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Advanced Health Monitoring of Composite Structures Through Deep Learning-Based Analysis of Lamb Wave Data for Developing Health Indicators

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ABSTRACT

A health indicator (HI) serves as an intermediary link between structural health monitoring (SHM) data and prognostic models, and an efficient HI should meet prognostic criteria, i.e., monotonicity, trendability, and prognosability. However, designing a proper HI for composite structures is a challenging task due to the complex damage accumulation process during operational conditions. Additionally, designing a HI that is independent of historical SHM data (i.e., from the healthy state until the current state) is even more challenging as HI and remaining useful life prediction are time-dependent phenomena. A reliable SHM technique is required to extract informative time-independent data, and a powerful model is necessary to construct a proper HI from that data. The lamb wave (LW) technique is a useful SHM method that can extract such time-independent data. However, translating the LW data at each time step to the appropriate HI value is a challenge. AI—deep learning in this case—offers significant mathematical potential to meet this difficulty. A semi-supervised learning approach is developed to train the model using the simulated ideal HIs as the targets. The model uses the current LW data, without prior or subsequent data, to output the current HI value. Prognostic criteria are then calculated using the entire HI trajectory until the end-of-life. To validate the proposed approach, aging experiments from NASA's prognostics data repository are used, which include composite specimens subjected to a tension-tension fatigue loading and monitored using the LW technique. The LW data is first processed using the Hilbert transform, and then, upper and lower signal envelopes in two states – baseline and current time – are used to feed the deep learning model. The results confirm the effectiveness of the proposed approach according to the prognostic criteria. The effect of different triggering frequencies of the LW system on the results is also discussed in terms of the prognostic criteria.

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INTRODUCTION

Composite structures are becoming more popular in a variety of industries owing to their beneficial mechanical characteristics, such as lightweight and high strength. Because of the continual stress redistribution triggered by the non-homogeneous and multi-interface structure of composite laminates, in addition to the possibility of manufacturing imperfections, the damage mechanisms of composite laminates during cyclic fatigue loading are complex [1]. Therefore, predicting the structure's behavior, particularly its remaining useful life (RUL), is critical for important structures such as airplanes, ships, wind turbines, etc., as it not only improves safety and efficiency but also saves time and money on maintenance.

A health indicator (HI) is a valuable index that is required to first indicate the structure's health status (diagnostics) and then to predict its RUL (prognostics) [2–5]. Developing (or discovering) a HI that meets the requirements for both diagnostics and prognostics is a challenge, and it appears to be more challenging in complicated cases such as composite laminates. If no maintenance and self-healing take place, a structure's HI (or damage index) is always decreasing (or increasing) throughout operational conditions due to damage growth. This fact should be incorporated into the design of a HI and examined using a metric known as monotonicity (Mo). The comprehensive HIs of an ensemble of associated components that have reached their end-of-life (EoL) should ideally arrive at the same value, signifying the failure threshold. However, HIs at the EoL change and do not always end up with an identical value; this discrepancy can be quantified using a metric called prognosability (Pr). HIs are more predictable if they have comparable trends and a similar correlation in terms of usage time for similar structures. By using the trendability (Tr) criterion [6], it is possible to quantify the resemblance in HIs. A HI must satisfy the three evaluation criteria of Mo, Pr, and Tr from the viewpoint of prognostics, which is the primary focus of the current work.

Without online condition monitoring, also known as structural health monitoring (SHM) for structures, complex time-dependent patterns (such as progressive damage scenarios in composite structures) and unexpected occurrences (such as a bird strike on an aircraft) would not be considered. Therefore, SHM is crucial for the diagnosis of structures [7]. Regarding the prognosis of structures, prognostics and health management (PHM) technology is an extension of SHM that is more thorough and includes RUL prediction.

The fact that prognostic and HI construction models are time-dependent is one of their common drawbacks, which means that in order to enhance the performance of the HI and RUL prediction models, the relationship between historical data from the starting point (often in a healthy state) until the present moment should be taken into consideration. As a result, prognostic and HI construction models function less efficiently when prior SHM data, either entirely or partially from the beginning, is missing. In this regard, a robust SHM method is needed for extracting informative time-independent evidence, and a strong model is required to create an appropriate HI from those data. Such time-independent pieces of evidence may be extracted using guided wave (GW) approaches, such as Lamb waves (LW). GW is among the most widely utilized SHM methods, termed GWSHM, for thin-walled structures in the aviation industry [1]. Investigations into the practical issues of applying GWSHM to aerospace applications with wide fluctuations in operating and environmental circumstances have also been conducted. Several trustworthy compensating approaches have been put forth and tested. The capacity of GW to characterize materials has received attention recently. It should be noted that from an engineering perspective, what counts is whether the structure can continue to bear the load for which it was intended [1]. The traditional GWSHM techniques, on the other hand, emphasize local approaches in which local variations in material characteristics driven by the damage incidence can be tracked (position, severity). With this in mind, a HI may be seen as adopting engineers' perspectives and attempting to determine how all of the separate and spatially dispersed fatigue damage contributes to overall structural deterioration, which will be useful from a structural design standpoint.

In addition to the previously discussed aspects, it is important to note that translating LW data to the appropriate HI value at each limited time step when LW inspections are conducted is a challenging task. This is due to the fact that the data to be exploited is available only at an individual LW inspection time step, without access to prior or subsequent data. However, in order to meet prognostic criteria, the HI must consider the entire historical trajectory. Moreover, composite-made components lack a true comprehensive HI. To address these challenges, data-driven approaches, such as artificial intelligence (AI), can be utilized due to their ability to discover complex and nonlinear relationships. To tackle the lack of true health indicators, a semi-supervised learning (SSL) approach has been employed to train the model using simulated ideal HIs as labels [6].

NASA's prognostics data repository is utilized to analyze aging investigations that involved composite dogbone specimens that were subjected to tension-tension (T-T) fatigue loading monitored by the LW technique. Signal processing methods are used to initially process the LW data for feeding the semi-supervised deep learning network. The outcomes support the practicality of the suggested strategy in light of the prognostic criteria. In terms of the prognostic criteria, the impact of various LW system triggering frequencies on the outcomes is also examined. The rest of the paper includes The remainder of the paper is divided into six sections, including HIs' evaluation criteria, signal processing, semi-supervised criteria-based fusion model, experimental fatigue data set, results and discussions, and conclusion.

HEALTH INDICATOR EVALUATION CRITERIA

Three verified criteria (Mo, Pr, and Tr) are used to assess the prognostic signature (HI)'s quality [2–5] and are formulated as follows:

$$Mo = \frac{1}{M}\sum_{j=1}^{M}\left|\frac{\sum\limits_{i=1}^{N_j}\sum\limits_{p=1,p>i}^{N_j}(t_p - t_i).sgn(x(t_p) - x(t_i))}{(N_j - 1)\sum\limits_{i=1}^{N_j}\sum\limits_{p=1,p>i}^{N_j}(t_p - t_i)}\right| \tag{1}$$

$$Pr = exp(-\frac{std_j(x_j(N_j))}{mean_j(|x_j(1) - x_j(N_j)|)}) \;; \quad j = 1, 2, ..., M \tag{2}$$

$$Tr = \min_{j,k}|\frac{cov(x_j, x_k)}{\sigma_{x_j}\sigma_{x_k}}| \;; \quad j, k = 1, 2, ..., M \tag{3}$$

where $x_{(t_p)}$ and $x_{(t_i)}$ represent the measurements at the times of t_p and t_i, respectively. cov is the covariance, where x_j is the vector of measurements on the j^{th} specimen (among M specimens) that has N_j measurements. σ_{x_j} and σ_{x_k} are the standard deviations of x_j and x_k, respectively. The selected metric for Mo in Eq. (1), the so-called modified Mann-Kendall (MMK), compared to the other versions (Sign and Mann-Kendall), is more robust to noise and also considers the relation of data points with a time gap of more than one unit [6]. All three criteria get a score in the range of [0 – 1], with 1 representing the optimum score for the HIs. After considering all of the above-mentioned criteria, the Fitness metric is defined as follows:

$$Fitness = a \cdot Mo_{(HI)} + b \cdot Tr_{(HI)} + c \cdot Pr_{(HI)} \tag{4}$$

which ranges from 0 (minimum quality) to 3 (best quality) for the assessed HIs, assuming that the constants a, b, and c are 1.

SIGNAL PROCESSING

Before utilizing the deep learning (DL) model, certain steps can be taken to enhance performance and reduce the complexity of the subsequent DL model. One popular technique is to process the signals by extracting the envelopes of LW signals using the magnitude of their analytic signal. This is accomplished by applying the filtering process known as the Hilbert transform (HT). However, in discrete-time signal processing, the HT is substituted with a finite impulse response (FIR) filter, which helps decrease computational complexity. This specific FIR filter is referred to as the Hilbert transform FIR (HT-FIR) filter. The length of the filter is determined based on the frequency of the excitation in the current study. For example, a frequency of 400 kHz corresponds to an HT-FIR filter length of 400. To create the filter, an ideal brick-wall filter is windowed using a Kaiser window with a shape parameter $\beta = 8$. Figure 1 displays Lamb wave signals captured at baseline and at the 50000^{th} cycle, with an excitation frequency of 150 kHz, for the path between actuator 5 and sensor 12. Similarly, all signals undergo processing to generate upper and lower envelopes.

SEMI-SUPERVISED CRITERIA-BASED FUSION MODEL

This section explains the overall learning framework first, followed by the DL architecture and training adjustments.

Learning framework

Due to the absence of an actual HIs value, an imaginary function is employed to generate the ideal HIs labels, and an SSL paradigm is applied by implicitly integrating the prognostic indices (Mo, Pr, and Tr) and leveraging the existing EoL [6]. This approach falls under the category of intrinsically semi-supervised inductive learning algorithms, which are advancements over existing supervised algorithms that allow for the direct use of labeled and unlabeled data for optimizing an objective function with elements. The optimal generator function, which is expressed in terms of the usage time (t), has the

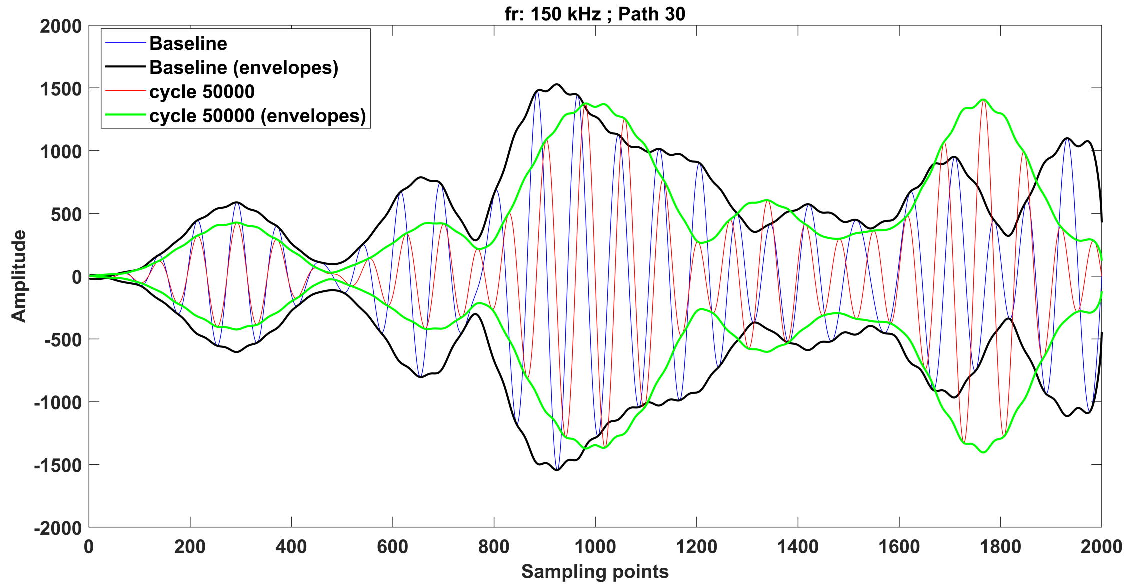

Figure 1. Sensed Lamb wave signals at baseline and 50000 cycle with an excitation frequency of 150 kHz for path 30 (actuator 5 and sensor 12).

form of a quadratic polynomial ($HI_{(t)} = t^2/t^2_{EoL}$). The labels in the current work are scaled by a factor of 100 as well, giving them a range of [0, 100], where 0 denotes the initial state and 100 denotes the failure threshold (EoL).

Deep learning architecture and training

The convolutional neural network (CNN), as depicted in Figure 2, has been specifically designed to optimize the fitting of LW inputs to the ideal simulated HI. This network is referred to as the semi-supervised CNN (SSCNN) from now on, as it follows a fusion model based on the SSL paradigm. To prepare inputs, a 3D form of 36×2000×4 is considered, which includes 36 paths between 6 actuators and 6 sensors, 2000 sampling points, and 4 signals of upper and lower envelopes (see Section SIGNAL PROCESSING) in two states – baseline and current time. The leakage coefficient for all leaky rectified linear unit (Leaky ReLU) functions is 0.01. As the regression loss function between predictions and targets, a mean squared error (MSE) is used.

DATA SET OF FATIGUE EXPERIMENTS

In this study, four carbon fiber reinforced polymer (CFRP) samples (L1S11, L1S12, L1S18, and L1S19) were considered for evaluation of the proposed approach. These samples had a layup configuration of $[0_2/90_4]_s$ and underwent accelerated aging experiments, specifically T-T fatigue, conducted at Stanford Structures and Composites Laboratory (SACL) in collaboration with the Prognostics Center of Excellence at NASA Ames Research Center [8–10]. Each specimen was monitored with a total of 36 transmission paths of LWs, consisting of one-shot and one-receiving PZT sensor array.

The excitation frequencies ranged from 150 to 450 kHz with 50 kHz intervals, using an average input voltage of 50 V and a gain of 20 dB. Measurements were recorded under

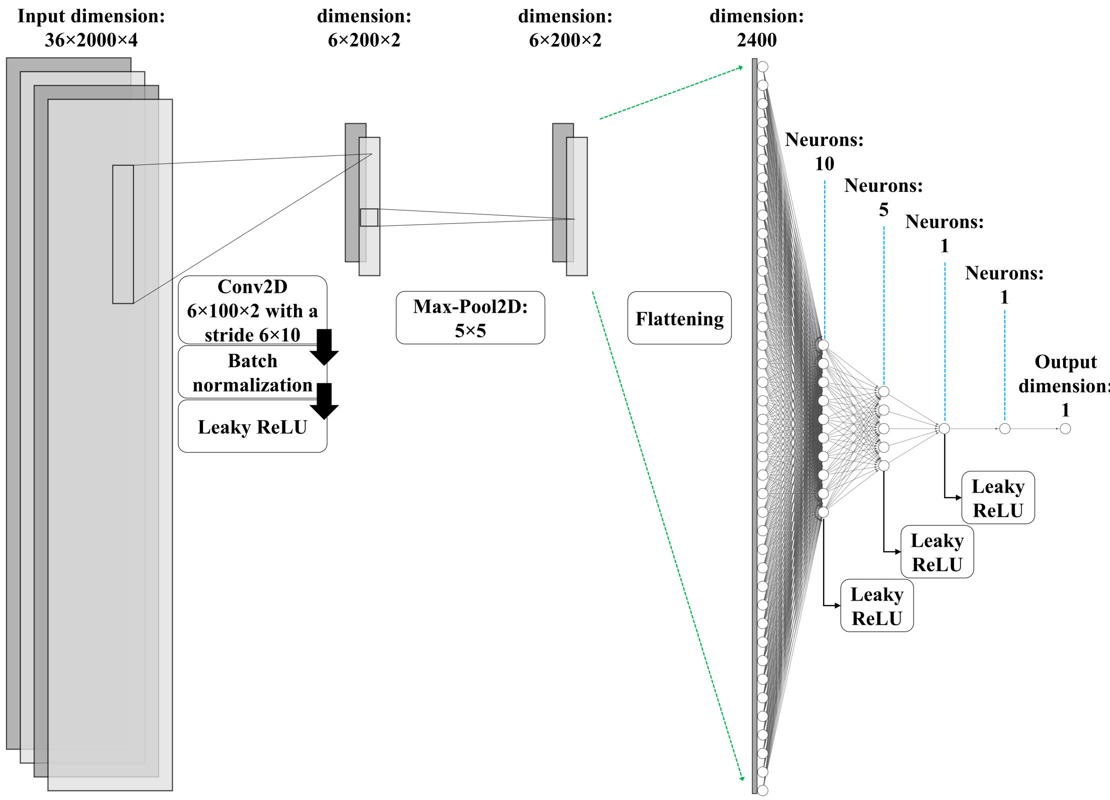

Figure 2. The architecture of the proposed CNN model.

three different boundary conditions: traction free, clamped, and loaded. However, for purposes of this study, only measurements under the clamped boundary condition were considered due to their closer resemblance to real-world scenarios. In some cases, multiple measurements were recorded at the clamped boundary condition, with a preference given to the first one in this study.

RESULTS AND DISCUSSIONS

An Adam optimizer was utilized to train the SSCNN with 28800 learnable parameters, employing an initial learning rate of 0.001. The SSCNN model was trained using the first two specimens (L1S11 and L1S12), while the third specimen (L1S18) was utilized for validation and the fourth specimen (L1S19) for testing purposes. The maximum number of training epochs was set to 200, with a batch size of 10 and shuffling of samples performed every epoch. However, the network's output is determined based on the best validation loss, and the validation check was performed every 10 iterations (the number of trained batches). The constructed HIs by the SSCNN model are shown in Figure 3. The results are also smoothed using a moving average filter with a window length of 3, i.e., two elements before the current position are taken into account. The evaluation metrics for the constructed HIs are presented in Table I.

As seen in Table I, the Fitness scores for the raw constructed HIs range from 1.53 to 1.98, while the minimum and maximum Fitness scores for the smoothed constructed HIs are 2.03 (at the frequency of 250 kHz) and 2.53 (at the frequency of 200 kHz), re-

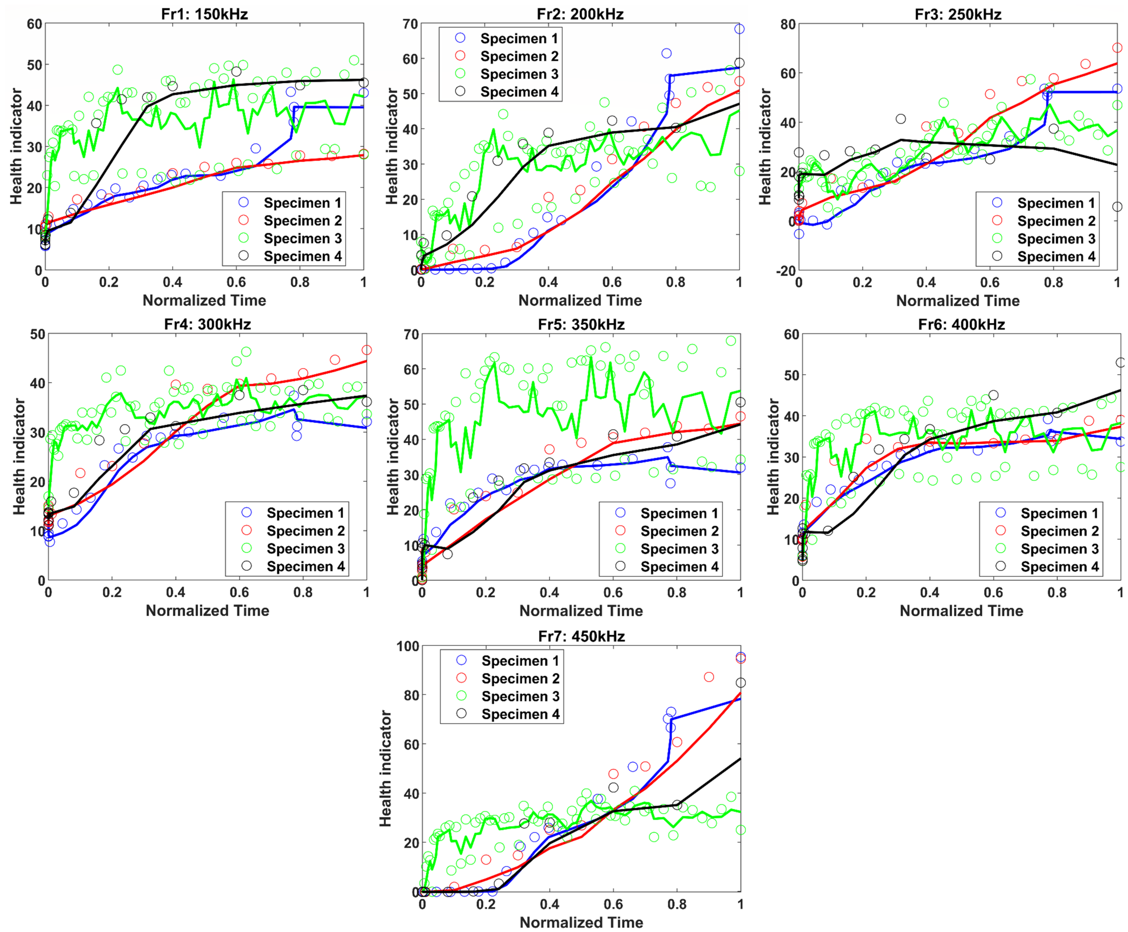

Figure 3. The constructed HIs by the SSCNN model. The first two specimens were used for the training phase, while specimens 3 and 4 were considered for the validation and testing phases, respectively. The main and smoothed outputs are shown with circles and solid lines, respectively.

TABLE I. THE EVALUATION METRICS FOR HEALTH INDICATOR CONSTRCUTED BY THE SSCNN MODEL (RAW / SMOOTHED).

HIs' metrics	150 kHz	200 kHz	250 kHz	300 kHz	350 kHz	400 kHz	450 kHz
Mo	0.57 / 0.94	0.67 / 0.98	0.96 / 0.93	0.64 / 0.91	0.54 / 0.86	0.56 / 0.88	0.60 / 0.93
Pr	0.72 / 0.78	0.71 / 0.89	0.51 / 0.62	0.77 / 0.80	0.80 / 0.80	0.72 / 0.86	0.64 / 0.69
Tr	0.37 / 0.64	0.54 / 0.65	0.05 / 0.48	0.58 / 0.75	0.48 / 0.70	0.48 / 0.67	0.51 / 0.60
Fitness	1.66 / 2.36	1.92 / 2.53	1.53 / 2.03	1.98 / 2.46	1.82 / 2.36	1.76 / 2.41	1.75 / 2.21

spectively. These results demonstrate the acceptable performance of the SSCNN model. It is important to emphasize that the training phase involved completely separate CFRP coupons, which closely resembles real-world applications. The excitation frequency of 250 kHz yielded the least favorable HIs, whereas the 200 kHz and 300 kHz frequencies produced the highest-quality HIs.

CONCLUDING REMARKS

Designing a reliable health indicator (HI) for composite structures under fatigue is very difficult without access to historical data. In this regard, the LW system was used to monitor the health of composite laminates in the current work. SSCNN, a deep learning model, was suggested and validated using accelerated aging experiments from NASA's prognostics data repository to generate a HI that meets prognostic criteria utilizing only the most recent LW data. The results showed that the proposed approach is effective, and the effect of different excitation frequencies on the prognostic criteria was explored.

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REFERENCES

1. Yue, N., A. Broer, W. Briand, M. Rébillat, T. Loutas, and D. Zarouchas. 2022. "Assessing stiffness degradation of stiffened composite panels in post-buckling compression-compression fatigue using guided waves," *Composite Structures*, 293:115751.
2. Coble, J. and J. W. Hines. 2009. "Identifying optimal prognostic parameters from data: a genetic algorithms approach," in *Annual Conference of the PHM Society*, vol. 1.
3. Coble, J. B. 2010. "Merging data sources to predict remaining useful life–an automated method to identify prognostic parameters," .
4. Lei, Y. 2016. *Intelligent fault diagnosis and remaining useful life prediction of rotating machinery*, Butterworth-Heinemann.
5. Moradi, M., P. Komninos, R. Benedictus, and D. Zarouchas. 2022. "Interpretable neural network with limited weights for constructing simple and explainable HI using SHM data," in *Annual Conference of the PHM Society*, vol. 14.
6. Moradi, M., A. Broer, J. Chiachío, R. Benedictus, T. H. Loutas, and D. Zarouchas. 2023. "Intelligent health indicator construction for prognostics of composite structures utilizing a semi-supervised deep neural network and SHM data," *Engineering Applications of Artificial Intelligence*, 117:105502.
7. Kralovec, C. and M. Schagerl. 2020. "Review of structural health monitoring methods regarding a multi-sensor approach for damage assessment of metal and composite structures," *Sensors*, 20(3):826.
8. Saxena, A., K. Goebel, C. C. Larrosa, V. Janapati, S. Roy, and F.-K. Chang. 2011. "Accelerated aging experiments for prognostics of damage growth in composite materials," Tech. rep., NATIONAL AERONAUTICS AND SPACE ADMINISTRATION MOFFETT FIELD CA AMES RESEARCH . . . .
9. Saxena, A., K. Goebel, C. Larrosa, and F. Chang. 2015. "Cfrp composites dataset, nasa ames prognostics data repository," *NASA Ames Research Center, Moffett Field, CA*.
10. Chiachio, M., J. Chiachio, A. Saxena, and K. Goebel. 2013. "Documentation for the fatigue dataset in composites," *NASA Ames Res. Center, Tech. Rep*.