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Artificial Intelligence Supported Aircraft Maintenance Strategy Selection with q-Rung Orthopair Fuzzy TOPSIS Method

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Abstract

In the aviation sector as unscheduled maintenance, repair and overhaul cost too much and these activities also negatively affect the prestige of the companies, deciding the most appropriate maintenance strategy is crucial. Today artificial intelligence methods, especially machine learning techniques facilitate failure detection and predict the wear and tear of the equipment before the occurrence of a serious failure. In this paper, artificial intelligence-supported corrective, predictive, and prescriptive maintenance methods are examined. Those most common aircraft maintenance approaches are compared regarding cost, reliability, failure detection, and downtime period using decision makers' subjective evaluations with the help of the q-rung orthopair fuzzy TOPSIS method which mitigates the drawbacks of uncertainty in human decision making. Stable and efficient results are obtained regarding the selection of an appropriate maintenance strategy. This article might be the first quantitative research that evaluates and compares AI-supported aircraft maintenance strategies.

1. Introduction

Since the end of the Second World War to today, maintenance has been transformed from failure repairment to preventing and predicting the overall failure process. In the 21st century, maintenance approaches are mostly based on system-level analysis which aims to preserve the functions of the equipment (Ahmadi et al., 2007). The aviation sector is a highly expensive and rapidly developing industry, and this rapid development has increased the expectations of preparedness of the aircraft and equipment. Aircraft maintenance provides us with safer and more reliable flights however, a minor failure in the air may cause fatal problems for all crew and passengers. The use of artificial intelligence (AI) in aviation, fuel saving, and successful management increase operational efficiency, and these issues can support to control of air traffic. Besides these benefits, AI techniques might also be used in aircraft maintenance to detect failures in advance and predict wear and tear before they cause a serious breakdown.

Adhikari and Buderath (2016) examines aircraft maintenance strategies and propose a framework for condition-based maintenance. They asserted that to decide the maintenance type, a maintenance strategy should include the criteria; failure characteristics (pattern, rate, consequence, severity), failure detectability and diagnosability, cost, system availability, and certifiability of the method. Regarding uncertainty; Samaranayake (2006) studied the aircraft maintenance issues and constraints of the new maintenance approaches including uncertainty. Samaranayake and Kiridena (2012) studied CBM under uncertainty and found that implementation of uncertain maintenance operations requires dynamic planning and scheduling which includes rectification, re-assembly, materials changes, re-scheduling spare parts, and other sources. They claimed that current ERP systems are not able to plan simultaneously and dynamically as they are not integrated into all data structures of whole aircraft maintenance operation, hence they proposed a unitary structure to mitigate this drawback.

Regarding AI techniques in aircraft maintenance; Delft University of Technology leads a Project that aims to modernize aircraft maintenance using AI techniques. For a 6-month real-time experiment duration they claim that they are successful in modeling the overall maintenance process, performing health predictions, and finally simplifying very complex maintenance planning. Regarding this project, Andrade et al. (2021) used Reinforcement Learning (RL) for optimization of the aircraft maintenance scheduling. In their real case study, the maintenance data of 45 aircraft were used. They found that with the help of this ML technique aircraft availability increases, and the number of checks reduces, and the fleet availability increases. Basora et al. (2021) used supervised machine learning techniques to describe the data workflow in aircraft maintenance to determine the difficulties regarding the health monitoring of the system.

Rengasamy et al. (2018) studied deep learning approaches to aircraft maintenance, and they identified four main architectures Convolutional Neural Networks, Deep Belief Networks, Long Short Term Memory, and Deep Autoencoders. Eickemeyer et al. (2013) claim that Bayesian

Networks (BNs) are one of the best AI techniques to solve the uncertainty problem of capacity planning in maintenance as BNs are suitable to solve new problems and process accurate forecasts with fewer data. Therefore Dinis et al. (2019) apply big data and predictive analytics to aircraft maintenance and get positive results in deciding maintenance workloads. From this literature review it can be inferred that there are many studies on AI supported maintenance however there is almost no research on the comparison of these maintenance strategies conducted with quantitative decision making methods.

In this paper, in the second section aircraft maintenance strategies are examined in an artificial intelligence context. In the third section, with a case study, the three most common maintenance approaches are compared using a quantitative multi-criteria decision-making technique, besides results and discussions are given. In the last chapter, the research is concluded.

2. Maintenance in Aviation

2.1. Maintenance Types in Aviation

There are many maintenance classifications in the aviation industry, main breakdowns are; preventive, predictive, prescriptive, and corrective/breakdown maintenance. Corrective or breakdown maintenance is performed after the failure occurs, it may interrupt flight schedules and might cause serious negative effects on the reputation of the company, and certainly costs far more expensive than the scheduled maintenance. According to its complexity light, heavy, base, and hangar maintenance is another classification. Regarding periodic checking types, divided into A, B, C, and D checks which depend on the scope, duration, and frequency of the maintenance requirement. A check is the most frequent and has to be done about every 65 hours (Sriram & Haghani, 2003), however, a D-check consists of painting, stripping, and cabin refurbishment, which is performed only one time in 4 years (Beliën et al., 2012).

Regarding scheduling, it can be classified as scheduled/routine/preventive and unscheduled/non-routine maintenance. Generally, preventive and scheduled maintenance terms are used interchangeably, as predictive and condition-based maintenance is used (Van den Bergh et al., 2013).

Prescriptive maintenance combines the advantages of descriptive and predictive analyses to predict the failures, functionalities, wear and tears. This improves the reliability of equipment and saves cost (Koukaras et al., 2022). Prescriptive maintenance is more than providing real-time recommendations, but having the most appropriate course of action during the operation continues. It analyses data patterns and trends to provide the best recommendation (Marques & Giacotto, 2019). Meissner et al. (2021) studied a prescriptive maintenance approach using a simulation model of 30 days and found that it supports reducing waiting times of an aircraft on the ground.

Civil Aviation Authority (CAA) of the United Kingdom defines three types of maintenance: (1) Hard time; is preventive maintenance performed at specific times, mostly including overhaul, servicing, or replacement of spare parts according to manuals. (2) On condition; is also preventive maintenance but includes testing and inspecting the components in a periodical manner to be sure about the equipment's functional status. (3) Condition monitoring; is a non-preventive maintenance process that includes continuous data collection, analysis, and interpretation about the equipment's status (Knotts, 1999).

Three main aircraft maintenance strategies are explained with their advantages and disadvantages in Table 1. For the first alternative, all non-preventive maintenance like unscheduled, corrective maintenance and conditional monitoring techniques are merged, as their characteristics are similar.

Table 1 Aircraft Maintenance Strategies

No.	Maintenance Type	Pros&Cons	Sources
1	Corrective /Unscheduled Maintenance and Condition monitoring	• Low cost • Non-preventive maintenance process • Problem-based repairment process • Risk for long and unplanned breakdown durations	(Knotts, 1999) (Paz & Leigh, 1994) (Basri et al., 2017) (Chen et al., 2012)
2	Predictive Maintenance	• Failure detection and prediction • Identify problems in critical components (turbines, landing gear, etc.) • Analyze data and predict the components potential failure • Develop inspection • Provides advance warnings for some failures	(Karthik & Kamala, 2021) (sparkcognition.com)
3	Prescriptive Maintenance	• Identify the best course of action for failures and supports root cause analysis • Provides AI-driven analysis of historical maintenance • Reducing turnarounds by an average of 20 minutes per incident • Predicts the remaining useful life of items • High cost	(Meissner et al., 2021) (Marques & Giacotto, 2019) (Koukaras et al., 2022) (sparkcognition.com)

2.2. AI Techniques in Aviation Maintenance

Airlines suffer from high costs stemming from delays and cancellations 30 percent of which are caused by unplanned maintenance activities. In the aviation industry, artificial intelligence techniques support predictive maintenance to predict failures and reduce unscheduled activities by managing big data. In the aircraft maintenance process, a serious amount of data is generated and processed during the planning stage. Especially in unscheduled maintenance, the uncertainty of capacity planning affects budgeting, materials management, capacity planning, and resource allocation (Samaranayake & Kiridena, 2012).

Many artificial intelligence techniques support the prediction and early detection of failures. Artificial Neural

Network (ANN) algorithms are applicable to older machines and adaptable to new machines. ANN gives satisfactory results in measuring equipment failures e.g. classifies fault with a %92 success rate (Biswal & Sabareesh, 2015; Hesser & Markert, 2019). Random Forest technique is successful at fault detection, prediction of machine states, and identification of disk failure (Paolanti et al., 2018). Support Vector Machine algorithm which performs regression analysis and pattern recognition has the advantage of being low-cost compared to classical maintenance, besides its high detection accuracy it needs a long training time (Cawley & Talbot, 2010). K-means algorithm used for clustering for fault detection which has a 93% of prediction accuracy in maintenance. It is easy to implement however, it has difficult to decide the number of clusters (Durbhaka & Selvaraj, 2016; Amruthnath & Gupta, 2018). After reviewing the studies on AI Techniques and maintenance types in aviation, to the best of my knowledge, this study is unique in the literature regarding the comparison of artificial intelligence-supported aircraft maintenance approaches.

3. Case Study

To determine the most appropriate alternative for aircraft maintenance a multi-criteria decision-making method is adopted. Regarding the uncertain nature of the maintenance operations, q-ROF TOPSIS method (Pinar & Boran, 2020) is applied which is successful in modeling and quantifying human subjective decision making. Then Pinar et al. (2021) and Taghipour et al.(2022) used q-ROF TOPSIS method in their research on supplier selection and speech recognition product selection. In this section first, the basics of fuzzy sets are mentioned, then the methodology is briefly given and finally, a case study is presented.

3.1. Fuzzy Set Theory

Zadeh (1965) proposed the fuzzy set, Atanassov (1986) extended it to intuitionistic fuzzy set (IFS), in which A in X can be described as:

$$A=\{\langle x,\mu_A(x),v_A(x)\rangle \mid x\in X\} \tag{1}$$

where the functions; $\mu_A(x): X \to [0,1]$ is the degree of membership of x, $v_A(x): X \to [0,1]$ is the degree of non-membership of x, and,

$$0 \le \mu_A(x)+v_A(x) \le 1 \tag{2}$$

Yager (2013) extended IFS to Pythagorean fuzzy sets (PFS) and then (Yager, 2016); Yager and Alajlan (2017) generalized IFS and PFS and proposed q-rung orthopair fuzzy sets (q-ROFs). In these fuzzy sets, the sum of the q^{th} powers of the membership and non-membership degrees is equal to or less than one and they are formulized as follows:

$$A=\{\langle x,\mu_A(x),v_A(x)\rangle \mid x\in X\} \tag{3}$$

where $\mu_A : X \to [0,1]$ and $v_A : X \to [0,1]$ are membership and non-membership degrees of $x \in X$ to A respectively and:

$$(\mu_A(x))^q + (v_A(x))^q \le 1 \tag{4}$$

The hesitation degree $\pi_A(x)$ is as follows:

$$\pi_A(x)=\left(1-(\mu_A(x))^q-(v_A(x))^q\right)^{1/q} \tag{5}$$

3.2. Methodology

In this subsection to save some space q-ROF TOPSIS methodology (Pinar & Boran, 2020) is briefly mentioned. Let A = $\{A_1, A_2, A_3, ..., A_m\}$ be a set of alternatives and X = $\{X_1, X_2, X_3, ..., X_n\}$ be a set of criteria the steps are:

Step 1: Decision makers' weights are calculated using linguistic terms as described in (Pinar & Boran, 2020).

Step 2: Criteria are determined by DMs and alternatives are evaluated in linguistic terms. These terms are converted to q-ROF numbers like $\alpha_k=\langle \mu_k(x), v_k(x)\rangle (k=1,2,3,...,l)$ and aggregated by the q-ROFWA aggregation operator (Liu & Wang, 2018). So, aggregated q-ROF decision matrix is obtained.

Step 3: Criteria weights are determined in linguistic terms and calculated according to q-ROF TOPSIS method.

Step 4: Build up the aggregated weighted q-ROF decision matrix aggregating the criteria weights with the decision matrix obtained in the second step.

Step 5: Calculate the Positive Ideal Solution (q-ROFPIS) and Negative Ideal Solution (q-ROFNIS) as usual in TOPSIS method. While calculating take into consideration the benefit and cost criteria.

Step 6. Determine the separation measures by calculating the difference between maintenance strategy alternatives using Euclid distance.

Step 7. Calculate the relative closeness coefficient C_{i*} using Eq.(6) and rank all the alternatives.

$$C_{i*}=\frac{S_i^-}{S_i^+ + S_i^-} \quad where \;\; 0 \le C_{i*} \le 1 \tag{6}$$

3.3. Case Study of Maintenance Strategy Selection

Corrective, predictive, and prescriptive maintenance which are the most common three aircraft maintenance strategies are determined as alternatives. There are also some other maintenance methods such as A-D checks or preventive maintenance in the aviation industry. These approaches are excluded in this study as they are mostly routine checks or time based/periodic maintenance methods.

In the first step, the decision makers' expertise is determined as DM1:Very High, DM2:High, and DM3: Medium High and converted to numbers as DM1: 0.384, DM2: 0.331, and DM3: 0.285.

Table 2.a Linguistic Term Scale

Linguistic terms	Abbreviation
-Extremely High level	(EH)
-Very high level	(VH)
-High level	(H)
-Medium High level	(MH)
-Medium level	(M)
-Medium Low level	(ML)
-Low level	(L)
-Very low level	(VL)
-Extremely Low level	(EL)

In the second step after a literature search (Kumar et al., 2013; Parida & Chattopadhyay, 2007; Syan & Ramsoobag, 2019) and using my maintenance job experience following evaluation criteria are determined as performance indicators; (1) maintenance cost, (2) reliability (minimization of the failure rate), (3) failure detection (identifying the failure in advance with high accuracy), (4) downtime period (maximization of the readiness of the aircraft). Then DMs evaluate all alternatives regarding these criteria with linguistic terms as indicated in Table 2.b. using the scale in Table 2.a.

Table 2.b DMs Evaluations in Linguistic Terms

	KV1			KV2			KV3		
	A_1	A_2	A_3	A_1	A_2	A_3	A_1	A_2	A_3
X_1	M	H	VH	ML	MH	H	ML	H	EH
X_2	MH	H	VH	H	VH	EH	H	VH	VH
X_3	M	VH	EH	M	H	VH	M	VH	VH
X_4	EH	MH	M	H	M	M	VH	MH	M

After the conversion of these terms to q-ROF numbers, all three DMs evaluations are aggregated, and the decision matrix (R) is obtained as follows:

		X_1	X_2	X_3	X_4
	A_1	[0.494;0.610;0.867]	[0.717;0.385;0.831]	[0.550;0.550;0.874]	[0.887;0.230;0.661]
R=	A_2	[0.722;0.380;0.828]	[0.819;0.284;0.753]	[0.824;0.279;0.748]	[0.622;0.481;0.865]
	A_3	[0.874;0.242;0.683]	[0.897;0.211;0.645]	[0.903;0.205;0.634]	[0.550;0.550;0.874]

In the third step, importance degrees are evaluated by DMs and their weights are determined as:

X_1	X_2	X_3	X_4
0.225	0.287	0.226	0.262

In the fourth step criteria weights are aggregated with the decision matrix obtained in the second step and as a result, the weighted aggregated q-ROF decision matrix (R') is obtained as follows:

		X_1	X_2	X_3	X_4
	A_1	[0.305;0.895;0.634]	[0.498;0.761;0.758]	[0.343;0.873;0.664]	[0.646;0.680;0.746]
R'=	A_2	[0.465;0.805;0.723]	[0.589;0.697;0.770]	[0.553;0.749;0.743]	[0.411;0.825;0.717]
	A_3	[0.603;0.727;0.735]	[0.675;0.640;0.755]	[0.639;0.699;0.735]	[0.360;0.855;0.690]

In the fifth step the positive (A^+) and negative (A^-) ideal solutions are calculated and presented in Table 3 (a-b):

Table 3.a. Positive Ideal Solutions

		μ	v	π
	X_1	0.305	0.895	0.634
$A^+=$	X_2	0.675	0.640	0.755
	X_3	0.639	0.699	0.735
	X_4	0.360	0.855	0.690

Table 3.b. Negative Ideal Solutions

		μ	v	π
	X_1	0.603	0.727	0.735
$A^-=$	X_2	0.498	0.761	0.758
	X_3	0.343	0.873	0.664
	X_4	0.646	0.680	0.746

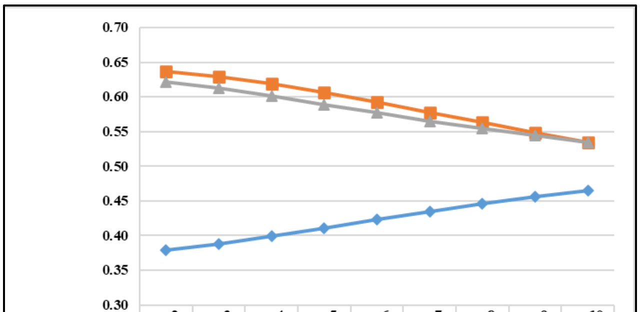
In the sixth step the differences between three maintenance strategy alternatives are calculated by the help of Euclid distance, S_i^+ and S_i^- values and results (C_{i*}) are indicated in Table 4.

Table 4. Results

	S_i^+	S_i^-	C_{i*}
A_1	0.214	0.136	0.388
A_2	0.099	0.169	0.630
A_3	0.136	0.214	0.612

In the last step we calculate and rank all the alternatives from the most appropriate aircraft maintenance strategy to less appropriate one as **A_2> A_3 >A_1** which indicates that predictive maintenance is better than other strategies.

To validate the results parameter analysis is performed using the q parameter values between 2 and 10 as indicated in Figure 1.



	q=2	q=3	q=4	q=5	q=6	q=7	q=8	q=9	q=10
Alternative 1	0.379	0.388	0.399	0.411	0.423	0.435	0.446	0.456	0.465
Alternative 2	0.637	0.630	0.619	0.607	0.593	0.578	0.563	0.548	0.534
Alternative 2	0.621	0.612	0.601	0.589	0.577	0.565	0.554	0.544	0.535

Figure 1. Results of Parameter Analyses

3.4. Results and Discussion

As three maintenance approaches are examined and compared it's obviously seen that the first alternative (corrective /unscheduled maintenance and condition monitoring) has a lower performance than the other two approaches. The main reason might be the nature of the corrective maintenance which has no preventive action and begins its performance after a problem occurred. Even some AI techniques are used, it might be too late to take measures after a failure occurs and increases the suspension period of the flight schedule. Although the maintenance cost is relatively high in both two methods, reliability and readiness of the aircraft, and failure detection performance are far better compared with the first alternative maintenance approach.

Comparing predictive and prescriptive maintenance there seems a minor difference on behalf of predictive maintenance which may come from the effect of prescriptive maintenance costs a bit higher than the other one. In both approaches AI methods especially machine learning techniques such as RF, ANN, SVM, and k-means algorithm support the maintenance process positively and make the aircraft maintenance performance better.

Regarding the results of the parameter analyses, due to the nature of the q-ROF sets, while the q level increases the ratings of the alternatives approach to 0.5. Hence, q=3 generally gives us the most stable results, however in between 2-10 its obviously seen that the Alternative 2 and 3 are far more better than Alternative 1. Therefore, these results of the parameter analyses clearly shows the validity of our method and the positive effect of AI in aircraft maintenance.

4. Conclusion

Maintenance is a serious and expensive process in the aviation industry different from other sectors. Losing time with repair and unscheduled maintenance also costs too much for aviation companies. Even though they have some costs in the beginning phase, predictive and prescriptive maintenance strategies help these companies on preventing aircraft failures and reduce breakdown periods. Therefore, a decision method for an optimum aircraft maintenance strategy is proposed and three strategies are compared concerning cost, reliability, failure detection, and downtime period. The results of q-ROF TOPSIS method show that the support of AI techniques is highly important for aircraft maintenance. A parameter analysis is also performed to validate the method. The main contributions of this article are (1) reviews the AI supported aircraft maintenance strategies (2) evaluates and compares Artificial Intelligence-supported aircraft maintenance strategies with a fuzzy quantitative decision making method.

As a future study, specifically machine learning techniques effects on aircraft maintenance might be studied. Besides, other q-ROF decision making methods can be applied on AI supported aircraft maintenance approaches to make quantitative comparisons.

Ethical approval

Not applicable.

Conflicts of Interest

The author declares that there is no conflict of interest concerning the publication of this paper.

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