

A Sustainability-based Framework for Predicting the Remaining Useful Life of a Complex Engineering Asset

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Abstract

As climate change became recognised as a major global challenge, the ability to define and account for the environmental performance of an asset became an important attribute aiding the sustainable development strategies towards net-zero. Remaining Useful Life (RUL) indicator allows for optimised maintenance scheduling and the life extension of an asset. However, the existing RUL prediction methods do not fully consider the environmental performance (EP) of an asset. This paper aims to develop a sustainability-based framework for complex engineering assets' RUL prediction based on a systematic review of key literature. The proposed framework introduces a new concept, so-called 'sustainable-RUL' (S-RUL), which refers to the estimated remaining lifetime that an item is able to function reliably and be environmentally sustainable. The Scopus database is used to develop the PRISMA framework. Finally, a generic S-RUL framework is introduced which incorporates the environmental sustainability aspect into the RUL prediction. Hence, the decision-maker is provided with a single predictive indicator, that accounts for the asset reliability and EP at the same level of granularity, thus facilitating the selection of maintenance policies that establishes a condition for ecological and economic stability.

Keywords: Sustainability; Environmental Performance; Maintenance; Prognosis; Reliability; Remaining Useful Life Prediction; RUL.

1. Introduction

With the knowledge that the biophysical environment surrounding us has its limits [1], [2], we started acknowledging the major global challenges which are climate change and global warming. Environmental sustainability (ES) has thus become a key consideration over the life cycle of products in all sectors. ES seeks to balance the use of natural resources and sinks while keeping them within their limits for human welfare. Moreover, since ES is a prerequisite for social sustainability [1], this research will focus on ES.

Complex engineering assets refer to the high-value assets that are designed to have a long service life. As a result, their use phase, which comprises of asset operation and maintenance, is the most consequential from an environmental impact perspective [3]. So far, the use phase of such assets has mostly been directly influenced by its economic performance, and downtime. Therefore, a key performance indicator (KPI) that accounts for variations in the performance of an asset and informs on maintenance scheduling requirements, with economic performance in mind, is critical. Remaining Useful Life (RUL) is such a KPI. RUL is based on structural and functional degradation, and it informs the maintenance decision-maker (DM) of the time left until the maintained system fails or reaches a critical failure threshold [4], [5].

With the enhanced focus on ES, there is a need to establish a condition for ecological and economic stability for assets that is sustainable into the future. This translates into accounting for both the economic performance and 'Environmental Performance' (EP) of maintained systems. The regenerative characteristic of maintenance has a net positive impact on the EP of a system [6]. This emphasises the role of maintenance in achieving this stability for complex engineering assets. RUL is based on the reliability level of the asset, i.e., the ability to perform an 'intended function.' However, this 'intended function' is based on the mechanical and/or electrical performance of the asset and excludes its EP. Hence, RUL does not indicate the time left for an asset to operate at a compromised EP level. However, its role in triggering maintenance activities does make RUL an indirect contributor towards ES. These indicate that RUL should not be singularly used for achieving this ecological and economic stability. This mandates a direct approach towards ES.

The green transition being embedded across all sectors have made net-zero roadmaps and emission targets a commonality [7]. This further emphasises the need for a direct approach to ES by accounting for the EP evolution of a system at the same level of granularity as that of RUL. This corresponds to an additional KPI that is based on structural and functional degradation, and explicitly indicates the

time left until the maintained system reaches a critical EP level. The latter should align with the relevant net-zero roadmap and emission target. Furthermore, since both RUL and this additional KPI are related to the degradation of a system, but likely via different system parameters, they have to be considered in tandem. The sole use of RUL as a maintenance KPI underestimates the achievable ES improvement and limits the measurement and monitoring of the EP of a system.

This research therefore aims to present a novel framework that integrates ES in the existing RUL prediction methodology framework. Section 2 provides the reader with the methodology adopted for this research. Section 3 presents the review of the existing literature to identify the research gaps. The proposed framework is presented and described in Section 4. In Section 5, the research contribution, the limitations, and the verification of the framework are discussed. Finally, key results and contributions are summarised in Section 6 along with future work recommendations.

2. Systematic review methodology

This research is mainly built from a systematic review of existing literature on maintenance, RUL, and ES. A systematic literature search was carried out using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to establish the state-of-the-art within the scope of this research.

Table 1. Search strategy adopted for the systematic review.

Search string	TITLE-ABS-KEY ("Preventive Maintenance" OR "Condition-based Maintenance" OR "Condition Based Maintenance" OR "proactive maintenance" OR "Predictive Maintenance" OR prognostic* OR "Condition Monitoring" OR "Health Monitoring" OR inspection OR "non-destructive testing" OR ndt OR thermography) AND TITLE-ABS-KEY (sustainab* OR emission OR environment* OR ecolog* OR carbon) AND TITLE-ABS-KEY ("remaining sustainable life" OR "remaining useful life*" OR "Remaining Useful Live*" OR rul OR "Remaining Useful Life Prediction*") AND NOT TITLE-ABS-KEY (social)
Database	Scopus and citation searching
Document type included	Articles, conference papers and reviews in the English language
Subject area excluded	Agricultural sciences, biochemistry, chemistry, earth sciences, health professions, neuroscience, psychology, medicine, molecular biology, and social sciences
Exclusion criteria	Publications related to degradation diagnosis; maintenance scheduling optimisation; sustainability consideration in the form of RUL prediction of renewable energy sources; digital twins for structural and health management

The search questions used to establish the search string and the inclusion criteria were about understanding existing RUL calculation methods, the links between RUL and maintenance, and the integration of sustainability aspects in RUL prediction and maintenance. Table 1 lists the search string used, the research database considered, the document type considered, the subject areas excluded, and the exclusion criteria. Since the research is focused on ES, the search string excluded the word 'social'. After screening through 458 papers using the PRISMA guidelines as illustrated in Fig. 1, 31 of those were shortlisted for this research and shared among the authors to extract data to answer the search questions. The excluded publications did not have RUL prediction methods or sustainability considerations as the primary focus of their research.

3. Related works

Using ISO 13381 [8], RUL prognosis can be broken down into three main stages: 1. Data collection and pre-processing, where raw data from sensors is converted into health indicators; 2. Prognosis model, where predictions are made about the evolution of the health of the asset over a period; 3. Prognosis evaluation, where the predictions are evaluated. Prognosis modelling methodologies can take either a model-based, a data-driven or a hybrid approach. For complex systems where the behaviour is dependent on the interrelationship among its components, data-driven and hybrid methods have received a great deal of attention, especially with the introduction of machine learning (ML) and deep learning (DL) techniques [9], [10]. The current research trends for RUL have also expanded onto maintenance decision-making; taking the RUL prediction and understanding its implications before proposing a maintenance policy that meets certain requirements [11], [12]. The net positive impact of maintenance on the EP of an asset [6] and the dominance of the use phase, with respect to environmental impacts for maintained systems [3], makes RUL an indirect contributor towards ES. Rebaiaia & Ait-Kadi [12] combined RUL with on the renewal theory to propose a decision support model for maintenance to minimise waste.

For assets in use, maintenance serves as an indirect medium for achieving the emission targets and reducing environmental impacts in the short-term [6], with long term effects possible through feedback to other life cycle phases [13]. The maintenance and sustainability research area centred on the development of ecologically conscious maintenance strategies. Abdi & Taghipour [14] and Rebaiaia & Ait-Kadi [12]

investigated repair and replacement strategies. However, the lack of adequate environmental sustainability indicators that informed maintenance decision-making, became apparent. Senechal [15] mapped the performance indicators from EN 15341 [16] to the Triple Bottom Line (TBL) dimensions to show the inaptness of conventional maintenance dashboards vis-à-vis the environmental aspect of sustainability. Senechal et al. [11], [17] recognised that the functional state of a system is commonly considered for its maintenance. This led to the introduction of sustainability-related concepts such as sustainable state, sustainable value, sustainable signature, and sustainable level to help maintenance DMs develop environmental awareness [11]. Hoang et al. [18] proposed an ES health indicator, called ‘Energy Efficiency Indicator’ (EEI), that captured the performance degradation of the maintained system based on its energy consumption and useful output. The recommendation to apply an anticipative vision, similar to RUL, to subsequent EP indicators led to Hoang et al. [18] introducing ‘Remaining Energy Efficient Lifetime’ (REEL). The latter indicates the time left for the EEI of a system to reach a pre-determined critical threshold. Senechal et al. [11], [17] then used a similar idea to propose a more holistic predictive EP indicator, the ‘Remaining Sustainable Life’ (RSL). This captures the future evolution of the sustainable value (e.g., energy efficiency) of the monitored system.

Senechal & Trentesaux [11] then proposed the ‘Sustainable Condition-based Maintenance’ (SCBM) to foster environmental awareness amongst maintenance DMs. SCBM uses TBL-adapted KPIs and dashboards to choose a maintenance policy. Senechal [15] pointed out the lack of awareness of the environmental consequences of maintenance actions. Subsequently, Ghaleb et al. [19] and Saihi et al. [20] concatenated a list of TBL sustainability indicators that measure the sustainability performance and impacts of maintenance practices. Furthermore, through an inference model, Abdi & Taghipour [14] linked the physical degradation of a system to its EP degradation. This link between functional and structural degradation illustrates the intrinsic correlation between RUL and RSL suggesting that they can be combined. So far RUL

is viewed separately from RSL wherein RSL prognosis is triggered after a failure has been diagnosed to determine how long a system can function reliably in its failure state until it is not sustainable anymore. This approach does not monitor the evolution of a system’s EP during its operation irrespective of its state.

The review indicated that the research trends have been mainly on improving the prediction accuracy of RUL, and on developing sustainability-focused maintenance strategies. The prognosis framework that investigates the types of condition parameters to be collected and the prognostic model to be used for EP were not developed. Moreover, the unsustainable behaviour of the system in use was not considered as a trigger point for maintenance. Hence, the subsequent research questions that this research aims to answer are:

1. What prognosis framework can be used for EP-related predictive indicators?
2. How can the reliability and sustainable behaviour of a system be used simultaneously as maintenance trigger points to incorporate sustainability aspects across its life cycle?

4. Proposed framework

The gaps identified from the data extracted from the reviewed literature led to the proposal of a generic ‘Sustainable-RUL’ (S-RUL) framework illustrated in Fig. 2. The S-RUL framework is an adapted RUL prediction framework from Ansari et al. [5] that was extended to integrate EP via RSL. S-RUL is introduced as a predictive indicator which informs the maintenance DM of the time left for a system to perform reliably at a compromised EP level. The S-RUL framework is made up of three distinct stages: 1. Condition monitoring; 2. Prognostic model; 3. Prognostic evaluation.

4.1. Stage 1: Condition monitoring

This stage covers the data collection, data pre-processing, and feature selection steps. In addition to the collection of data associated with conventional failure and performance condition parameters (e.g., vibration, temperature, current), we propose the collection of data associated with ES condition parameters (e.g., air pollution

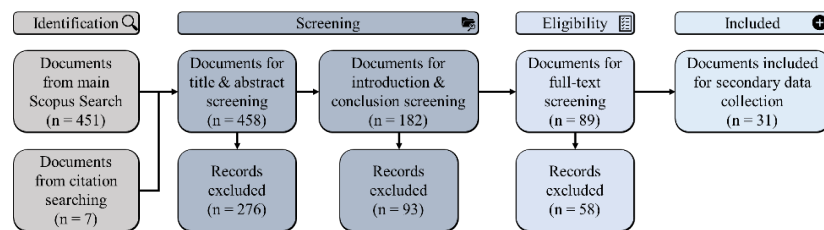


Fig. 1. PRISMA flow diagram demonstrating the paper selection process.

emission, noise, energy, land use). The latter inform on the family of data that has to be considered to enable RSL prognosis. The ES condition parameters to consider for a given system are identified using the Life Cycle Assessment approach proposed by Azapagic & Clift [21].

The correlation between RUL and RSL, which arises from the common denominator of functional degradation, is intrinsically captured by these two datasets, and the subsequent pre-processing and feature selection steps. Data pre-processing converts the raw data from sensors, linked to both the failure and ES condition parameters, into an understandable format suitable for feature extraction. The redundancies that arise from the correlation between the two datasets are also eliminated. The feature selection stage labels data relevant to the RUL and EP subsets, where the EP health indicators represent the sustainable states which combine to give the sustainable value of the maintained system.

The output from this stage to the prognostic model stage are subsets of features from the pre-processed input data that are linked to the RUL and EP health indicators.

4.2. Stage 2: Prognostic model

For each of the conventional approaches introduced in Section 3, we propose an extension to incorporate the prediction of EP health indicators.

For the model-based approach, we propose the inclusion of a ‘Sustainability performance degradation model’ to predict the RSL of a system. The latter mathematically expresses how the EP of the maintained system varies over time with pre-

processed data from the first stage used as the independent variables. An example of such an expression is the calculation of the emission footprint of aircraft engines where the fuel flow rate and flying hours are the independent variables. The ‘Failure-mode degradation model’ is made up of known physics-based expressions describing failure behaviours such as crack propagation, fatigue, etc, and it predicts the RUL of the system.

For the data-driven approach, DL techniques such as CNN, RNN, LSTM and Bi-LSTM are the most favourable method [10], [22]. Moreover, DL techniques such as Deep Neural Network, LSTM, and Bi-LSTM have also been suggested for predicting carbon emissions [23], [24]. To circumvent the complexity and extra computing power that is brought forward by retraining, or the use of two separate neural network models, we propose the use of multi-task learning (MTL) techniques [25] such as Transformer, Graph Neural Networks, and Retrieval-Augmented Generation to facilitate the introduction of the additional predictive indicators for EP [26], [27]. Consequently, a shared neural network model is trained to prognosticate both RUL and RSL. The proposed technique can cope with the correlation between the two datasets. In addition to the above, the absence of a training dataset for RSL similar to those for RUL suggest the use of supervised learning techniques to train its task-specific layer.

For the hybrid approach, the proposed extensions from the model-based and the data-driven approaches are combined with exchanges between the system state(s) to predict both the RUL and RSL. Moreover, the lack of EP and/or physical degradation trajectories for RSL and RUL can be

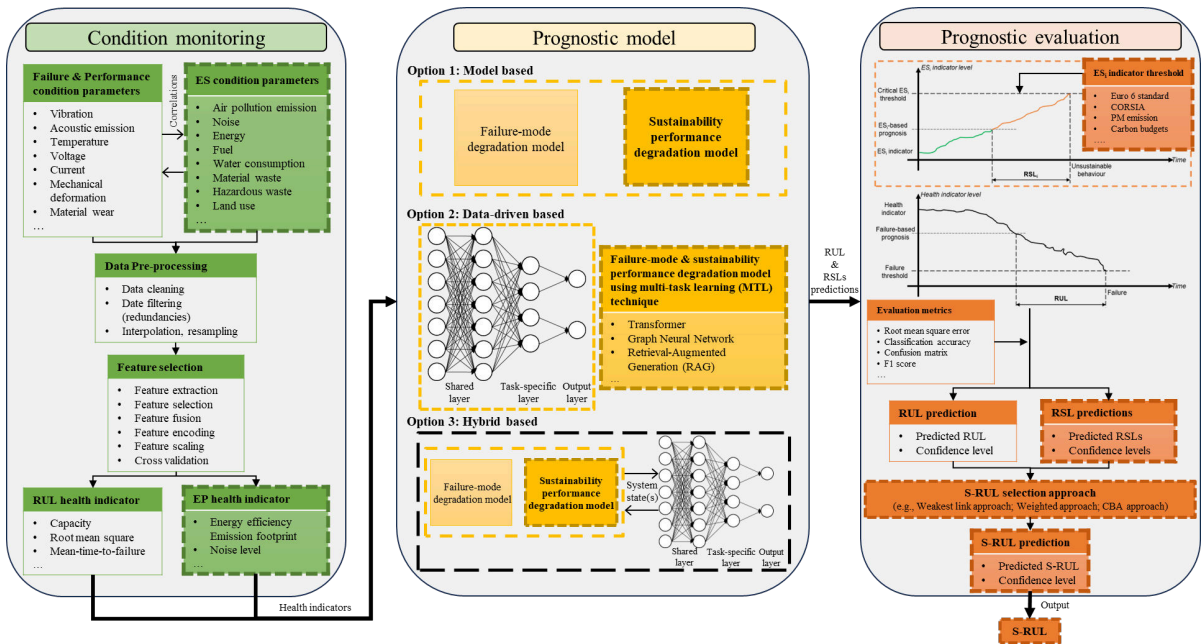


Fig. 2. A generic framework for S-RUL prediction (dashed lines indicate the modifications).

supplemented using the controlled model-based approach proposed by Xiong et al. [9].

4.3. Stage 3: Prognostic evaluation

This stage has two main steps. The first one serves to evaluate the predictions from the prognostic model using evaluation metrics such as Root Mean Square Error, F1 score, and Confusion Matrix. These determine the confidence levels associated with the predictions. Moreover, the RSL prediction for each sustainability state has an associated critical EP threshold, which performs the same function as the failure threshold, and is defined according to environmental or legislative standards such as Euro 6 for vehicles, Particulate Matter emission standard based on environmental targets, Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), and industry carbon budgets. These thresholds indicate when unsustainable behaviour occurs.

The second step is the S-RUL selection approach that uses the RUL and RSLs predictions, and their confidence levels to provide the maintenance DM with a single prediction based on pre-determined preferences. This step brings together the RUL and RSL prognostics that have been running in parallel so far. There are multiple selection approaches that can be used:

(a). The weakest link approach, where the predictive indicator that crosses its critical threshold first is used as the S-RUL prediction. This is possible as the same temporal dimension (time on x-axis) is used for all predictions.

(b). A weighted approach, where weights are assigned to each predictive indicator with respect to the maintenance DMs' preferences to provide an aggregated and compromised value for the S-RUL.

(c). A cost-benefit analysis (CBA) approach that evaluates the maintenance benefits on the performance of the system and the related cost associated with each predictive indicator. The predictive indicator for which the difference between monetarised benefits and costs is the greatest is chosen for the S-RUL prediction. However, CBA is a controversial technique in environmental decision making because it expresses the quality of the environment in financial terms based on indefinite individual preferences [21].

The subsequent S-RUL prediction is then used to identify a suitable maintenance plan.

5. Discussion

The proposed S-RUL framework provides the solution to the research questions. The RSL prognosis process was illustrated using an adapted

RUL prediction framework. The LCA approach facilitates the selection of ES condition parameters and informs on the type of EP health indicators to consider. The parallel running of the RUL and RSL prognosis allows the framework to predict both when the system reaches critical failure and critical EP thresholds at the same level of granularity. The presence of multiple predictive indicators, where each suggests a particular course of action, complicates the task of the DM. The S-RUL selection approach helps in that respect.

With the introduction of RSL prognosis, the S-RUL framework requires more data and thus more processing power and data storage than conventional RUL prediction frameworks [28]. Consequently, there is a need to consider the extra cost and environmental impact this additional requirement entails. With the advent of Industry 4.0 and Industry 5.0, data centres have proved to be crucial in the move towards digitalisation. They are physical facilities that store these data digitally. The maintenance of these data centres has been shown to have significant environmental impacts in the form of greenhouse gas emissions from energy consumption, and of water consumption from the cooling system [29]. Therefore, there is a need to avoid 'burden-shifting'; the environmental and economic benefits associated with the S-RUL framework should exceed the environmental and economic burdens from the additional data requirement for RSL prognosis.

The Delphi method served as a verification tool for the proposed S-RUL framework. Academic experts from predictive and condition-based maintenance, ML and DL research areas provided feedback on the framework. The feedback resulted in the adoption of the MTL technique.

6. Conclusion

The S-RUL framework is proposed following a systematic review of literature and is validated using the Delphi method. The RUL prediction framework was adapted to integrate RSL prediction. Life Cycle Assessment allows the selection of which sustainability state to prognosticate, and the additional data collection requirement for ES condition parameters. Of the proposed modifications to the prognosis modelling approaches, the addition of a 'Sustainability performance degradation' model and the use of MTL for the data-driven approach are the main ones. A S-RUL selection approach provides the DM with a single predictive indicator which facilitates the selection of maintenance policies.

Further works proposed are the identification of the optimal S-RUL selection approach, the demonstration of the framework with an

appropriate use-case, and the development of a 'Feedback to Design' step that reduces the gap between RUL and RSL at the design stage.

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