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An RUL-informed approach for life extension of high-value assets

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ABSTRACT

The conventional approaches for life-extension (LE) of industrial assets are largely qualitative and focus only on a few indicators at the end of an asset's design life. However, an asset may consist of numerous individual components with different useful lives and therefore applying a single LE strategy to every component will not result in an efficient outcome. In recent years, many advanced analytics techniques have been proposed to estimate the remaining useful life (RUL) of the assets equipped with sensor technology. This paper proposes a data-driven model for LE decision-making based on RUL values predicted on a real-time basis during the asset's operational life. Our proposed LE model is conceptually targeted at the component, unit, or subsystem level; however, an asset-level decision is made by aggregating information across all components. Consequently, LE is viewed and assessed as a series of ongoing activities, albeit carefully orchestrated in a manner similar to operation and maintenance (O&M). The application of the model is demonstrated using the publicly available NASA C-MAPSS dataset for large commercial turbofan engines. This approach will be very beneficial to asset owners and maintenance engineers as it seamlessly weaves LE strategies into O&M activities, thus optimizing resources.

1. Introduction

There is an ever-increasing number of industrial assets approaching the end of their design lives, and quite a larger number have even exceeded their life expectancy. Many industrial assets are designed for a long service life. For instance, offshore oil and gas assets are typically designed to last for 20–25 years (Erdsal et al., 2018; Nezamian et al., 2012). Wind turbines also have a design life of about 20–25 years (DNV-GL, 2016; Nielsen et al., 2019). The life of an aircraft in the aviation sector often varies between 20 and 25 years, depending on the flight cycles or flight hours (Jiang, 2013; Ghosh et al., 2018; Wang et al., 2018). When the assets reach the end of their design lives, they will need to undergo an end-of-life (EOL) process. At a high level, the EoL strategies of industrial assets can be divided into three major categories: in-situ abandonment, use-up and decommissioning, and life extension (LE) (Shafiee & Animah, 2017). The first EOL strategy, in-situ abandonment, entails leaving an asset in place at the site of operation upon attaining EoL, with the site prepared, made safe and all previously powered components de-energized. The second EOL strategy, use-up and decommissioning entails using the asset until failure or until the end of its design life and then decommissioning it by removing the asset from the site and restoring the site to its pristine condition. The third EoL strategy, LE, involves extending the operational life of an asset beyond the original design life and extracting more value from the asset. When opting for LE, the decision for either in-situ abandonment or decommissioning is effectively deferred to a later date, depending on regulatory requirements.

The conventional approaches to LE for complex assets involve performing a series of activities by a project team on different components of an asset at the end of its design life. During the LE process, data is gathered through inspections and condition assessments and then some plans for Asset Integrity Management (AIM) and Structural Integrity Management (SIM) are prepared for LE implementation, subject to regulatory approval (Hua et al., 2017; Shafiee et al., 2016; Stacey, 2011). A comprehensive review by Shafiee and Animah (2017) reported some other issues that must be considered during LE decision-making, including lack of good quality data, workforce ageing, obsolescence management, and robust RUL prediction methods. The project-like approach to LE may lean overly towards SIM; however, we will show that such an approach is anachronistic when put side-by-side the methods proposed in this paper, which are drawn on practices from reliability centered maintenance (RCM) and data-driven prognostics and health management (PHM).

PHM involves four core areas, namely: data acquisition and

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management; diagnostics; prognostics (which involves predicting the remaining useful life (RUL) of an asset); and decision-making (Lei et al., 2018). There are in total three approaches to PHM: model-based, data-driven, and fusion approaches. The details of these three approaches can be found in the work by Ochella et al. (2022). Data-driven PHM, the approach used in this paper, involves using sensor data from various monitoring devices installed in an asset, along with machine learning (ML) algorithms, to determine the state of health of the asset and then predicting its RUL to make accurate maintenance decisions. However, it can be argued that sensors do not necessarily provide detailed information regarding failure modes of the monitored asset since such information is typically obtained by a detailed Failure Mode, Effects and Criticality Analysis (FMECA) study. To overcome this challenge, Ochella et al. (2021) proposed a data-driven method which combined ML methods and RCM concepts to prioritize assets for LE consideration. The approach involved continuous monitoring of the asset via sensors, determination of their state of health using a condition indicator called the potential failure interval factor (PFIF), and subsequently, the grouping of different equipment with similar condition indicators together for the purpose of LE. These results contribute to the first phase of the LE decision-making model proposed in this study.

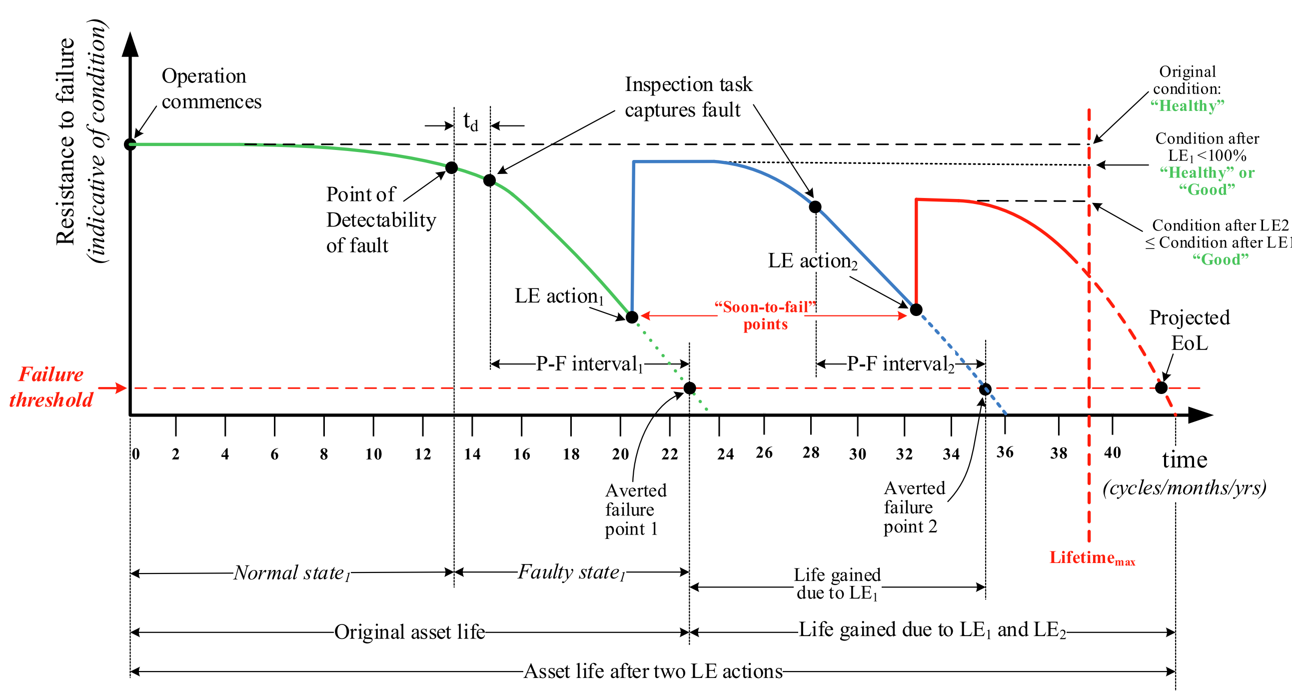
The focus of LE decision-making approach will be on critical equipment (i.e., equipment that are close to EoL and their failure will result in unsafe conditions). In specific terms, we use a PHM metric called “alert time”, in combination with RUL predictions into which uncertainties have already been incorporated, to establish actionable decisions with implications for logistics planning and LE process. A novel criterion, called the acceptability criterion, is also proposed to address those aspects of LE decision-making involving regulatory approvals and certification by third-party bodies or classification societies. Furthermore, the decision-making approach proposed in this study considers the impact of AI-enabled PHM solutions and the associated regulatory environment on LE decisions. To the best of our knowledge, this is the first attempt at bringing these disparate research endeavors together as an integrated, end-to-end data-driven decision-making model. Our model has the capability to be adopted in different industries, as it relies heavily on data gathered from the operational assets, rather than the technicalities of a specific sector, industry, or class of assets.

The remaining part of this paper is organized as follows. Section 2 provides an overview of LE practices, culminating in the need for RUL-informed LE decision-making models. The details of our proposed decision-making model are presented in Section 3. A demonstration of the applicability of the entire approach is presented in Section 4, along with its limitations and suggestions for future work. Section 5 concludes the paper.

2. Overview of LE practices

The justifications that typically need to be made for LE are in two broad categories, technical and economic. The technical aspect includes safety, reliability, and availability of the asset, while the economic aspect looks at return on investment (ROI), overall asset life cycle cost (LCC) and benefit-to-cost ratio (BCR). At the core of this is the realization that an asset undergoing degradation requires a slightly different approach towards operation and maintenance (O&M). An overall asset can be grouped into different systems, subsystems, components and parts, so that the impact of degradation at any of these levels on the overall asset can be assessed. Assets are considered to have reached their EoL when a performance or degradation threshold is reached, as illustrated in Fig. 1.

Such thresholds are usually determined through classical statistical approaches like accelerated life cycle tests, or in more recent times, using run-to-failure data and ML algorithms. Another way for an asset to reach EoL is through obsolescence, when the asset becomes unserviceable and thus economically and functionally impractical to operate and maintain (Macchi et al., 2018). Our study focuses on assets that have reached or are approaching EoL via degradation and are thus repairable, replaceable, or serviceable. Fig. 1 shows the impact of single and multiple LE actions on an asset. From a data-driven PHM context, LE essentially restores the condition indicator for an asset from a state of “soon-to-fail” to a “healthy” or “good” state. Condition indicator charts



Note: t_d = time delay between occurrence of fault and actual detection

Fig. 1. The impact of single and multiple life extension actions on an asset (adapted from Ochella et al., 2021).

will form a part of the decision-making model proposed in this paper. The following sub-sections, however, provide a review of conventional approaches to LE, and map a trend leading to the need for data-driven approaches, especially in the present era of big data and Industry 4.0.

2.1. Approaches to LE

As stated earlier, conventional LE practice involves setting up a project team, which then embarks on and drives the LE process. Typically, an overall asset or fleet of assets, say an offshore platform for instance, will first be broken down into systems, subsystems, and components. The subdivisions are then further grouped into different categories, depending on failure modes and criticality. Afterwards, the condition of the critical equipment and structures are assessed for the eventual application of suitable LE strategies. The detailed review of LE research by Shafiee and Animah (2017) showed that the LE process can be broadly grouped into five, viz: defining the premise and scope of the LE program, asset condition assessment, RUL prediction, evaluation and selection of LE strategies, and implementation. Obtaining regulatory approval, which is core to the whole activities, straddles the entire five processes because all activities must comply with standards and government regulations. A high-level breakdown of the typical LE workflow is illustrated in Fig. 2.

Two key technical aspects that inform decision-making are the condition assessment (which indicates the health state of the asset via a Health Index (HI)), and RUL prediction (which represents how much longer the equipment can operate before failure). To arrive at a health index that gives an indication of the technical condition for an equipment, techniques must be developed to appropriately weigh health factors (like testing/inspection frequency, degradation checks, maintenance, etc.) and history factors (like age, failure history, location/terrain, operating environment, etc.) (Animah & Shafiee, 2016). The condition indicator used in this work, known as the potential failure interval factor (PFIF), was developed in our earlier paper (Ochella et al., 2021). Other similar health indices in the literature include the grey health index proposed by Kalgren et al., (2006), the Asset Health Index proposed by De la Fuente et al. (2018) and the condition health and system refurbishment index proposed by Wang, Tian et al. (2015).

2.1.1. Structural components of assets

Although this study does not cover structures, conventional approaches to LE tend to be more focused on structures, as they are considered to be the foundation or framework upon which the operation of other assets and equipment are built. The development of an SIM plan for use during the LE phase involves data collection, evaluation, remaining fatigue life prediction, inspection planning, obtaining regulatory approval and the implementation of the approved LE and inspection program (Boutrot & Legregeois, 2015; Galbraith et al., 2005; Gibbs & Graf, 2014; Rashad, 2017). A common approach is to use probabilistic methods to model fatigue damage accumulation by trending stress versus number of cycles (i.e., *S-N* curves) (Liu & Frangopol, 2019). As such, the structural degradation or damage mechanisms typically considered include fatigue due to repeated cyclic loading over the asset's lifetime, various forms of corrosion, direct physical damage due to impacts like dropped objects or collisions, creep, and accumulated plastic deformation, amongst others (Aeran et al., 2016). When assessing a structure for LE, the variation of loads on the structures over the lifetime is analyzed and modelled, including dead load, live load, wave load, current load, and wind load, as may be applicable to the asset under consideration (Aeran et al., 2017). These various loads are typically modelled to obtain a time-dependent damage index, which serves as an indicator for the condition of the structure and can then be used as the basis for making LE decisions.

In recent times, practices similar to those used in the field of data-driven PHM have been extensively applied to Structural Health Monitoring (SHM) to estimate the condition of structures and predict remaining fatigue life (Bull et al., 2021; Entezami et al., 2019; Entezami et al., 2021). Again, the data used for data-driven SHM and health condition assessment for asset structures are from sensors which typically log vibration and environmental condition data (Bhowmik, 2020). With such data, knowledge about the health state of the asset's structure at any time instant is available, hence enabling the determination of LE actions which are triggered only as necessary, based on predictions from ML models (Basso & Copello, 2019).

2.1.2. Impact of uncertainties on LE decision-making

RUL prediction is a core technical aspect of the LE process. However, there are always uncertainties involved in the prediction process. It is therefore important to be able to quantify the uncertainties in RUL prediction, and subsequently exploit such quantification in the process of LE decision-making. Most studies in the literature propose point estimates of RUL; however, the predicted RUL values are often affected by uncertainties in the data, the model used, the environmental conditions and future loading conditions, amongst other factors. There are a few approaches for quantifying the uncertainty in RUL prediction, which yield RUL values as probability distributions rather than point estimates. The study by Elwany & Gebraeel (2008) used sensor data to predict RUL distributions for obtaining the parameters of an exponential degradation model as inputs to a spare parts replacement and inventory management decision-making model. Sensor-data was collected from accelerated

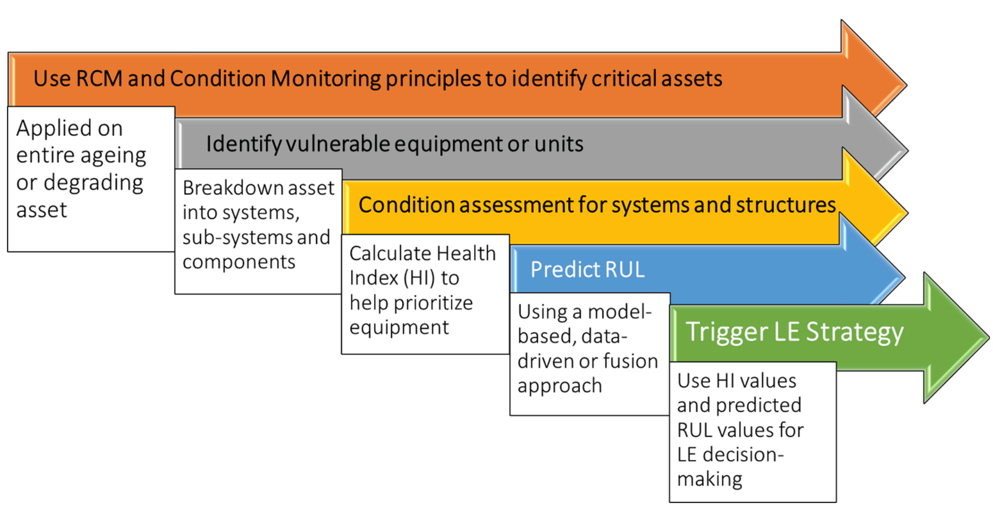


Fig. 2. The general workflow for technical assessment during LE process.

degradation tests for rolling element bearings and used to compute the RUL distributions analytically. The performance of the sensor-based prognostic model in terms of number of failures and total maintenance costs was compared to that of a fixed-time-interval maintenance policy. However, the model was tested on a single-unit replacement and inventory model and did not consider the overall life-cycle costs. Moreover, only the mean values were used in the RUL calculations and the variance information which addresses additional uncertainty was not fully exploited. A similar study was conducted by Wang, Hu et al. (2015) to formulate a prognostics-based spare parts ordering and system replacement policy for deteriorating systems. In their research, the lead time to order spare parts was modelled as a stochastic process with a probability density function rather than as a fixed value. The sensitivity of predictive replacement costs with respect to variations in lead time was derived, however it was only applied to non-reparable degrading systems and hence, the opportunities for LE were not fully explored.

With regards to uncertainty management in LE, Ramírez and Utne (2015) used Dynamic Bayesian Networks (DBN) as a tool to support LE decision-making for ageing repairable systems. Several parametric models were proposed to describe the deterioration process, imperfect maintenance, safety and risk variables as well as evaluate costs during the LE period. The EoL options considered were use-up and replacement. In terms of the potential for failure during the LE phase, the study revealed that the use-up option had a higher level of uncertainty than the replacement option. However, the replacement option involved a higher capital cost which made the overall assessment to favor use-up, from a cost perspective. Spare parts inventory and lead times to order parts were not modelled in the study.

2.1.3. LE strategies

There are several LE strategies adopted by different industries to sustain acceptable levels of reliability and reliability during the LE phase. Table 1 lists and explains various LE strategies, along with their potential application cases.

Table 1
Different life extension strategies with their meanings and potential application cases.

LE strategy	Meaning and application scenario
Replacement/ repowering	Mostly applicable to power generation units. Involves replacing an existing equipment with a new one or upgrading the system to a higher nameplate capacity. Typically returns equipment to "as good as new (AGAN)" condition.
Reconditioning	Involves actions such as cleaning, restoration of material properties, assembling, and fastening. Returns equipment to a better state than before but not up to AGAN.
Repair	Involves restoring a system to a functional condition, upon failure or on a planned maintenance. Applicable to components or subsystems of a more complex asset and typically carried out using new or existing parts.
Remanufacturing	Attempts to restore a system to original equipment manufacturer (OEM) functional specification with warranty. Integrates reconditioning, replacement, and repair.
Retrofitting	Involves replacing old components or equipment with modern equivalents, thus improving functionality, availability, and safety. This is a good strategy to combat early onset of obsolescence.
Use-up	Involves using a component or an equipment until the end of its economic life. This strategy is driven by economics; as such, it may be inappropriate for application to safety–critical assets.
Refurbishment	Applicable to components, equipment, or systems to return them to a higher level of functionality. Integrates partial replacement, reconditioning, and some elements of redesign.
Reclaiming	Applicable to systems requiring regular lubrication over their lifetime. Involves cleaning the oil through filtration and other means to eliminate contaminants and particles, and then reusing the same oil.
Retrofilling	Applicable to systems requiring regular lubrication over their lifetime. Involves changing out of the lubricant, for example, changing out of a transformer's oil.

Condition monitoring (CM) has gained increasing popularity as one of the methods of gathering data about the health of an equipment to help arrive at the right decision regarding when to implement LE actions. Aside conventional CM methods which rely on asset data stored in databases, a concept that is rapidly evolving is the digital twin. Proposals have been made on how to deploy a digital twin as a decision-making tool for LE of ageing assets. To build a digital twin of an asset's structural components, a high-resolution modelling of the asset is conducted. Then, the model is updated using the data obtained by sensors and the remaining fatigue life is estimated on a continuous basis. This approach is currently being implemented on one of Shell's oil and gas production platforms in the Southern North Sea (Knezevic et al., 2019). As regards the integration of PHM with asset LE strategies, Varde et al. (2014) proposed a framework that evaluates refurbishment as a strategy for LE of electronic systems subjected to different failure modes. They derived the cost-to-benefit ratio and performed a detailed risk analysis to aid LE decision-making. Other studies exploring the full integration of PHM with asset LE strategies include **Lukens and Markham (2018) and Tiddens et al. (2015), who looked at issues around data quality, data analysis, integration of legacy assets with modern ones and engineers' understanding of how to transition from conventional RCM practices to full PHM practices.

2.2. Fundamental requirements for LE

There are two broad requirements that drive asset LE decision-making; technical and economic requirements (Picard et al., 2007). On the technical side, the asset must maintain the required level of functionality, safety, reliability, availability, efficiency, compliance with changes in regulations and amenability to obsolescence management. On the economic side, the fundamental philosophy is that the overall asset LCC and the long-term cost of ownership and operation must be kept to a minimum, while continuing to extract value from the asset. These two broad categories of drivers should ideally be satisfied to achieve optimal outcomes. In the following sub-sections, some of the requirements are discussed further.

2.2.1. Performance requirements

One of the basic criteria for LE is that the asset must maintain an acceptable level of safety and reliability. In addition, the device must continue to meet or surpass a minimum threshold of functionality; otherwise, LE may become an unviable option. Although these basic criteria appear simplistic, it is challenging to achieve them for a degrading asset under constantly evolving environmental and process conditions, changing standards and regulatory requirements, and emerging uses of technology. This is why LE decisions must factor in the degradation process or changing health condition of the asset, future operating conditions, environmental loads, and several other parameters (Vaidya and Rausand, 2011). It is clear that since these critical factors which influence LE decisions are constantly evolving, collecting asset CM data to reflect this evolution and thereafter trending the future path is a potentially robust approach towards decision support. In order to help demonstrate whether or not the performance requirements for LE process have been satisfied, the data collected during the early operation as well as during the degradation process are harnessed to develop a condition indicator, which serves as a basis for determining safety thresholds, reliability thresholds, functionality thresholds, and other performance thresholds.

Another key factor that influences an asset's ability to continue to meet minimum performance requirements, and thus support LE, is obsolescence management. The stages of any technology's evolution include introduction, growth, maturity, saturation, decline and phase-out (Jennings et al., 2016). Once phased-out, the ability for an asset owner to continue to get the right support for operation and maintenance of the asset is greatly diminished. Thus, it is important to duly consider obsolescence forecasting and management as a critical factor that influences LE decision-making.

2.2.2. Regulatory requirements

The regulatory agencies in most countries have stringent requirements for granting approvals for LE programs. Most government regulations are targeted towards the oil and gas industry, the wind energy sector (Ziegler et al., 2018), the nuclear energy sector, the aviation industry, and the transportation industry, particularly the rail transport sector. The philosophy behind government regulations places the onus on asset owners to demonstrate that continued operation of their assets will ensure safety, reliability, and environmental protection. Government regulatory agencies also rely on certification of assets by class societies like Det Norske Veritas Germanischer Lloyds (DNV-GL), American Bureau of Shipping (ABS), Lloyd's Register (LR), and so on, for the approval of assets for LE, particularly offshore structures (Liu et al., 2016). With such certifications obtained, regulatory agencies are more inclined to approve LE programs. However, in this present era of big data and industry 4.0, there are only a few standards and regulations to guide LE decision-making for systems implementing data-driven and AI-enabled PHM. In this paper, an acceptability criterion (A_c), which considers all the important factors and performance requirements, in the context of data-driven LE decision-making, and explores if all factors or requirements are satisfactorily met, is used to help determine suitability of an LE plan for regulatory approval.

2.2.3. Other requirements

The ultimate goal of applying PHM technologies is asset health management (Kalgren et al., 2006). Consequently, the final form of the output from a data-driven PHM system should be an actionable plan for LE implementation. The RUL prediction results, along with the confidence intervals to account for uncertainties, should be easily interpretable into meaningful, real-life course of actions for asset managers regarding when to trigger an LE strategy and what the most suitable LE strategy should be. Lifetime prediction can also help with inventory and stock management optimization so that parts for equipment are not kept in storage in excess of required levels, thus taking up space, tying down the resources used to buy the excess spares, and potentially undergoing deterioration in storage. For instance, as revealed in the study by Andreacchio et al. (2019), in the aviation industry, the actual cost of aircraft maintenance, at any given time, is typically equivalent to the cost of spares maintained in the stock inventory, which usually translates into a huge stock level to keep and amounts to poor use of resources. LE plans based on advanced analytics methods should be well implemented to help optimize the entire process.

2.3. Overview of decision-making models in asset LE

Decision-making under the scenario of various competing strategies, multiple criteria or optimization objectives and inherent uncertainties is a complex process (Niknam et al., 2015). Maintenance decision-making and asset life-cycle management are examples of such a complex process because of the need to continuously ensure safety and reliability, eliminate or minimize unexpected failures while deriving the best possible ROI from the asset. When LE processes are added to the mix, the decision-making problem even becomes more complex. A typical approach by most researchers and asset managers is to focus on the optimization of cost, from an economics perspective, using one or more of the following tools: benefit-to-cost analysis, life-cycle cost optimization or ROI analysis (Animah et al., 2018; Woodhouse, 2012; Herrmann et al., 2011; Gu et al., 2012; Jones & Zsidisin, 2008). Other approaches focus on technical aspects that mostly deal with SIM and AIM, with the core components being safety, reliability, and availability (Animah and Shafiee, 2018; Boutrot et al., 2017; Nielsen and Sørensen, 2021; Trampus, 2019). A few approaches combine both technical and economic aspects in the form of a techno-economic analysis, such as the work by Shafiee et al. (2016) and by other authors (Golmakani and Pouresmaeeli, 2014; Picard et al., 2007). Obviously, considering just one or two of the various criteria leads to a multiplicity of approaches. Consequently, some researchers have attempted approaches that aim at analyzing the various criteria and their interdependencies to obtain optimization models for LE decision-making, with the most common being multiple criteria decision analysis (MCDA) (Kabir et al., 2014; Niknam et al., 2015; Shafiee, 2015; Shafiee et al., 2019; Shafiee and Animah, 2020). Of course, most MCDA approaches try to balance the inherently competing objectives of minimizing overall LCC (i.e., maximizing ROI) while ensuring high levels of safety, reliability, and availability during the extended period of operation.

From a PHM perspective, the concept of LE is not new. Reinertsen (1996) conducted an extensive review about diagnosis, RUL prediction and LE of technical systems. The review, which looked at methodologies for both repairable and non-repairable systems, revealed the inadequacy of the statistical methods in use and highlighted the need for further research in the area. Finkelstein et al., (2020) proposed a model for LE of degradable equipment by using the data gathered during preventive maintenance (PM). In their model, the failure threshold for the system was first considered to be deterministic, but then it was adapted as a random parameter. Although the information gathered during PM was used to trend the monotonically increasing degradation, the overall method used was analytical in nature, with the degradation process modelled as a Poisson process and then as a Gamma process. Overall, the idea of using data gathered during inspection and maintenance activities for the purpose of LE has been explored in the past (Labeau and Segovia, 2011; Ratnayake, 2015). Nguyen and Medjaher (2019) proposed a dynamic predictive maintenance framework comprising a prognostic process and a post-prognostic decision-making process. The methodology compared the cost-rate implication of adopting such DPM framework with a periodic maintenance policy and an ideal predicted maintenance, under a perfect maintenance scenario. The framework, which was tested on the NASA CMAPSS dataset, showed that decisions such as doing nothing, ordering of spares (if unavailable), taking urgent actions, etc., can be made based on the predicted probability that the RUL lies within a given range.

Chen, Lu et al. (2021) proposed a risk-averse RUL estimation model, along with a post-prediction maintenance decision-making framework. The prediction model used a support vector regression (SVR), a long short-term memory (LSTM), and a hybrid of both techniques to make RUL predictions. A maintenance cost rate (MCR), which was formulated to consider the costs for two scenarios, namely, maintenance before failure (predictive) and repair after failure (corrective), was used as a metric to judge the performance of the overall approach. The study showed that the hybrid approach yielded RUL results that led to lower MCR while the MCR for predictive maintenance actions was consistently lower than that for corrective maintenance actions. In another study by Chen, Zhu et al. (2021), an ensemble of a deep autoencoder and a bi-directional LSTM was used for predicting the degradation, health states, and the RUL of industrial systems. The health states were divided into four states, namely, normal state, mild degradation, moderate degradation, and severe degradation. Based on the predicted health states, the effective RUL threshold for carrying out maintenance tasks and the optimal degradation level at which spare parts should be ordered were determined.

As observed, all the above reviewed studies used the maintenance cost per unit operating time (i.e., cost rate) as the basis for measuring the effectiveness of proposed approaches. As opposed to economic frameworks, this work focuses on the impact of using prognostic information as the basis for the technical analysis to make LE decisions, particularly using a condition indicator derived by ML algorithms, RUL predictions with uncertainty quantification, and the impact of emerging AI-enabled PHM regulations.

3. Methodology

Optimization objectives for LE include maximization of operational lifetime and minimization of asset LCC while ensuring that reliability, availability and safety are not compromised (Cha and Finkelstein, 2020). Our study puts forth a wide range of considerations that can be made in the process of conducting technical assessment for LE. At the core of our methodology is the use of a tool from RCM and CM known as the potential failure (P-F) curve, which illustrates the point P where failure can first be detected followed by point F when failure begins. Most of the other information required by the decision-making model are mapped onto the P-F curve. Some of the required information for the LE decision-making model include the potential failure interval factor (PFIF) which stands for the health index (HI), the RUL with uncertainty quantification expressed in terms of confidence intervals (CI) and the alert time (t_a), which is a PHM metric that represents the minimum time needed for planning and executing the appropriate LE action. To set the stage for a clear understanding of the methodology, all the assumptions and prior preparations regarding the asset are laid out as follows.

3.1. Assumptions, initial conditions, and background assessments

As we stated earlier, this work assumes that a separate economic justification for LE has been conducted and thus focuses strictly on the technical aspects of LE decision-making.

3.1.1. Integration of RCM and CM practices with PHM practices

This methodology proposes and implicitly assumes the integration of RCM and CM practices with PHM technologies for the asset under consideration. Therefore, the asset undergoes a formal technical assessment process (typically FMECA or other similar analysis) which breaks it down into systems, subsystems, and components, all of which have sensors or other data acquisition devices installed on the equipment.

3.1.2. Component-level and unit-level HIs

Another implicit assumption is that run-to-failure data is available for the various components, units or systems that make up the asset. With such data, the P-F curve can be plotted for each unit as shown in Fig. 3. The instantaneous PFIF for each unit is calculated using Eq. (1) as defined by Ochella et al., (2021):

$$PFIF_{i,t} = \frac{P - F\_Interval_{i,t}}{Unit\_Lifetime_i} \tag{1}$$

where $\mathrm{PFIF}_{i,t}$ is the PFIF of unit i at time t, $P - F\_Interval_{i,t}$ is the P-F interval of unit i at time t, and $\mathrm{Unit\_Lifetime}_i$ is the design life of unit i. The P-F interval is the time from the detection of a fault to the point of functional failure (see Fig. 3). The PFIF is a useful indicator as it is a scale-independent quantity, which helps to ease grouping of equipment with different ranges of total lifetime, thereby serving as an indicator of the state of health of any unit under operation.

To ensure that there is appropriate comparison of the predicted PFIF values with the true PFIF values, the true PFIF values should be scaled to achieve the same range [0,1] as the predicted PFIF values. The scaled true PFIF value ($TruePFIF_{scaled}$) is obtained using the formula in Eq. (2), given as:

$$TruePFIF_{scaled} = \frac{TruePFIF - min(TruePFIF)}{max(TruePFIF) - min(TruePFIF)} \tag{2}$$

where $max(.)$ and $min(.)$ represent the arguments of the maximum and minimum, respectively.

3.1.3. System-level HI

The various component-level HIs can be aggregated based on a weighting scheme as used in a paper by Wang, Hu et al., (2015) to obtain a system-level HI. This is given by Eq. (3):

$$HI_{system} = \sum_{j=1}^{N} w_j X_j \tag{3}$$

where N is the number of components in the system, j represents the j^{th} component, w_j is the weight of the j^{th} component, and X_j is the HI of the j^{th} component. The value of HI_{system} is in the range [0,1] and $\sum_{j=1}^{N} w_j = 1$. The system-level HI, when plotted in real-time, yields a curve as shown in Fig. 4. Thus, an asset manager who chooses to use HI information as a preliminary basis or the sole basis for LE decision-making can find the optimal window to take LE action based on the acceptable HI threshold for the system.

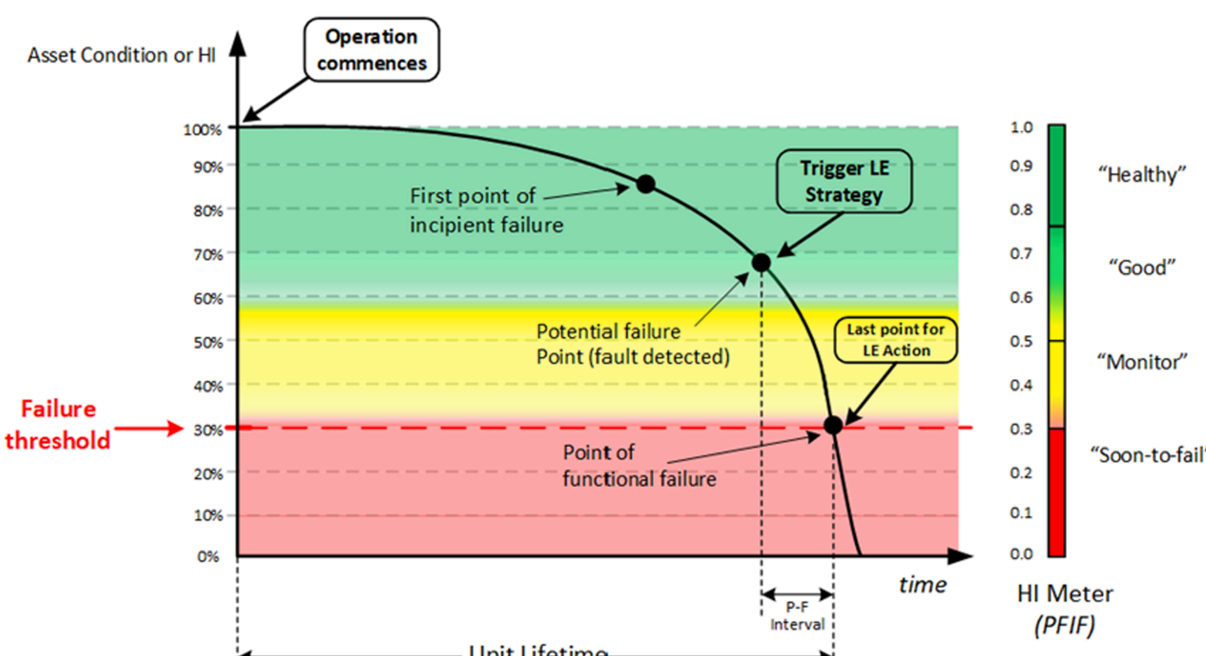


Fig. 3. Annotated P-F curve showing the important points during the degradation of a system (adapted from Kalgren et al., 2006).

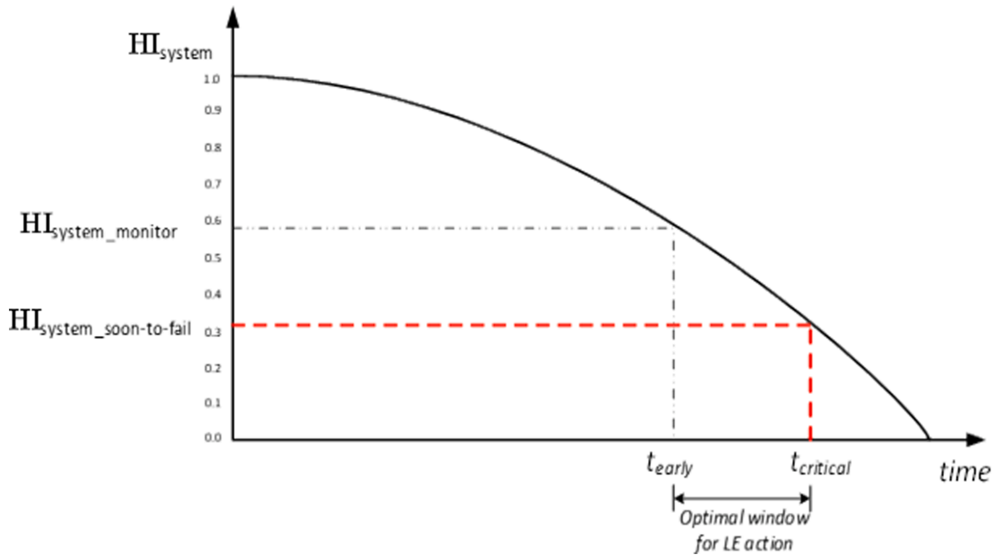


Fig. 4. The system-level HI versus time, showing the critical intervention window to prevent failure.

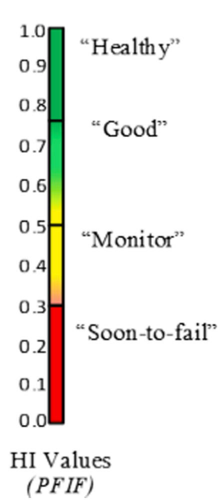
3.2. Implication for logistics planning and LE action

The HIs not only serve as useful indicators for the health condition of the units or asset but also have intrinsic implications for logistics planning and the associated LE actions. Even though more rigorous tools will be used later to aid LE decision-making, at the HI assessment stage the asset managers are expected to have an idea of relevant actionable information that can be extracted from the HI values. Fig. 5 shows a typical HI chart and the implications as it relates to logistics planning and LE.

3.3. RUL prediction with uncertainty quantification

After calculating the HIs of various systems, subsystems and components and grouping the equipment based on their HI values, the LE strategy can then focus on the most vulnerable groups, i.e., those with the lowest HIs. The RUL for the units in the most vulnerable groups can then be predicted using the CM data from the commencement of operation up to the present time (i.e., the time at which the ML algorithm is used to make predictions). To account for the inherent uncertainties in the data, prediction model and environmental loading conditions, it is important to use methodologies that yield RUL predictions as probability distributions having mean RUL values along with uncertainty bounds or confidence intervals (CI). One of such algorithms is Bayesian Neural Networks (BNNs), and the results used for the demonstration of this study were obtained using RUL values predicted by BNNs. Fig. 6 shows how the failure probability increases with time for any given unit. Note that RUL is continuously predicted as CM data becomes available, thus predicting the EoL at any given time, along with confidence bounds. An accuracy metric would have previously been used to validate the algorithm, thus establishing confidence levels for the mean RUL falling within the range (EoL ± CI).

For the purpose of this study, we use a PHM metric known as alert time (t_a) which was first proposed by Leão et al. (2008) and is annotated in Fig. 6. The value of t_a specifies the minimum time required to schedule LE tasks, order required parts, and execute LE. Since the predicted EoL does not always coincide with the true EoL, the importance of the CI is that it provides a buffer to help maintain t_a within tolerable margins. It should be noted here that wasted life is also likely to occur if LE action is taken too early, while the unit or component still has reasonable lifetime left. Wasted life, as defined by Leão et al. (2008), is the additional time that a unit would have served if it is not taken out too early. So, in order



Functional Status	Implication for Logistics	Implication for LE
Fully functional	No action required	No action required
Functional with degraded performance	Initiate logistics sparing based on lead time to order required parts	Trigger LE strategy in preparation for LE action
Reduced functionality	On-demand or emergency logistics sparing and parts requirements	Take scheduled LE action now or use opportunistic windows for LE action
From severely impaired to not functional	Emergency logistics sparing and parts requirements. Unit should reflect as "out of service"	Take LE action now

Fig. 5. HI values and the associated actionable decision support implications (adapted from Kalgren et al., 2006).

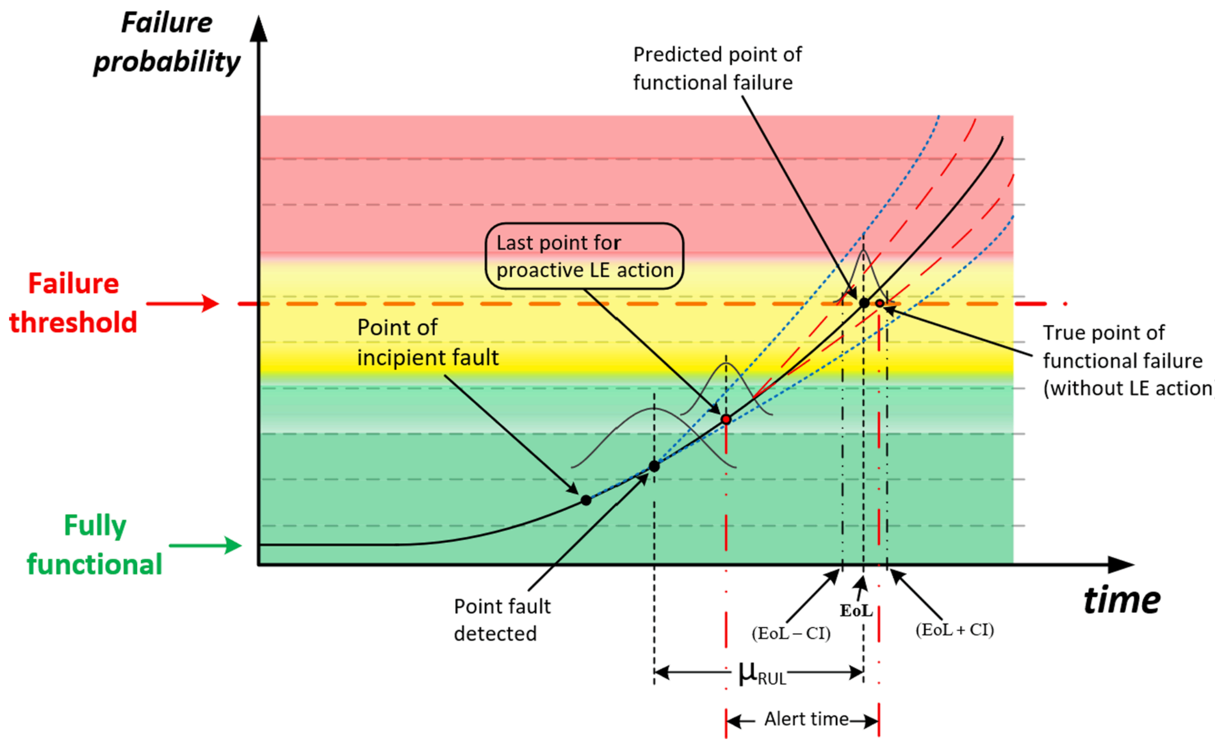


Fig. 6. Plot showing increasing failure probability as asset degrades with time. RUL at each point obtained as distributions.

to find the sweet spot and ensure that LE action is taken before failure occurs, while at the same time minimizing wasted life, the mean RUL is continuously monitored to comply with Eq. (4):

$$t_a \geq \mu_{RUL} - CI \tag{4}$$

The LE action is initiated immediately upon observing the first point where the requirement in Eq. (4) is satisfied. The overall flow of the LE decision-making model, comprising both the RCM and CM modules as well as the AI-enabled online monitoring and RUL prediction module, is illustrated in detail in Fig. 7.

3.4. Acceptability criterion for regulatory approval

Reference was earlier made to the need to obtain regulatory approval for LE, which is indeed the case for most industries. Typically, regulatory authorities need the conviction that due diligence was made in establishing the technical justification for LE and that minimum acceptable standards for safety and reliability must be maintained for all safety and environmentally critical elements (SECE) during the LE period. In this section, all the critical factors for the effective implementation of LE from a data-driven perspective are consolidated, thus proposing a unifying criterion for regulatory approval of the LE plan. The critical factors include safety and reliability, explainability, interpretability, accuracy of predictions, compliance with industry standards, actionability of AIM and SIM inspection plans, and third-party testing and verification of results. As part of the regulatory approval process, all the important factors mentioned should be checked off as either satisfactory or unsatisfactory. If the results from such a process are collated as an array, F, we propose an acceptability criterion, A_c, as given in Eq. (5):

$$A_c = \beta F \tag{5}$$

where β is a normalizing array of $1 \times n$ dimension which indicates the importance or weight assigned to each of the factors considered, while F is an array of $n \times 1$ dimension whose elements are either 1 or 0, representing whether each factor is satisfactory or unsatisfactory, respectively. The value of A_c lies in the range [0,1]. The matrix product, $\boldsymbol{\beta}\mathbf{F}$, can be expressed as a sum, given in Eq. (6) as:

$$Ac = \sum_{i=1}^{n} \beta_i \times F_i \tag{6}$$

where i is an index representing the number of factors considered, ranging from 1 to n; β_i is the importance weight for the i^{th} factor; and F_i represents whether the requirement for the i^{th} factor is satisfied or not. The sum of the weights must be equal to 1, as given in Eq. (7):

$$\sum_{i=1}^{n} \beta_i = 1. \tag{7}$$

The criterion is formulated to provide both robustness and flexibility, allowing for adjustments to the factors which are considered important, depending on the peculiarities of the asset and the subsisting regulatory environment or context. Fig. 8 shows an illustration of the entire process for implementing a data-driven LE plan involving AI-enabled PHM integrated with RCM, including the stage of obtaining regulatory approval.

4. Case studies

In this section, the proposed model is tested on NASA's publicly available C-MAPSS dataset (Saxena and Goebel, 2008) and the results are reported.

4.1. Dataset description and mapping to asset portfolio

C-MAPSS stands for Commercial Modular Aero-Propulsion System Simulation and the dataset consists of four different run-to-failure datasets under different fault modes and varying operational conditions. The training sets commence at a point where all units are in a healthy state and end at the point of failure of each unit. For the test sets, the data for all units commence at a healthy state and are terminated at an unknown point during each unit's lifetime. This is similar to the scenario on a real multi-component or multi-system asset, with subsystems and subcomponents, or the scenario for a fleet of similar systems being managed under the same portfolio by the same asset manager. The

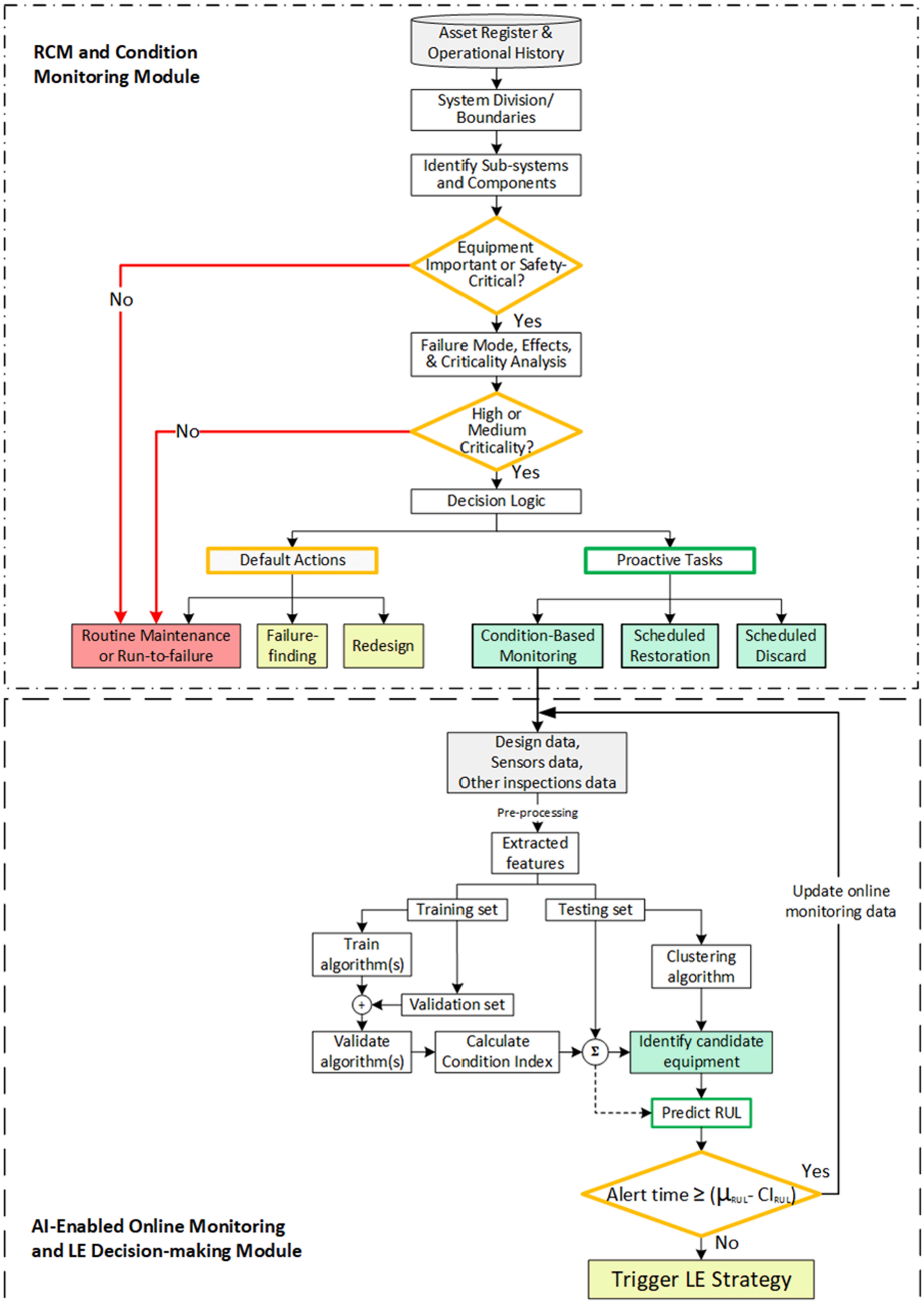


Fig. 7. The overall flow of the LE decision-making model.

intent here is to apply an LE strategy for a group of units that have been identified as vulnerable or at risk of failure. For more details about the dataset, the readers can refer to Saxena et al., (2008). For the purpose of this work, we used one of the datasets, FD001, containing a training set, a test set, and the ground truth RUL values. The training set comprises run-to-failure data for 100 identical turbofan engines subjected to similar failure modes and same operating conditions while the test set comprises data which begins from when each unit was put into

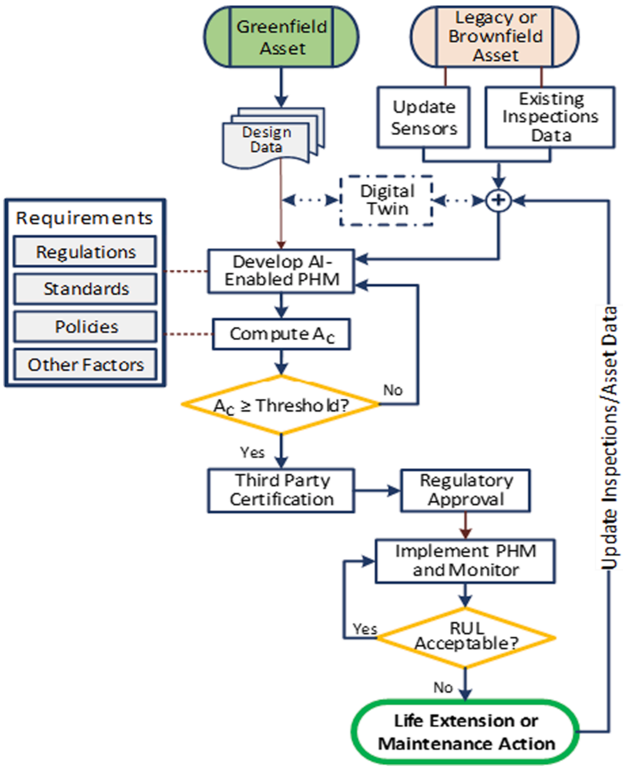


Fig. 8. The process of implementing a data-driven LE plan involving AI-enabled PHM and regulatory approval requirements.

operation (i.e., healthy), up to a certain point during the operation of the engine (i.e., the present time, in the context of this work). Each of the 100 engine units has a distinct lifetime, t_i, with three columns representing operating condition settings and another 21 columns representing sensor data. These parameters, taken as the CM variables, are presented in Table 2.

Table 2
Parameters in the C-MAPSS dataset.

S/N	Measured parameter	Unit of measurement
1	Unit number	–
2	Time	cycles
3	Operational setting 1	–
4	Operational setting 2	–
5	Operational setting 3	–
6	Total temperature at fan inlet	°R
7	Total temperature at LPC outlet	°R
8	Total temperature at HPC outlet	°R
9	Total temperature at LPT outlet	°R
10	Pressure at fan inlet	psia
11	Total pressure in bypass-duct	psia
12	Total pressure at HPC outlet	psia
13	Physical fan speed	rpm
14	Physical core speed	rpm
15	Engine pressure ratio (P50/P2)	–
16	Static pressure at HPC outlet	psia
17	Ratio of fuel flow to Ps30	pps/psi
18	Corrected fan speed	rpm
19	Corrected core speed	rpm
20	Bypass Ratio	–
21	Burner fuel–air ratio	–
22	Bleed Enthalpy	–
23	Demanded fan speed	rpm
24	Demanded corrected fan speed	rpm
25	HPT coolant bleed	lbm/s
26	LPT coolant bleed	lbm/s

4.2. Data-driven condition assessment

Using the sensor data and the ground truth RUL values, an ML algorithm was developed on MATLAB to fit a linear model to the data, thus obtaining a condition indicator for each of the 100 units. The full details of this were presented in a previous paper by the authors, Ochella et al. (2021), but Fig. 9 shows the condition indicators obtained for all 100 units, which are, in essence, the P-F curves for each unit.

The pseudocode for the algorithm used in the work by Ochella et al. (2021) is illustrated in below.

Pseudocode for grouping units into different health states

1: **Data:** CMAPSS_FD001
2: /* Read and import training data*/
   $X_{train} \leftarrow$ train_FD001;
3: /*Calculate group statistics: mean, median, variance, std dev*/
   groupstats $\leftarrow$ *groupsummary*(X_{train}, ['var', 'std', 'mean', 'median'])
4: /*Eliminate variables with zero variance*/
   $X_{train\_reduced} \leftarrow X_{train}$ ('var'=0);
5: /*Normalize data from selected sensors*/
   $X_{train\_reduced\_norm} \leftarrow (X_{train\_reduced} - mean(X_{train\_reduced}))/\ std(X_{train\_reduced})$;
6: Select data for most trendable sensors to obtain: $X_{cluster\_data}$
7: /*Calculate each unit's training PFIF*/
   $PFIF_{train} \leftarrow (P - F_{Interval}/Unit\_Lifetime)$
8: /*Fuse sensors by fitting linear model on $X_{cluster\_data}$*/
   $PFIF_{train} \leftarrow \theta_o + X_{cluster\_data}\theta$;
   ($learner$ = 'leastsquares'; $regularization$ = 'ridge')
9: /*Read and Import test data*/
   $X_{test} \leftarrow$ test_FD001
10: Prepare test data as in lines 3 to 7 to obtain: $X_{cluster\_data}$
11: /*Predict PFIF for units in test data as*/
   $PFIF_{test} \leftarrow \theta_o + X_{test\_cluster}\theta$
12: /*Extract last element of $PFIF_{test}$ for each unit as the present health state for each unit*/
   $PFIF_{unit} \leftarrow PFIF_{test\_unit}(end)$
13: **Result:** /*Group engine units as below*/
   "Healthy" $\leftarrow 0.75 < PFIF_{unit}$
   "Good – no action" $\leftarrow 0.75 \leq PFIF_{unit} < 0.50$
   "Good – monitor" $\leftarrow 0.50 \leq PFIF_{unit} < 0.30$
   "Soon-to-fail" $\leftarrow 0.30 \leq PFIF_{unit}$

4.2.1. Unit-level HIs and unit groupings

Having trained an ML algorithm and fit a linear model to the training data, the instantaneous PFIF for all the units were subsequently predicted based on their sensor values at the present time, as captured in the test data. The units were then grouped using a four-stage HI division, as illustrated in the HI chart in Fig. 5. The HI division was achieved as follows; "Healthy": $0.75 < \text{PFIF} \leq 1.00$; "Good": $0.5 < \text{PFIF} \leq 0.75$; "Good – monitor": $0.3 < \text{PFIF} \leq 0.5$; "Soon-to-fail": $0.0 \leq \text{PFIF} \leq 0.3$. These boundaries were defined for the purpose of this work, and may be made more stringent or less stringent, depending on the safety,

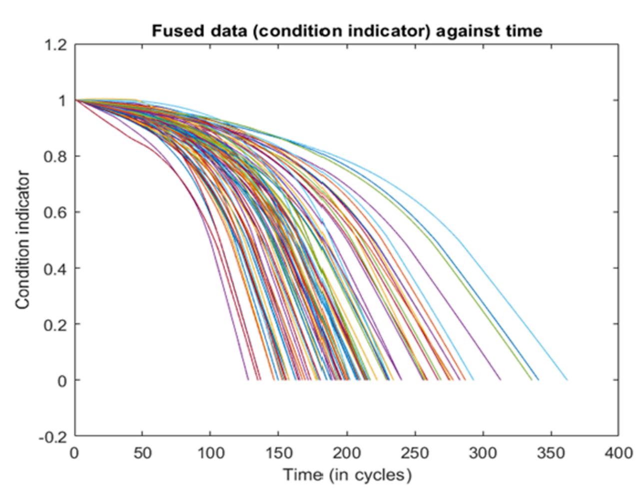


Fig. 9. P-F curves for 100 turbofan engines within the asset portfolio.

reliability and functional requirements of the specific unit or asset. For brevity, only a list of the units categorized as "healthy" and "good" are provided in this paper. Given that the focus is on candidate equipment for LE, results for all units categorized and "good – monitor" and "soon-to-fail" will be fully presented and discussed.

4.2.2. True and predicted RUL

The FD001 C-MAPSS dataset provides the ground truth RUL values for all 100 units under monitoring. However, the key task is to use the test data to arrive at predicted RUL values using advanced analytics techniques, and then use the true RUL values as bases for comparison. Given our interest in the predicted RUL values as distribution functions rather deterministic values, results from the study by Kim & Liu, (2021) will be extracted for the units identified as vulnerable units for LE, with the lifetime units rounded down to the nearest number of cycles. The study used a Bayesian Deep Learning algorithm to model the uncertainties in model parameters and the stochastic nature of the degradation process. RUL predictions were therefore obtained as probability distributions, with a mean RUL value, μ_{RUL}, along with confidence interval (CI) estimates, which are useful for the purpose of applying constraints around the alert time (t_a) in our decision-making model. The predicted μ_{RUL} and CI values are presented in Table 3 and Table 4 under Section 4.3.1.

4.3. Results and discussion

The application of the steps in the decision-making model, so far, leads to the identification, at every time instant, of the group of equipment that may be approaching failure based on the predicted HIs. Using the HI division boundaries stated in Section 4.2.1, a total of 31 units were predicted as "healthy" and they are: 1, 2, 6, 9, 11, 14, 15, 22, 25, 26, 33, 39, 44, 47, 48, 50, 55, 59, 65, 67, 69, 71, 75, 78, 83, 85, 86, 87, 88, 96, and 99. Similarly, a total of 31 units were predicted as "good – no action", namely: 3, 4, 5, 7, 8, 12, 16, 19, 21, 23, 27, 28, 29, 30, 38, 45, 51, 54, 57, 60, 63, 70, 73, 74, 79, 80, 89, 94, 95, 97 and 98. These groupings were in agreement with the ground truth RUL values, when used to calculate the scaled true PFIF values. It is important to note here that categorizing faulty units as "healthy" or "good" has dire implications for the avoidance of unplanned or unforeseen failures, and each healthy or good prediction must be thoroughly scrutinized so that impending failures are not missed due to false negative predictions.

4.3.1. Candidate units for LE

Ultimately, the goal of the proposed decision-making model is to identify equipment that are close to their EoLs by using CM data and ML algorithms, so as to trigger an LE strategy in good time to extend their useful lives and avoid failure. The predicted PFIF values, the units' lifetimes, as well as other lifetime parameters for the units grouped as "good - monitor" and "soon-to-fail" are presented in Table 3 and Table 4 respectively.

In the case of grouped units to be considered for LE due to low HIs, false positive results, which involve wrongfully grouping healthy units as "soon-to-fail", do not have any safety implications because a healthy unit wrongly thought to be about failing will not fail. However, false positive categorizations have economic implications since otherwise healthy units may be taken out of service, thereby leading to either wasted life in terms of the unit or wasted resources in terms of the time and personnel that would have been allocated for work on a healthy unit wrongfully classified as faulty. So, overall, the accuracy of predictions remains an important factor that should be satisfied in order to end up with a viable LE plan.

4.3.2. Lead time for LE scheduling

From the ground truth values for the 100 units in the FD001 dataset, the overall lifetime for the units range from a minimum of 141 cycles for unit #41 to a maximum of 341 cycles for unit #12, with an average operational lifetime of about 206 cycles before failure. Given that these lifetime values were obtained from accelerated degradation tests, let us assume broadly, for the purpose of this work, that the minimum time needed to schedule for LE, order spare parts and implement the appropriate LE strategy is 20 cycles. This is the value of t_a, which will be similar for all units since the units within the asset or fleet of assets are identical or homogeneous. From Eq. (2), to take LE actions before any failure occurs, the condition $t_a \geq (\mu_{RUL} - CI)$ must be satisfied. The governing constraint to ensure timely LE action is therefore $(t_a + CI) \geq \mu_{RUL}$. So, the values for $(t_a + CI)$ greater than μ_{RUL} in Table 3 and Table 4 indicate units for which there is enough window to schedule for LE. For such units, an opportunistic window can also be used to trigger and implement LE strategy, since an LE plan will already exist. However, for units which the governing constraint has been satisfied and the values of $(t_a + CI)$ are less than μ_{RUL}, there is no longer enough window to plan in advance since even the tolerance built into the RUL values through uncertainty quantification in terms of the confidence intervals has been used up. From Fig. 5, the logistics and LE implications for such units are "emergency logistics sparing and parts requirements" and "take LE

Table 3
Units grouped as "good – monitor" (19 units) (measurement units for lifetime, including RUL, CI and t_a are in number of cycles).

Unit	Predicted HI (PFIF)	Unit Lifetime	True μ_{RUL}	Predicted μ_{RUL}	Predicted σ_{RUL}	95% CI* ($\pm 1.96\sigma_{RUL}$)	$(t_a + CI)$	Implication for LE
10	0.47	288	96	80	16	31	51	Schedule LE or opportunistic action
13	0.46	290	95	89	16	31	51	Schedule LE or opportunistic action
17	0.38	215	50	49	10	19	39	Schedule LE or opportunistic action
18	0.32	161	28	**25**	**7**	**13**	**33**	**Take LE action now**
32	0.43	193	48	49	13	25	45	Schedule LE or opportunistic action
36	0.36	145	19	**19**	**7**	**13**	**33**	**Take LE action now**
40	0.43	161	28	**25**	**7**	**13**	**33**	**Take LE action now**
43	0.47	231	59	65	16	31	51	Schedule LE or opportunistic action
46	0.42	193	47	35	8	15	35	Schedule LE or opportunistic action
53	0.32	190	26	**27**	**7**	**13**	**33**	**Take LE action now**
56	0.34	151	15	**14**	**5**	**9**	**29**	**Take LE action now**
66	0.37	161	14	**14**	**4**	**7**	**27**	**Take LE action now**
72	0.44	181	50	51	13	25	45	Schedule LE or opportunistic action
84	0.41	230	58	65	16	31	51	Schedule LE or opportunistic action
90	0.37	174	28	**20**	**7**	**13**	**33**	**Take LE action now**
91	0.34	272	38	**29**	**10**	**19**	**39**	**Take LE action now**
92	0.32	170	20	**19**	**5**	**9**	**29**	**Take LE action now**
93	0.42	329	85	54	12	23	43	Schedule LE or opportunistic action
100	0.31	180	20	**21**	**7**	**13**	**33**	**Take LE action now**

* *RUL distribution was modelled as a normal distribution; hence 95% confidence interval was computed as* $\pm 1.96\sigma_{RUL}$.

Table 4
Units grouped as "soon-to-fail" (19 units) (measurement units for lifetime, including RUL, CI and t_a are in number of cycles).

Unit	Predicted HI (PFIF)	Unit Lifetime	True μ_{RUL}	Predicted μ_{RUL}	Predicted σ_{RUL}	95% CI ($\pm 1.96\sigma_{RUL}$)	$(t_a + CI)$	Implication for LE
20	0.19	200	16	15	6	11	31	Take LE action now
24	0.21	206	20	20	6	11	31	Take LE action now
31	0.09	204	8	6	5	9	29	Take LE action now
34	0.06	210	7	6	3	5	25	Take LE action now
35	0.22	209	11	11	5	9	29	Take LE action now
37	0.25	142	21	20	7	13	33	Take LE action now
41	0.27	141	18	18	8	15	35	Take LE action now
42	0.16	166	10	8	4	7	27	Take LE action now
49	0.09	324	21	18	6	11	31	Take LE action now
52	0.23	218	29	29	9	17	37	Take LE action now
58	0.30	213	37	31	9	17	37	Take LE action now
61	0.24	180	21	21	7	13	13	Take LE action now
62	0.29	286	54	**46**	**9**	**17**	**37**	**Schedule LE or opportunistic action**
64	0.28	196	28	27	7	13	33	Take LE action now
68	0.13	195	8	7	4	7	27	Take LE action now
76	0.09	215	10	9	4	7	27	Take LE action now
77	0.27	196	34	26	8	15	35	Take LE action now
81	0.09	221	8	7	4	7	27	Take LE action now
82	0.14	171	9	9	5	9	29	Take LE action now

action now" respectively. These are also shown on Table 3 and Table 4.

Note that the initial grouping of equipment into "good – monitor" and "soon-to-fail" was done using only the predicted HIs. From the calculated mean RUL values, the 95% confidence intervals and the application of the alert time metric, it can be observed that most of the recommended decisions are in agreement with the initial group assignments based on just the HIs. This demonstrates that using the HIs is indeed a good basis for prioritizing the equipment for closer monitoring, before eventually calculating the RULs and CIs for the vulnerable set.

4.3.3. Acceptability criterion for regulatory approval

Regulatory approvals need to be sought for the implementation of LE programs. To grant approvals, most regulatory agencies will not only actively participate in the process of drawing out an LE plan, but also rely on compliance to known standards or on certification by classification societies. To determine whether all the critical factors have been duly considered, importance or weight assignments are given to each factor, based on the peculiarity of the industry and the operating environment. For this case study, the weights of the critical factors have been ranked in descending order and shown in Table 5. Out of the seven factors considered, safety and reliability were considered the most important and assigned a weight of 0.3, while explainability was ranked least important with a weight of 0.05. These weights, of course, do not undermine the actual need for any AI-enabled PHM system to have all these critical factors addressed. The weights assigned in Table 5 were arrived at based on the judgement of the authors and the factors were assessed in a manner similar to the guidance in the International Organization for Standardization (ISO) standard, ISO 13381–1:2015. For real-life applications, a team of engineers would typically arrive at these weights based on more detailed analysis, expert judgement, and experience.

Table 5
Typical application of acceptability criterion (A_c).

i	Factor	Satisfied?	F	Weight, β	βF
1	Safety and reliability	Yes	1	0.30	0.30
2	Algorithm produces accurate predictions	Yes	1	0.20	0.20
3	Workable of AIM and SIM inspection plan	Yes	1	0.20	0.20
4	Interpretable results and outputs	Yes	1	0.15	0.15
5	Compliance with industry standards	Yes	1	0.10	0.10
6	Third party testing and verification of results	No	0	0.05	0.00
7	Explainable AI methods used	No	0	0.05	0.00
A_c (i.e., $\Sigma\beta F$) = 0.85					

Given the weight assignments in Table 5, the acceptability criterion is calculated using the formula in Eq. (2) to obtain $A_c = 0.85$. An appropriate acceptance threshold can then be determined by the regulatory agency or certification body, for instance $A_c \geq 0.9$ may be the requirement for accepting the LE plan, depending on how safety–critical the industrial sector is (oil and gas or nuclear, for example). To achieve certification, therefore, the critical factors which have not been satisfied, namely explainability and third-party testing and verification in this case, must be revised and improved to a satisfactory level, such that the value of A_c meets or exceeds the minimum threshold. For instance, further improvements in the LE plan by subjecting it to a successful third-party verification, for the illustration given, will raise the A_c score to 0.95, which is greater than 0.9, thus meeting acceptance and approval requirements. This demonstration, albeit simplistic, shows how flexibly the acceptability criterion can be applied and contextualized. Furthermore, its robustness property stems from its amenability to different levels of scrutiny, which may be very high level, or very detailed.

4.4. Additional comments and future work

The model proposed in this paper addresses LE decision-making, end-to-end, from a strictly data-driven perspective. The dataset used to demonstrate the use of this model, which comprises run-to-failure data for a multi-unit system, similar to real-life assets, has been used by a number of authors in the literature for both RUL prediction as well as post-prognostic decision-making purposes. The dynamic predictive maintenance framework proposed by Nguyen & Medjaher (2019) used a probability confusion matrix, which measures the probability that the predicted RUL falls within a given time window, hence typical prognostics metrics like the RMSE, MAE, etc., could not be used. The performance was therefore measured by comparison to the true RUL, and when the probability is high that the RUL is within a given range or less than a given value, different actions are triggered, such as doing nothing, ordering spares (if unavailable), using stock if available, or taking urgent action. The cost of maintenance decision is then determined on the basis of availability or unavailability of spares and the maintenance action taken. Chen, Lu et al. (2021) used the MCR criterion to assess the effectivity of online prognostics, where the predicted RUL that yielded the lowest MCR was considered to have better performance. Chen, Zhu et al. (2021) also combined the dynamic predictive maintenance strategy, measurement of performance using the probability confusion matrix and the concept of MCR to determine the effectiveness of the proposed strategy.

From the foregoing, it is apparent that direct comparison between the performance of the proposed approach and other frameworks is inexpedient. Moreover, most decision-making models are unique, and, in the demonstration provided in this work, the ground truth RUL values which were available for the dataset used, served as a guide to evaluate the timeliness for initiating LE plans for the units within the asset portfolio. On that note, the timeliness metric may be an appropriate metric that can be explored to benchmark the performance of data-driven decision-making approaches. In which case, how timely decisions are made for specific engine units can therefore be compared.

For real-life assets, it will be interesting to find out how the component-level HIs can be aggregated to subsystem or system-level HIs using Eq. (3), before eventually grouping units, and applying the model to determine suitable LE strategies. System level HIs were not calculated in the case study because CM data for components were not available and the units were considered to be independent homogeneous units. For a scenario where an equipment has different degradable sub-components and the data for each component is collected via sensors, and where each component has different lifetimes and required reliability levels, system-level HIs can be calculated based on the individual HIs for the sub-components. An LE scenario for such an equipment may involve applying the appropriate strategy, such as replacement or repair, to just one sub-component of the equipment, in order to improve the HI for the equipment and extend its overall useful life.

Another area that will need to be assessed more critically is the determination of the various factors that can affect the alert time, t_a. A deterministic value was used to demonstrate the application of the model, however, t_a is stochastic in nature and its value can be influenced by factors such as whether the unit has redundancies, the specific part needed to implement the LE strategy, the availability of the part either as a warehouse item, as an off-the-shelf purchase or as a special-order part. Other factors that can influence the alert time include the specific LE strategy to be implemented, given that repair, replacement, or refurbishment times can vary. A deterministic alert time, like the one used in this work, will only work when the LE strategy is the same and all other conditions which may affect parts ordering and availability of engineers are assumed to be the same, which is hardly the case. Another inherent challenge with advanced analytics approaches to PHM is the availability of real-life run-to-failure data for the equipment. For real-life operational assets, a practical advanced analytics approach will involve using design data, a digital twin of the asset, and continuous online monitoring and PHM model updating.

Knowledge retention and ageing workforce are well known challenges with conventional LE and later life operation of old assets. Data storage capabilities necessary for the use of advanced analytics approaches, along with the continuous monitoring and trending associated with it, provides a potential path towards solving the loss-of-knowledge conundrum. Such systems will have long usage histories, trends, and accompanying baseline and operations data for each monitored system, subsystem, or component, which can easily be recalled and analyzed as required. The important aspect, from a staffing perspective, is that the advanced analytics-based PHM systems should be easily interpretable by new staff with minimal training, and should have direct correlation to decision-making, as was demonstrated in this work.

5. Conclusion

This paper proposes an advanced analytics approach for asset life extension (LE) decision-making. At its core, the approach involves the integration of practices from reliability-centered maintenance (RCM) and data-driven prognostics and health management (PHM). This approach of LE decision-making, which considers LE as an ongoing activity during an asset's operational lifetime, is more relevant to the present era of big data and Industry 4.0, as against conventional LE approaches that involve setting up a project team at the end of an asset's overall design life. The proposed approach is more intuitive, as different equipment or units within an overall asset often have varying design lives and will thus benefit from a philosophy which views LE as an ongoing strategy, similar to operations and maintenance.

The proposed approach focuses on the technical assessments that need to be made to justify LE. The process involves the prediction of health indices for each unit, grouping the units according to their health indices, focusing on units with low health indices, predicting their remaining useful life (RUL), and then making LE decisions based on uncertainty quantification and a key PHM metric known as alert time. A sample application case using a publicly available asset degradation dataset for multiple units showed that the integrated approach led to interpretable results and actionable outcomes, which would help ensure that the useful life of each unit on an asset was extended before it was due to fail – this will inevitably lead to the extension of the overall asset's lifetime. An acceptability criterion, which was developed to aid regulatory agencies and certification bodies in approving LE plans, was also presented and its application was demonstrated. The acceptability criterion was designed to ensure that the critical aspects of an AI-enabled or advanced analytics-based PHM system are duly considered and satisfied. Satisfying such factors, which include safety, reliability, compliance with standards and regulations, ensuring interpretability, and so on, helps the asset owner demonstrate that the asset is able to meet the minimum safety and health condition requirements during the LE phase, while continuing to deliver value to the owner, which is the ultimate aim of LE.

CRediT authorship contribution statement

Sunday Ochella: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. **Mahmood Shafiee:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – review & editing, Visualization, Supervision. **Chris Sansom:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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