emissions, with dependability, maintainability, and availability falling under the aircraft downtimes category.

3. Methodology

This research paper proposes the utilization of a genetic algorithm for the multi-objective optimization of aircraft engine characteristics. Optimization is the process of maximizing outcomes by improving a system or process. Classical and evolutionary optimization are the two main types, with the latter employing a population-based approach. In multi-objective optimization, conflicting objectives are considered, resulting in a set of optimal solutions.

The genetic algorithm, a type of evolutionary algorithm, is employed in this study. It selects a collection of random solutions, represented as chromosomes, and evolves them through iterations. Many real-world engineering optimization problems involve multiple objectives that are often in conflict. Therefore, no single optimal solution can satisfy all objectives simultaneously. Trade-offs between objectives require the generation of a set of solutions to represent the optimal trade-off solutions.

The mathematical formulation of the multi-objective optimization problem is provided here, including decision variables and objective functions [20]. The decision variables represent choices related to purchasing, loaning, and repairing engine components. The objective functions aim to minimize the engine maintenance cost, total lead time, and engine emissions while maximizing quality. Constraints ensure the selection of at least one output and maintain the binary nature of decision variables.

In this study, the efficiency of the engine components was evaluated using the following scale:

Original Equipment Manufacturer (OEM) = 4

FAA/EASA approved = 3

Civil Aviation Authority Malaysia (CAAM) = 2

Miscellaneous state aviation organizations = 1

Bogus or salvaged part = 0

The mathematical formulation for multi-objective optimization is defined as:

Decision Variables

Xij: Binary variable indicating whether material i is bought for task j (1 if bought, 0 otherwise).

Yij: Binary variable indicating whether material i is loaned for task j (1 if loaned, 0 otherwise).

Zij: Binary variable indicating whether material i is repaired for task j (1 if repaired, 0 otherwise).

Three binary decision variables, Xij, Yij, and Zij, were used. Xij represents a purchase decision, where 1 denotes buying and 0 denotes not buying the material. Yij represents a loan decision, where 1 denotes loaning and 0 denotes not loaning the material. Zij represents a repair decision, where 1 denotes repairing and 0 denotes not repairing the material.

The mathematical model can be implemented using MATLAB or a Python-based compiler. The researcher can expect to obtain a diverse set of solutions that offer the best possible results. The mathematical modeling in this study was performed using Python.

Figure 2 illustrates two different visualizations and the implementation of the genetic algorithm for investigating various functionalities and optimizing performance. These figures offer insights into the relationships between different parameters and the algorithm's effectiveness. It is comparing the minimized engine cost with the minimized total lead time. The graph was generated using the genetic algorithm, with the parents representing actual values and the offspring generated by the algorithm. The graph is generated by the algorithm, with parents representing actual values and offspring generated during the algorithm's execution. The genetic algorithm iteratively searches for local minima until it discovers reduced and optimally minimized values. The algorithm follows four primary steps: initial population, fitness function evaluation, selection, and crossover/mutation.

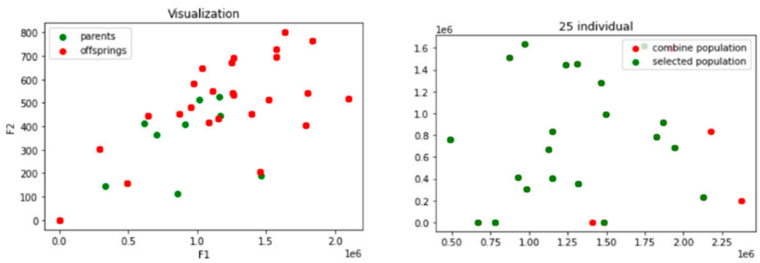

Figure 2. Visualizations and the implementation of the genetic algorithm.

Figure 3 depicts the visualization for the engine cost and engine maintenance. It was generated using the genetic algorithm, with the parents representing actual values and the offspring generated by the algorithm.

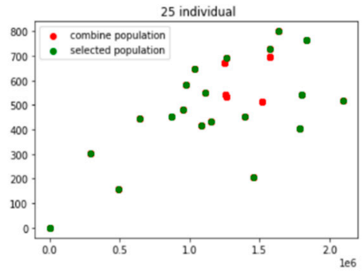

Figure 3. Visualization for the engine cost and engine maintenance.

The genetic algorithm is executed until optimal values are obtained for linear relationships. The performance of the optimization model is then evaluated using a receiver operating characteristics (ROC) curve, which serves as a measure of performance. The ROC curve helps to evaluate the optimization of different functionalities.

4. Conclusions

In this research paper, the optimization of different functions for any machine was studied in order to evaluate to what degree the functions are interlinked to each other. This is so that, based on their parameter optimization, their performances can be enhanced and improved. The main motive of conducting this research was to minimize the high maintenance cost related to aviation engines and to minimize the hazardous emissions caused by the release of gases from airplane engines for the protection of the environment. This was achieved by optimizing the function parameters using the genetic algorithm.

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