

TITLE OF THE INVENTION

A multivariate system for calculating reliability, scrappage probability and Remaining Useful Life (RUL) of aircraft components and a method thereof.

TECHNICAL FIELD OF THE INVENTION

[001] The present invention relates to maintenance of an aircraft engine and components / parts of the engine.

[002] Particularly, the present invention relates to calculation of reliability/ remaining useful life (RUL) of an engine based on a combination of operational and environmental parameters.

[003] The present invention further relates to the calculation of the scrappage probability of an aircraft engine part/ component based on a combination of operational and environmental parameters.

[004] More particularly, the present invention relates to prediction of the virtual aging of every repairable part / component of the engine or the airframe.

[005] The present invention further relates to calculation of the probability of failure of an aircraft engine part/ component based on a combination of operational and environmental parameters.

BACKGROUND OF THE INVENTION

[006] An aircraft engine is a connected multipart machine. They have a high running cost, which makes it necessary to optimize their management, operation, and maintenance in order to achieve cost efficiency. Thus, the upkeep of contemporary aircraft engines, is essential for the airlines to remain competitive, ensure passenger safety and minimize environmental impact. It involves regular maintenance, and a commitment to ongoing improvement in all aspects of engine performance and reliability.

[007] When an aircraft reaches the end of its operational life or is no longer economically viable to operate, it may be retired from active service. The decision

to retire an aircraft can depend on various factors, including its age, maintenance costs, fuel efficiency, and compliance with modern safety and environmental standards.

[008] The scrap and remaining useful life of an aircraft are important considerations in aviation maintenance and management. The scrap life of an aircraft refers to the point in its operational lifespan where it is no longer economically viable or safe to operate. The aircraft is disassembled, and the materials, such as aluminium, titanium etc. are recycled.

[009] The remaining useful life of an aircraft refers to the estimated amount of time in flight hours (FH) or flight cycles (FC), an aircraft can be safely and economically operated. The performance degradation of aircraft systems take place over time due to spontaneous wear and tear or damage caused by foreign objects and particulate matter. While natural wear and tear happen gradually, foreign object damages are accidents that occur randomly. Modelling the trend of this degradation process and eventually predicting the remaining useful life, always remains a key factor for manufacturing process, optimization for ensuring system safety and for improving assembly/disassembly operations during aircraft system maintenance. RUL assessments are critical for fleet planning, as they help operators make informed decisions about whether to continue operating an aircraft, invest in repairs or upgrades, or retire it.

[0010] The maintenance scheduling of aircraft and its components are very critical because it is directly proportional to the profitability of the aircraft. The scheduling also needs to account for unplanned events occurring randomly, such as accidents or other similar incidents with economic and human consequences. Hence there is a need of precisely predicting the reliability of the aircraft and its components which is emphasized by present invention of a multivariate system.

[0011] Maintenance of a system can be precisely scheduled only when reliability and lifetime conditions of the system and its components are known. Within the aviation domain, the aircraft certification process directly depends on various reliability measures of the aircraft and its components. In aviation industry,

we can perceive numerous methods to model the failure rate and predict the reliability of an aircraft and its components. There are existing methods to estimate the reliability of the engine as a function of the time in operation, however our multivariate system is measuring the same from multiple inputs such as time, environment, thrust derate, stage-length utilization and environmental and climate zone variables.

OBJECTS OF THE INVENTION

[0012] It is an object of the invention to provide a system for scheduling a maintenance for an aircraft and its components based on an estimate of when the system might fail.

[0013] It is another object of the invention to provide a multivariate system for calculating the reliability / remaining useful life (RUL) of an engine based on a combination of operational and environmental parameters.

[0014] It is yet another object of the invention to provide a multivariate model and a system for predicting the virtual aging of every repairable part/ component of the engine or the airframe.

[0015] It is yet another object of the invention to provide a multivariate model and a system for calculating the probability, of a part/ component of an aircraft engine, being scrapped during the upcoming build goal based on a combination of operational and environmental parameters.

[0016] It is still another object of the invention to provide a multivariate model and a system for calculating the probability of failure of a part/ component of an aircraft engine based on a combination of operational and environmental parameters.

SUMMARY OF THE INVENTION

[0017] The invention provides a multivariate model and a system for calculating reliability, Remaining Useful Life (RUL) and a scrap probability of a part/ component of an aircraft engine and a method thereof. The system for calculating the scrap probability of an engine part comprising a processor coupled to the memory; and at least one application stored in the memory and executable by the processor for:

- a) collecting a data related to the engine unit configuration; based on which a scrap data of each part with time parameters (CSN & CSR) and part numbers with each corresponding work-scope will be collected or inferred;
- b) predicting a work-scope based on the inputs given by the user;
- c) selecting the parts of the engine related to the above predicted work-scope;
- d) building a probabilistic global and local model for each part number using CSN and CSR at given scrap;
- e) providing scrap probabilities based on the global and the local model for each part of the engine for the given work-scope.

[0018] Additional aspects, advantages, features and objects of the present disclosure are made apparent from the drawings and the detailed description of the illustrative embodiments construed in conjunction with the appended claims that follow. It will be appreciated that features of the present disclosure are susceptible to being combined in various combinations without departing from the scope of the present disclosure as defined by the appended claims.

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] Further features and advantages of the present invention will become apparent from the following detailed description, taken in combination with the appended drawings, in which:

[0020] Fig. 1 depicts the highest-level dataflow of the system, accepting multivariant input.

[0021] Fig. 2 depicts the functional process of predicting scrap probability by a Global and a Local Scrap Models.

[0022] Fig. 3 depicts the parameters affecting a Global and a Local Scrap Model and the combined effect of them

[0023] Fig. 4 depicts the impact of Derate timed components using multivariate model.

[0024] Fig. 5 depicts the impact of Environment on LLPs and timed components using Multivariate System.

[0025] Fig. 6 depicts the impact of Stage Length on LLPs and timed components using Multivariate System.

[0026] Fig. 7 depicts how EGTM deterioration profile is been generated using historic data.

[0027] Fig. 8 depicts the combined effect of multiple parameters to calculate weightage.

DETAILED DESCRIPTION OF THE DRAWINGS

[0028] The present invention discloses a multivariate system for computing the reliability/ Remaining Useful Life (RUL) and scrap probability of a part/ component of an aircraft engine and a method thereof. The multivariate model in the present invention assists in predicting virtual aging of an engine, thereby aiding determination of maintenance schedule of a part of an engine.

[0029] Upon continuous operation of an engine, it ages due to which wear and tear happens to an engine, thus reducing reliability, increasing the chance of failure. The factors which induce wear and tear and thereby affect aging of an engine is not only a function of time but also function of the mode of operation.

That means the parameters of such damage, include not only the time in operation/ use but also the way in which it was used; severity of operation. These severity factors are operational and environmental parameters.

[0030] The multivariate model in the present invention is meant for calculating reliability thereby assisting prediction of repair/ maintenance of an engine part based on the remaining useful life (RUL). RUL and reliability are interchangeable measures of how much a part / component can be used. Reliability is computed fundamentally based on the age (time in operation measured in flight cycles) of the part /component of the engine. If the engine is well maintained, then a good operational condition will precede. The engine is under strain mostly when it is throttled to take off. When maintenance or repairs are performed the engine as a whole and the parts which are specifically repaired will gain more reliability conversely the chance of failure reduces; the repair basically reorders everything. This reordering is the *effect of repair*.

[0031] As shown in Fig.1, the multivariate system for calculating reliability, remaining useful life (RUL) and scrap probability of an aircraft component, comprising: a processor coupled to the memory; and at least one application stored in the memory and executable by the processor for: a) extracting data related to part numbers and a combination of severity factors from a bulk shop visit reports using aviation-specific language models, b) feature engineering being performed upon the extracted data which further comprises cleaning of data to remove outliers, duplicates, etc. and transforming the input data into the features by the methods of aggregation, normalization, etc., and c) based on the above obtained features, the model is first trained and then tested for the accuracy of its inferences.

[0032] The scrap information of any engine part will be present in engine shop visit findings report. These reports are in formats like word document, excel, pdfs of scanned copies. An aviation specific language model is used to identify the scrap information from these huge number of shop visit reports. Models use batch inference to handle such huge volumes of data. Once the scrappage data is extracted from the reports, feature engineering is performed which includes

cleaning of the data to remove outliers, duplicates etc. After cleaning, the data transformation process is performed which includes aggregation, normalization etc. Once the feature engineering process is done, models can be trained on the transformed data. The models being trained for calculating scrap probability are based on derate - stage length severity, environment severity and global and local Weibull distributions. Environment severity model gives the effect of possible deterioration based on a given climatic environment where the engine has flown. The global model is trained by using parameters which include but not limited to Cycles Since New, Time Since New, overall environment, overall stage length and overall derate. The local model uses parameters which include but not limited to: CSR, TSR, local climatic environment, repair stage length and repair derate. These models are linearly combined together to compute the final scrap probabilities for each engine part (Refer fig. 2).

[0033] According to an embodiment of the disclosure, the combination of severity factors that affect the aging of an engine comprises operational parameters and environmental parameters.

[0034] The operational parameters are thrust derate, stage length, specific fuel Consumption, EGTM etc. Thrust derate, which is a percentage of reduced maximum thrust, where an aircraft's engines are intentionally limited to operate at less than their maximum thrust capability during take-off and climb. This is done for several reasons, including fuel efficiency, engine longevity, and noise reduction. The distance between two consecutive stops or segments of a flight is referred to as an aircraft's stage length. It represents the time (in hours), an aircraft travels between take-off and landing at two different airports. Short-haul flights typically have shorter stage lengths, while long-haul international flights have longer stage lengths.

[0035] The environmental parameters are temperature, humidity, atmospheric NO₂ & SO₂, and particulate matter concentration (PM₁₀, PM_{2.5}). An engine produces massive amounts of thrust and higher presence of such pollutants and acidic compounds along with physical attributes like atmospheric pressure causes

damage with in it. The wear and tear of an engine increases or decreases based on factors like physical abrasion, temperature, humidity, etc.

[0036] Fig. 4 depicts the ideal impact of thrust derate on the parts of an aircraft engine. A regression model is created to generate the severity level for every derate and stage-length pair trained with historic observations of thrust derate to arrive at a function to measure the severity for each part in the engine assembly.

[0037] Fig. 5 depicts the impact of environmental parameters on the parts of an engine. Environmental factors affect different parts with varying weightages within the engine assembly. When an Engine flies across different environments, utilization and airport codes are mapped to split the weightages accordingly; this utilizes historic data or lease information that can confirm the operational conditions, or, simply an estimate inputted by the user based on experience on the type of environment.

[0038] Fig. 6 depicts the impact of stage-length on the failure probability of parts of an engine. Stage Length, in conjunction with time of operation parameters such as TSN, CSN, TSR and CSR impact is modelled using historic utilization data.

[0039] Fig. 7 depicts how EGTM deterioration occurs in historic data for an engine. EGTM trend data has not been made available across all engines used to train the models. Wherever the data is available, State space and stochastic models are trained to generate EGTM deterioration profiles using a given EGT Margin as reference (mapped against previous Shop Visit and subsequently accumulated Cycles and Hours by environment, thrust rating & derate. EGTM deterioration has more correlation with the local model and with the effect of repair and has less to do with the global model until the age catches up with the machine and restoration of EGTM becomes non-viable apparently.

[0040] Fig. 8 depicts the operational severity as a bed-sheet regression, which depends on stage-length and derate, for a continuum of combinations of the two parameters ; however, the real model is an n-D representation combining TSN,

CSN, TSR, CSR, stage-length, minimum average thrust derate, environmental severity, EGTM deterioration, specific fuel consumption (SFC), Atmospheric NO₂ & SO₂ concentration, Atmospheric particulate matter content etc.

[0041] The scrap estimation function of the system of the present invention is aided to train historic datasets by clustering Engines and Shop Visits by the above parameters and predict scrap rates & probabilities against parts across modules. The Weibull Distribution is used to model scrap probability of each part.

[0042] According to an embodiment of the present disclosure, as shown in fig. 3, the multivariate system for calculating the scrap probability of an engine part comprising: a processor coupled to the memory; and at least one application stored in the memory and executable by the processor for: a) collecting a data related to the engine unit configuration; based on which scrap data of each part with time parameters (CSN & CSR) and part numbers with along with individual work-scopes being collected; b) collecting engine operational parameters for the engine housing the said parts, related to the above predicted work-scope; c) building a probabilistic global and local model for each part number using CSN and CSR respectively at the time of scraping the part, along with environmental and operational parameters as shown in Fig 3; d) providing scrap probabilities based on a linear combination of all model outputs based on an anti-thetic variable that control ‘effect-of-repair’ aspect trained on empirical data.

[0043] The scrap probability distribution is thus computed for each part of the engine being calculated by the composite model based on combination of operational parameters and environmental parameters. The global scrap model predicts the scrap probability based mostly on CSN value whereas the local scrap model predicts the scrap probability based mostly on CSR values. Reliability is calculated based on the age of the engine in terms of the cycles. The global scrap model works on the actual aging of the engine cycles. Scrap prediction is for repairable parts of an aircraft and not for the engine as a whole, however, as the engine is the sum of its parts, reliability and practical age of the engine can be surmised from part level measures. The local model brings in the oscillating

nature of reliability in systems with repairable parts mostly explained by the effect-of-repair.

[0044] Immediately following a repair, effect-of-repair is strong, the original behaviour is disrupted and some order is reimposed, which gives it more reliability. Reliability effectively improves and then again it will start fading over the period of time. That time, repair is done and again reliability will improve and again it will start fading, thus the cycle goes on repeating until the point where cost effective repair cannot be done, and repair as a whole becomes economically non-viable; point of scrappage.

[0045] According to a preferred embodiment of the disclosure, the reliability of the engine part is calculated by the Weibull distribution as:

$$R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^\beta\right)$$

Where, η = scale parameter and β = shape parameter with data on part failures or scrappages we can train the shape and scale parameters using a regression fit from data by methods such as the Bernard's Method.

[0046] Reliability is a probability value, which is between 0 and 1. The reliability is the complement of probability of failure. So, for example, when the engine is 90% reliable, that means there is a 10% chance that it will fail. Failure probability is scrapping quotient or scrappage probability.

Thus,

$$1 - F(t) = \exp\left(-\left(\frac{t}{\eta}\right)^\beta\right)$$

This can be rewritten as:

$$\frac{1}{1 - F(t)} = \exp\left(\left(\frac{t}{\eta}\right)^\beta\right)$$

$$\ln\left(\frac{1}{1-F(t)}\right) = \left(\frac{t}{\eta}\right)^\beta$$

$$\ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right) = \beta \ln(t) - \beta \ln(\eta)$$

Linear regression can be used to model the distribution by taking the following form:

$$y = mx + c$$

where,

the dependent variable $y = \ln\left(\ln\left(\frac{1}{1-F(t)}\right)\right)$,

the independent variable $x = \log(t)$, the slope $m = \beta$ and

the y-intercept $c = -\beta \ln(\eta)$.

When we add other factors that affect the reliability such as environment, severity, etc., the new formulation of reliability can be written as

$$R(t) = e^{-\left(\frac{t(\sum_{i=1}^n w_i s_i)}{\eta}\right)^\beta}$$

where n is the total number of factors, w_i is the weight and s_i is each factor value.

Then to find the time t , when the reliability becomes very low, find the η and β parameters by fitting a linear regression and solve for t and is as follows:

$$\begin{aligned} R(t) &= e^{-\left(\frac{t(\sum_{i=1}^n w_i s_i)}{\eta}\right)^\beta} \\ \frac{1}{R(t)} &= e^{\left(\frac{t(\sum_{i=1}^n w_i s_i)}{\eta}\right)^\beta} \\ \ln\left(\frac{1}{R(t)}\right) &= \left(\frac{t(\sum_{i=1}^n w_i s_i)}{\eta}\right)^\beta \end{aligned}$$

$$\begin{aligned}
\ln\left(\ln\left(\frac{1}{R(t)}\right)\right) &= \beta \ln\left(t\left(\sum_{i=1}^n w_i s_i\right)\right) - \beta \ln(\eta) \\
\ln\left(t\left(\sum_{i=1}^n w_i s_i\right)\right) &= \frac{\ln\left(\ln\left(\frac{1}{R(t)}\right)\right) + \beta \ln(\eta)}{\beta} \\
t\left(\sum_{i=1}^n w_i s_i\right) &= e^{\left(\frac{\ln\left(\ln\left(\frac{1}{R(t)}\right)\right) + \beta \ln(\eta)}{\beta}\right)} \\
t &= \frac{e^{\left(\frac{\ln\left(\ln\left(\frac{1}{R(t)}\right)\right) + \beta \ln(\eta)}{\beta}\right)}}{\left(\sum_{i=1}^n w_i s_i\right)}
\end{aligned}$$

Global model uses CSN as its time while Local model is only valid within a window between two repairs and uses CSR. Both models are computing failure probability; it is also possible to compute global failure probability with Time Since New (TSN) and the local model, with Time Since (last) Repair (TSR)

The final scrap probability / reliability for the engine part being calculated by the formula:

$$R(t)_{final} = r * R(t)_{local} + (1 - r)R(t)_{global}$$

Where, r = hyper-parameter and an anti-thetic determiner for effect-of-repair. ‘ r ’ value can be estimated based on empirical data by employing methods such Bayesian optimization or genetic algorithm.

CLAIMS

- 1) A multivariate system for calculating reliability of an aircraft part/component, comprising:
 - a processor coupled to the memory; and
 - at least one application stored in the memory and executable by the processor for:
 - a) extracting a data related to part numbers and a combination of severity factors from a bulk shop visit reports using aviation-specific language models;
 - b) performing a feature engineering upon the extracted data which further comprises cleaning of data to remove outliers, duplicates, etc. and transforming the input data into the features by the methods of aggregation, normalization, etc;
 - c) training or giving inference based on the above obtained features
- 2) The system as claimed in claim 1, wherein, the combination of severity factors comprises operational parameters and environmental parameters
- 3) The system as claimed in claim 1, wherein, the operational parameters comprising: thrust derate, stage length, specific fuel consumption, EGTM.
- 4) The system as claimed in claim 1, wherein, the environmental parameters comprising: temperature, humidity, atmospheric NO₂ & SO₂, particulate matter.
- 5) The system as claimed in claim 1, wherein, the model being trained for calculating scrap probability based on Derate, Stage-length Severity Model, Environment Severity Model, Global and Local Weibull Reliability Model.
- 6) The system as claimed in claim 1, wherein, the Global model being estimated by using data driven and Bayesian techniques using parameters which include but not limit to: CSN, TSN, Overall environment, overall stage length, overall derate.

7) The system as claimed in claim 1, wherein, the Local Model being trained by using parameters which include but not limited to: CSR, TSR, local environment, repair stage length, repair derate.

8) The system as claimed in claim 1, wherein, the system for calculating the scrap probability of an engine part comprising:

a processor coupled to the memory; and

at least one application stored in the memory and executable by the processor for:

a) collecting a data related to the engine unit configuration; based on which a scrap data of each part with time parameters (CSN & CSR) and part numbers with each work-scope being collected;

b) selecting the parts of the engine related to the above predicted work-scope;

c) building a probabilistic global and local model for each part number using CSN or CSR at the time of scrappage of a part;

d) providing scrap probabilities based on the global and the local model for each part of the engine for the given work-scope

9) The system as claimed in claim 2, wherein, the scrap probability for each part of the engine being calculated by a Global Scrap Model and a Local Scrap Model based on various operational parameters.

10) The system as claimed in claim 2, wherein, the scrap probability being predicted by the Global Scrap Model based on CSN values.

11) The system as claimed in claim 2, wherein, the scrap probability being predicted by the Local Scrap Model based on CSR values.

The system as claimed in claim 1, wherein, the reliability of the engine part being calculated by the Weibull distribution as:

$$R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^{\beta}\right)$$

Where, η = scale parameter and β = shape parameter

12) The system as claimed in claim 1, wherein, the final probability of reliability for the engine part being calculated by the formula:

$$R(t)_{final} = r * R(t)_{local} + (1 - r)R(t)_{global}$$

Where, r = hyper-parameter and anti-thetic to effect-of-repair

13) A method for calculating probability of reliability and scrap probability of an aircraft component, comprising the following steps :

- a) extracting a data related to part numbers and a combination of severity factors from a bulk shop visit reports using aviation-specific language models;
- b) performing feature engineering upon the extracted data which further comprises cleaning of data to remove outliers, duplicates, etc. and transforming the input data into the features by the methods of aggregation, normalization, etc;
- c) training the model or giving the inference based on the above obtained features.

14) The method as claimed in claim 14, wherein, the combination of severity factors comprises operational parameters, environmental parameters and historic shop visit and scrap data

15) The method as claimed in claim 14, wherein, the training method for calculating scrap probability is based on Derate, Stage-length Severity Models, Environment Severity Models, a Global and a Local Weibull Reliability Models.

16) The method as claimed in claim 14, wherein, the operational parameters comprising: thrust derate, stage length, specific fuel consumption, EGTM.

17) The method as claimed in claim 14, wherein, the environmental parameters comprising: temperature, atmospheric NO₂ & SO₂, particulate matter.

18) The method as claimed in claim 14, wherein, the training method for calculating scrap probability is based on Derate - Stage length Severity Modelling

method, Environment Severity Modelling method, Global and Local Weibull Reliability Modelling method.

19) The method as claimed in claim 14, wherein, the parameters used for training the Global Model include but not limit to: CSN, TSN, Overall environment, overall stage length, overall derate.

20) The method as claimed in claim 14, wherein, the parameters used for training the Local Model include but not limited to: CSR, TSR, local environment, repair stage length, repair derate.

21) The method as claimed in claim 14, wherein, the method for calculating the scrap probability of an engine part comprising a steps of:

- a) collecting a data related to the engine unit configuration; based on which a scrap data of each part with time parameters (CSN & CSR) and part numbers with each workscope being collected;
- b) predicting a workscope based on the inputs given by the user;
- c) selecting the parts of the engine related to the above predicted workscope;
- d) building a probabilistic global and local model for each part number using CSN or CSR at given scrap;
- e) providing scrap probabilities based on the global and the local model for each part of the engine for the given workscope.

22) The method as claimed in claim 21, wherein, the scrap probability of an engine part being calculated by a Global Scrap Prediction method and a Local Scrap Prediction method based on a combination of operational parameters.

23) The method as claimed in claim 21, wherein, the scrap probability being predicted by the Global Scrap Prediction method based on CSN values.

24) The method as claimed in claim 21, wherein, the scrap probability of an engine part being predicted by the Local Scrap Prediction method based on CSR values.

25) The method as claimed in claim 21, wherein, the reliability of the engine part being calculated by the Weibull distribution as:

$$R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^{\beta}\right)$$

Where, η = scale parameter and β = shape parameter

26) The method as claimed in claim 21, wherein, the final reliability of an engine part being calculated by the formula:

$$R(t)_{final} = r * R(t)_{local} + (1 - r)R(t)_{global}$$

Where, r = hyper-parameter

ABSTRACT

The present invention discloses a multivariate system for calculating reliability, remaining useful life (RUL) and scrap probability of an aircraft part/ component and a method thereof. The said system is meant for predicting impact of a combination of operational and environmental parameters on a part of an engine, based on which it assists in calculating the probability of failure of a part/ component of an aircraft engine. These probabilities are being calculated by a Global Scrap Model and a Local Scrap Model. It further predicts the virtual aging of every repairable part/ component of the engine and thus guides scheduling a maintenance for an aircraft maintenance.