

From Raw Data to Monotonic and Trendable Features Reflecting Degradation Trends in Turbofan Engines

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Abstract—The performance of prognostic models relies heavily on the form and trend of the extracted features. However, the raw data collected from physical systems are inherently noisy, large in volume, and exhibit significant variability, which makes them unsuitable for direct use in prognostics. These characteristics poorly reflect the degradation behavior of physical systems and contribute to the uncertainty of prognostic outcome. Hence, transforming this data into relevant features and carefully selecting them is crucial for meeting the specific needs of prognostic models. This paper aims to address data processing challenges by focusing on extraction and selection of high-quality monotonic features which clearly reflect the degradation and can reduce prognostics uncertainty. The proposed framework comprises three main stages: Data pre-processing, feature extraction, and feature selection. It includes a fitness analysis to evaluate the monotonicity and trendability of features supplemented by visual inspections to identify relevant features. Applied to the Commercial Modular Aero-Propulsion System Simulation (CMAPSS) dataset from the NASA Ames Prognostics Data Repository, the framework reduces noise, improves feature monotonicity and trendability, and facilitates the selection of useful features — essential aspects for effective prognostic methods

Keywords—feature extraction, feature selection, monotonicity, trendability, prognostics, turbofan

I. INTRODUCTION

Managing engineering assets to ensure their reliability, availability, and safety is a significant challenge for operators. Traditional maintenance strategies often lead to unexpected failures, costly downtime and inefficient use of resources [1]. Prognostics and Health Management (PHM) has emerged as an important strategy to overcome these challenges by providing a systematic approach to asset management. Prognostics, a key component of PHM, is the process of evaluating the current health of systems and predicting when they will no longer function as intended. This, combined with health management, enables effective asset lifecycle management, improving operational efficiency and safety. This proactive approach allows organizations to anticipate failures, reducing downtime and extending asset life.

In this process, a large amount of data is collected from various sensors and monitoring devices. This data includes vibration levels, temperature readings, pressure values, and acoustic signals, and is crucial for gaining insights into the health and performance of an asset. However, due to the large volume of data, managing and analyzing this information presents a significant challenge. Ensuring data quality is important since critical information about the degradation process is often obscured by the noise, variability, and large

volumes of raw data [2]. These problems can lead to non-monotonic behaviors, non-trendable patterns, and the "curse of dimensionality" of features, all of which contribute to measurement uncertainty [3]. This uncertainty can have a significant impact on the accuracy of prognostic models used to estimate the remaining useful life (RUL) of machines, making it difficult to derive actionable insights.

Transforming this raw data into monotonic and trendable features and selecting relevant features is crucial for developing robust prognostic models that can accurately predict the RUL of components and enable effective predictive maintenance strategies. The accuracy and reliability of prognostic predictions depend heavily on how this data is pre-processed, as well as the extraction and selection of features used for analysis. Proper data pre-processing - such as cleaning, normalizing, and transforming raw data to remove noise and inconsistencies - is essential to minimize uncertainties in prognostic models. Additionally, the choice of features must accurately capture the health and performance characteristics of components, as inappropriate feature selection can lead to significant prediction errors.

Recent studies have shown the importance of features with consistent monotonicity and trendability for prognostic modelling to predict the RUL of degrading assets accurately [4][5][6]. Non-monotonic features that do not effectively represent the progression of failure can complicate the prognostic process and lead to unreliable results; such features should ideally be avoided during model construction. Fig.1 illustrates these challenges by showing examples of raw data signals and their respective feature types:

- Monotonic and trendable curves are desirable for accurate prediction with less uncertainty, as the predicted degradation is expected to progress consistently until it reaches the failure threshold.
- Non-monotonic and non-trendable curves can lead to significant prediction errors, results in significant uncertainties that could compromise decision-making.

This figure shows the impact of these feature types on RUL predictions, highlighting how extracting high-quality, trendable features can reduce prognostic uncertainty and improve prediction accuracy. Therefore, this paper addresses the aspects of extracting and selecting useful features for prognostics by proposing a framework for transforming raw sensor data into monotonic and trendable features, and demonstrates the application of this framework using the NASA turbofan engine dataset. The main contributions of the papers are as follows:

- Improved feature extraction by applying appropriate data pre-processing and smoothing techniques;
- Improved feature selection by analyzing the fitness of features based on monotonicity and trendability metrics.

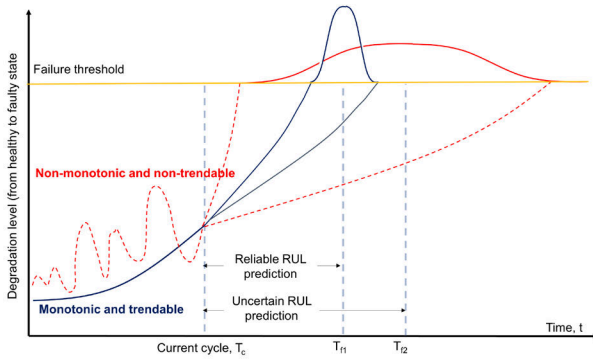


Fig. 1. Monotonic and trendable features and its impact to RUL predictions. Source: Adapted from [7]

The paper is organized as follows: Section 2 reviews existing literature on feature extraction and selection. Section 3 describes the proposed framework for data pre-processing, feature extraction and selection. Section 4 presents the application and results. Finally, Section 5 concludes the paper and outlines plans for future work.

II. LITERATURE REVIEW

Sensor data acquired from machinery typically has high noise levels, significant variability, and large volumes. Therefore, transforming this data into relevant features is necessary to meet the needs of prognostic models. Various signal processing techniques can be applied to extract valuable information from raw data in the time, frequency, and time-frequency domains, enabling the assessment of machinery conditions [8]. The time domain (TD) focuses on changes over time. Features are extracted by computing statistical metrics such as mean, median, variance, skewness, and kurtosis. However, it is worth to note that this domain can be sensitive to noise [9], making it difficult to detect underlying trends or discover fault related features without additional filtering or processing.

The frequency domain (FD) analyses signals based on the different frequencies rather than changes over time. By analysing signals in this domain, it is possible to identify fault-related features that are not detectable in TD. The Fast Fourier Transform (FFT) is the most widely used method in this category as demonstrated in [10][11]. In both studies, the authors used FFT to extract features from TD by converting it to the frequency spectrum and applying statistical analysis. Other methods in this domain include cepstrum, spectral analysis, higher order spectra and envelope analysis, as described in [7].

Feature extraction commonly involves analysis in both, TD and FD. Abdelfettah & Oualid [6] extracted health indicators from vibration signals in both domains, demonstrating their relevance in PHM. Soualhi et al. [12] highlighted the simplicity and rapid computation of TD analysis, making it a preferred method for initial feature extraction. However, a major drawback of these domains is their struggle with non-stationary signals, which are common in faulty machines [13]. To address this limitation, the time-frequency domain (TFD) analysis could be introduced, as it

allows for the observation of how a signal's frequency content evolves over time.

The TFD offers dynamic analysis of signals with varying spectral properties, making it ideal for accurately capturing and understanding complex variations within non-stationary signals. In this domain, frequently employed methods include the Short-Time Fourier Transform (STFT), the Wigner Ville Distribution (WVD), the Wavelet Transform (WT), and the Hilbert Huang Transform (HHT) [14]. Wavelet transforms (WT) have been widely used for feature extraction in PHM systems due to their ability to capture information in the TFD. Thoppil et al. [15] utilized WT to extract statistical vibration signature features, emphasizing the importance of these features in indicating machine component degradation. Similarly, Praveen et al. [16] applied continuous WT for signal processing, highlighting its effectiveness in capturing complex data patterns. However, it is important to note that researchers must carefully evaluate which method is most appropriate for their specific needs. No single method guarantees ideal features for prognostic applications, as performance varies significantly from case to case.

The features from time, frequency, and time-frequency domains are important for evaluating the condition of systems. However, engineering assets often involve dealing with high-dimensional datasets, which can lead to problems. Including all these features in the prognostics model can result in overfitting, poor performance, and reduced interpretability [17]. Therefore, it is important to select useful features that can better indicate the degradation of the machine component. Monotonicity and trendability are key criteria for feature selection, as highlighted by Moradi et al. [18] and Kurrewar et al. [19]. Monotonic features provide consistent and predictable behaviour, while trendable features enable effective prediction of equipment health. Together, they ensure the development of robust prognostic models.

Correlation coefficients are common methods for evaluating feature relevance to look the trendability and monotonicity of the features. Du et al. [10] utilized Pearson correlation to measure the correlation between two time points to determine trends over time and construct health indicators while Hsu et al. [20] applied Fisher's criterion to identify key TD feature parameters. Hybrid and advanced methods, which combine multiple criteria and domain knowledge, are also employed in feature selection. Wen et al. [21] integrated hybrid metrics and trendability to enhance feature selection, while Bai et al. [22] used sparsity measures and temporal correlation to evaluate feature robustness. Therefore, it is important to select useful, trendable, and monotonic features to improve the model's accuracy, reduce complexity, and improve interpretability of the results.

Previous research on feature extraction and selection in PHM systems highlights several limitations that could introduce uncertainty into prognostic models. Lin et al. [23] and Kong et al. [24] eliminated sensors with constant outputs and non-contributory readings, respectively, but did not employ comprehensive feature selection processes. Sharma et al. [25] addressed feature correlation inadequately, retaining all highly correlated sensors without applying any selection techniques. Wei et al. [26] focused solely on trendable features, neglecting other important data characteristics. Javed et al. [27] relied on past literature for feature selection without context-specific validation.

More precisely, most of the approaches discussed run the risk of overlooking important indicators that may be relevant under specific conditions. While this method might retain unnecessary features, it can also discard potentially useful ones, compromising the effectiveness and adaptability of prognostic models accuracy. In this context, the main issues from the previous research can be highlighted as follows:

- Data and measurement uncertainty and impact on feature extraction
- Selecting features that do not clearly reflect the actual degradation.
- Overlooking importance of features for prognostics

To address the above issues, this research proposes a framework aimed at improving the pre-processing, feature extraction, selection stages which can reduce uncertainty of prognostics. The details of the proposed framework are presented hereafter.

III. PROPOSED FRAMEWORK

The main goal of the proposed framework is to extract features that accurately reflect the behaviour of a degrading asset. The first step involves data pre-processing of raw data, which includes filtering to remove noise, handling missing or incomplete data, and normalizing to ensure that each feature contributes equally to the prediction process. Next, feature extraction is conducted to derive relevant information from the data, followed by feature selection, which ensures that only the most useful features are selected for the prediction model by evaluating their fitness. In this study, the NASA turbofan engine degradation simulation dataset are used (which is discussed in detail in the application and results section 4). The complete framework is illustrated in Fig.2.

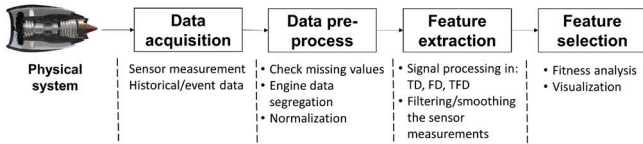


Fig. 2. Key steps in PHM framework – from raw data to useful features

A. Data Pre-processing

Effective data pre-processing is foundational to successful prognostic modeling. It involves transforming raw data into a clean, normalized form that is suitable for extracting meaningful features. Key-processing steps are as below:

Missing Values: It is important to check the data set for missing values, as this affects the accuracy and reliability of the prognostic's models. In this framework, the 'ismissing' function in MATLAB is used. This function checks the data set for missing entries and thus enables a thorough evaluation of all data gaps. Based on the results, decisions can be made about imputing or removing missing data points to ensure that the dataset is as complete and reliable as possible.

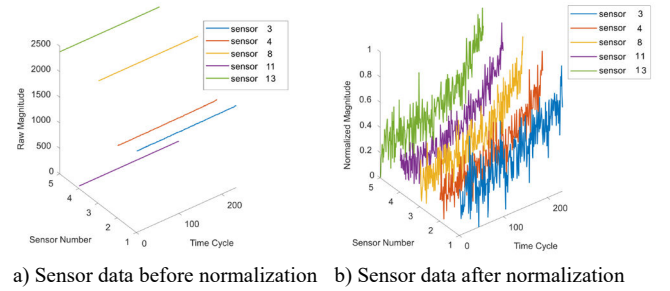
Data Segregation: In prognostics, this process involves dividing data into groups based on specific criteria, such as operational conditions or types of failure. This helps in creating accurate predictive models by training and testing them under varied but controlled conditions. The dataset for FD001 is simulated only under one operating condition, so segregating the data might not be applicable.

Normalization: To ensure that the raw sensor data is comparable across different sensors and conditions, normalization is essential. This is particularly important when dealing with features on different scales, as it can result in one attribute (at a lower scale) being less effective than another attribute with values at a larger scale. Although, there are several normalisation techniques, for this study the min-max scale is applied using the following equation [23]:

$$\hat{x}_i = \frac{x_i - \min_i}{\max_i - \min_i} \quad (1)$$

Where $\hat{x}_i$ is the normalized value of the i-th sensor's reading, x_i is the actual sensor reading, $\min_i$ and $\max_i$ are the minimum and maximum values observed for the i-th sensor, respectively. This equation normalizes the data to a scale where the minimum value becomes 0 and the maximum value becomes 1, making comparisons and further calculations more uniform regardless of the original data scale.

Fig.3 illustrates the data from five randomly selected sensors throughout the entire lifecycle of a single engine in the FD001 training set, presented both before and after normalization. The plots display how sensor values change over time, with the first plot showing raw data to highlight absolute measurements, and the second plot showing normalized data to facilitate consistent cross-sensor comparisons and analysis.



a) Sensor data before normalization b) Sensor data after normalization

Fig. 3. Illustration of five randomly selected sensors data of a single engine in the FD001 training dataset

B. Feature Extraction

Signal processing techniques: Signal processing techniques are crucial for extracting valuable information from raw data, especially in monitoring, diagnostics, and prognosis. These techniques are categorized into three domains: TD, FD, and TFD, each offering methods to identify patterns, anomalies, or important features that are not apparent in the raw data. These techniques were discussed in detail in Section 2. In this study, features are directly extracted from the TD data provided by the CMAPSS dataset, eliminating the need for additional signal processing due to the dataset's comprehensive and informative nature.

Feature smoothing: The main idea behind smoothing is to reveal important patterns in the data by filtering out less important features that are typically due to noise. The ultimate goal is to simplify the learning process in the later analysis stage. Various filtering techniques for smoothing are available in the literature, such as moving average, local regression, Savitzky-Golay filters, etc. In this study, two filtering techniques are used: moving average (MA) and locally weighted scatter plot smoothing (LOESS). MA filter is used to reduce random noise by averaging data points within a

predefined moving window across the time series. It helps to smooth out short-term fluctuations and reveal significant long-term trends, making the data more suitable for analysis. LOESS filter is commonly used in time-series analysis and scatterplot smoothing, where it helps to reveal underlying trends by reducing noise while being flexible enough to capture complex patterns in the data. The smoothing process using MA and LOESS filters is applied according to the formula shown in (2) and (3) respectively, as discussed in [28][29].

$$y_s(i) = \frac{1}{2n+1} [y(i+n) + y(i+n-1) + y(i-n)] \quad (2)$$

Where $y(i)$ is the measurement value at point i , n is the number of neighbouring points, and $2n + 1$ is the total number of data points used in the smoothing process.

$$w_i = \left(1 - \left(\frac{|x - x_i|^3}{d(x)^3}\right)\right)^3 \quad (3)$$

Where x is the value linked to the response y being smoothed, x_i is x 's nearest neighbor within a specific area, and $d(x)$ is the distance between x and its farthest neighbor

C. Feature Selection

Visualization: In the initial phase of feature selection, it is important to check trends visually. This approach allows practitioners to visually analyse the data visually in order to identify clear trends, patterns and anomalies. In this context, feedback from subject matter experts is invaluable to accurately identify these elements. By examining data visually, insights based on domain knowledge and contextual understanding can be integrated early in the analysis. This process is particularly valuable for quickly sifting through large datasets to highlight features that may have significant predictive potential. Visual inspection not only helps to identify key features, but also forms the basis for in-depth analysis, which is essential for the development of effective prognostic models.

Fitness Analysis: Following the visual identification of potential features, statistical methods are utilized to validate these observations. These techniques are effective in assessing features for strong monotonic relationships and clear trends, which are crucial for predicting system degradation or improvement as demonstrated in recent works [30][31][32]. Two metrics are used to evaluate the quality of features prior to selection:

- **Monotonicity (M)** describes a trend that consistently increases or decreases and can be quantified by calculating the absolute difference between the positive and negative derivatives of each feature [7]:

$$M = \frac{\text{no.of } \frac{d}{dx} > 0}{n-1} - \frac{\text{no.of } \frac{d}{dx} < 0}{n-1} \quad (4)$$

Where n represents the total number of observations in the feature. The value of M ranges from 0 to 1, where: $M = 1$ indicates a fully monotonic feature (either increasing or decreasing). $M = 0$ indicates a non-monotonic feature with equal numbers of increasing and decreasing movements or no movements.

- **Trendability (R)** refers to the functional form of an extracted feature and its correlation with time, which indicates how the state of an asset changes over time [13]:

$$R = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (5)$$

The correlation coefficient, R , quantifies the linear relationship between two variables and ranges from -1 (perfect negative correlation) to 0 (no correlation) to +1 (perfect positive correlation). Correlations can be positive (the variables move in the same direction), negative (one increases while the other decreases) or non-existent (no consistent pattern).

IV. RESULTS AND DISCUSSION

A. NASA CMAPSS Data Set

The proposed framework is applied to the CMAPSS dataset provided by NASA's Prognostics Center of Excellence [33]. This dataset simulates turbofan engine operations, documenting operating cycles across various conditions, including altitude, Mach number, throttle resolve angle, and data from 21 sensors. It covers one to six different operating conditions and provides a comprehensive overview of engine performance. The sensor readings capture important parameters such as temperatures, pressures, fan and core speeds as well as operating efficiency, which is indicated by pressure and fuel-air ratio. More detailed information on the simulated data can be found in reference [34].

As discussed, the main objective of this research is to obtain suitable features for prognostics that clearly reflect the degradation trends in Turbofan engines. For this purpose, the training and testing data of turbofan engine (FD001) are used to maintain consistent data processing and facilitate accurate fitness analysis for the selection of effective features as reliable inputs to the prognostics model. The information about this dataset is shown in TABLE 1. These data sets simulate a single failure mode of HPC degradation. TABLE 2 displays the sensor parameters from the CMAPSS dataset, outlining the types of measurements used to monitor and analyze turbofan engines.

TABLE 1. CMAPSS DATASET FD001

Dataset	Information
Number of training engines	100
Number of test engines	100
Operational regions	1
Failure modes	1
Type of failure modes	High pressure compressor (HPC) degradation

TABLE 2. SENSOR TYPES

Sensor	Symbol	Description	Units
1	T2	Total temperature at fan inlet	°R
2	T24	Total temperature at low pressure compressor outlet	°R
3	T30	Total temperature at high pressure compressor outlet	°R
4	T50	Total temperature at low pressure turbine outlet	°R
5	P2	Pressure at fan inlet	psia
6	P15	Total pressure in bypass-duct	psia
7	P30	Total pressure at HPC outlet	psia
8	Nf	Physical fan speed	rpm
9	Nc	Physical core speed	rpm

Sensor	Symbol	Description	Units
10	Epr	Engine pressure ratio (P50/P2)	--
11	Ps30	Static pressure at HPC outlet	psia
12	phi	Ratio of fuel flow to Ps30	pps/psi
13	Nrf	Corrected fan speed	rpm
14	NRc	Corrected core speed	rpm
15	BPR	Bypass Ratio	--
16	farB	Burner fuel-air ratio	--
17	htBleed	Bleed Enthalpy	--
18	Nf dmd	Demanded fan speed	rpm
19	PCNfR dmd	Demanded corrected fan speed	rpm
20	W31	HPT coolant bleed	lbm/s
21	W32	LPT coolant bleed	lbm/s

B. From Raw Data to Feature Extraction

CMAPSS dataset consist of 21 sensors measurement, however some sensor readings are not considered to be informative. Some of the sensors have constant outputs over the lifecycle of the engine, which not provide reliable information for prognostics model (weak correlation with the engine cycle). For FD001 data, the constant output sensors are: 1,5,6,10,16,18,19 excluded which leaves 14 sensors for further experiments. As discussed in preceding section, the framework is applied to both the FD001 training and testing datasets to ensure consistent data processing and to enable reliable evaluation of the data for the selection of useful features as reliable input for the prognostic model.

Fig.4(a) and Fig.4(b) show the normalized raw sensor data acquired from sensor #2, measuring the total temperature at low pressure compressor (LPC) outlet for the training and testing datasets, respectively. The data shows considerable variability, non-linearity and non-stationarity (indicated by changing mean and variance), which is reflected in noisy figures. This introduces significant uncertainty that can affects the accuracy of long-term prognostics models. To address this complexity, filtering techniques are necessary to smooth the data and improve the identification of reliable trends, which are essential for accurate predictions.

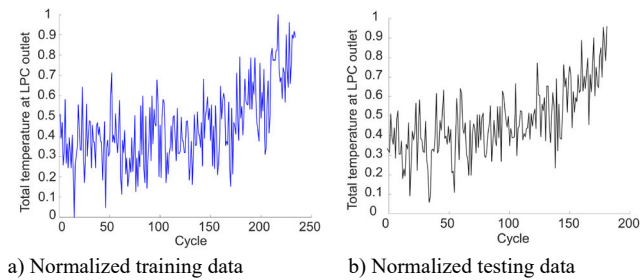
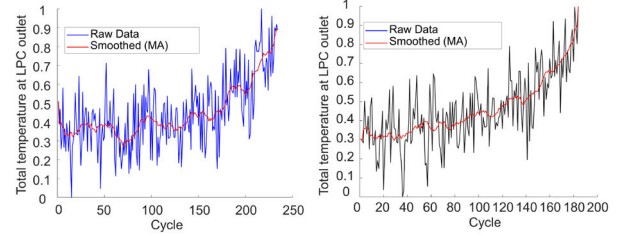


Fig. 4. Illustration of normalized sensor #2 measurements (engine #20 FD001)

A classical filtering approach, known as MA, is applied to reduce noise by averaging the data points over a specific window. Fig.5 shows the application of the MA filter to the sensor data in both the training and testing datasets. The filter effectively reduces the noise, making the underlying trends more visible. This is evident from the smoother lines in the plots compared to the raw data. However, the plots show significant variations, and the trends are not smooth enough to clearly reflect the degradation. In addition, it may not capture local variations and non-linear trends well, which could cause it to miss important features for predictive modelling.

To further improve the smoothing process, LOESS filter is utilized along with MA, as shown in Fig.6. This method is more flexible in adapting to the data, accommodating both

linear and non-linear trends. Different spans were selected empirically to achieve smooth trends that indicate degradation. Its adaptability makes it highly effective for noisy and nonlinear datasets, such as turbofan engine data. This approach provides a more detailed view of the underlying trends, preserving essential variations necessary for accurate prognostics.



a) MA-normalized training data b) MA-normalized testing data

Fig. 5. Illustration of smoothed - normalized sensor #2 measurements using MA (engine #20 FD001)

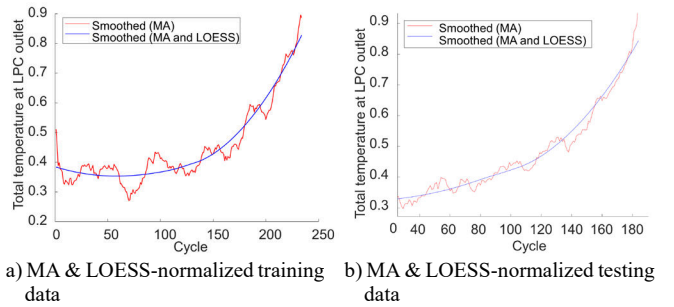


Fig. 6. Illustration of smoothed - normalized sensor #2 measurements using MA and LOESS (engine #20 FD001)

The integration of MA and LOESS significantly improves the feature extraction process and enables the identification of clear, consistent trends from noisy data. This improvement is critical for subsequent analysis as it highlights features that clearly indicate degradation and have significant predictive potential for the health of the system. However, a critical risk in this process is over-smoothing, which can remove essential information of prognostic features and obscure subtle but significant shifts in sensor readings, especially when the resonance peaks are narrower than the filter bandwidth [28]. Therefore, careful consideration and calibration of the smoothing parameters, known as span or filter bandwidth, is required. While a wider span improves the smoothing effect and increases the signal-to-noise (SNR) ratio, it must be carefully considered to avoid obscuring early indicators of system issues.

C. Feature Fitness Analysis and Selection

Fitness analysis is conducted on the extracted features from both datasets to highlight the improvements made by the proposed method compared to the raw data, specifically measuring metrics such as monotonicity and trendability. This evaluation aims to select useful features that accurately reflect the degradation trends in Turbofan engines. These features can be further used for prognostics behaviour and to estimate the RUL. TABLE 3 summarises the results of the fitness analysis for raw data, filtered data with MA and filtered data with MA and LOESS for the training dataset only. Moreover, the comparison of results for both the training and test datasets is shown in Fig.7.

TABLE 3. FITNESS ANALYSIS OF THE FEATURES (TRAINING DATASET)

Feature (Sensor)	Normalized raw data		Normalized Smooth with MA		Normalized Smooth with MA + LOESS	
	R	M	R	M	R	M
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.58	0.01	0.80	0.11	0.84	0.51
3	0.68	0.00	0.94	0.17	0.98	1.00
4	0.79	0.01	0.93	0.30	0.95	1.00
5	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00
7	-0.72	0.03	-0.90	0.19	-0.92	1.00
8	0.76	0.01	0.91	0.24	0.93	1.00
9	0.75	0.03	0.95	0.12	0.97	0.93
10	0.00	0.00	0.00	0.00	0.00	0.00
11	0.81	0.07	0.91	0.27	0.92	0.66
12	-0.71	0.03	-0.85	0.18	-0.87	0.51
13	0.73	0.10	0.89	0.18	0.91	1.00
14	0.59	0.00	0.94	0.08	0.98	1.00
15	0.64	0.00	0.84	0.24	0.86	0.61
16	0.00	0.00	0.00	0.00	0.00	0.00
17	0.68	0.05	0.92	0.23	0.96	1.00
18	0.00	0.00	0.00	0.00	0.00	0.00
19	0.00	0.00	0.00	0.00	0.00	0.00
20	-0.70	0.02	-0.93	0.18	-0.95	0.81
21	-0.68	0.02	-0.89	0.16	-0.90	0.68

The analysis showed that the raw sensor data had low scores, with significant noise and variability obscuring consistent trends necessary for accurate RUL predictions. Applying an MA filter significantly improved these metrics and clarified the trends by reducing the noise. However, caution is advised as over-smoothing can potentially mask subtle early indicators of degradation, resulting in the loss of valuable information. The most promising results were obtained with combined MA and LOESS smoothing, where monotonicity and trendability scores improved significantly, showing better preservation of critical trends while minimizing noise. These results indicate that the use of the combined MA and LOESS approach can significantly improve the quality of the features and thus increase the accuracy of prognostics.

Fig.7 illustrates the relationship between trendability and monotonicity for different sensors using training and test data. Sensors in the upper right quadrant are better suited for predictive modeling as they are highly trendable (showing a strong and consistent pattern or trend over time) and monotonic (consistent increase or decrease in trend). The consistency between the training and test datasets shows that the proposed preprocessing methods have been applied effectively. This analysis helps identify sensors that provide reliable trends for feature selection to improve predictive models for prognostics by excluding less reliable sensors and avoiding redundancies.

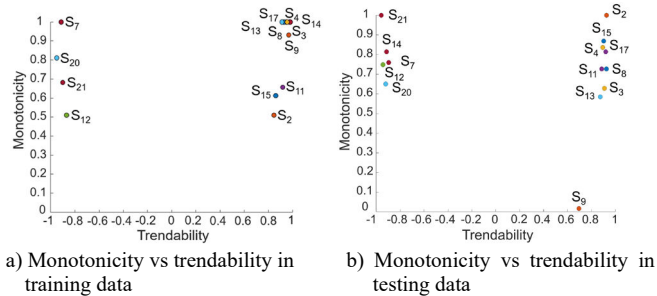
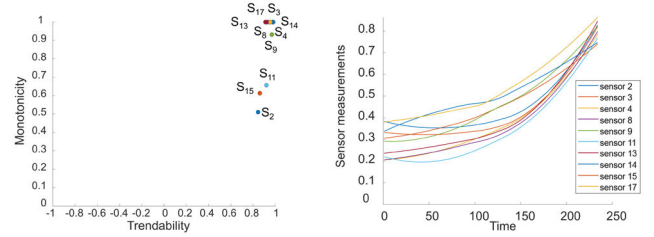


Fig. 7. Fitness analysis

The improved values of trendability (R) and monotonicity (M) in the smoothed datasets indicate a clearer and more reliable representation of degradation trends, which can benefit prognostics modeling. Next, a conservative threshold of 0.5 was applied to identify features with strong trendability and monotonicity. Fig.8(a) shows the selected features surpassing this threshold and indicates consistent and reliable trends over time. This is crucial for prognostic modeling. The importance of selecting useful features for the prediction of RUL is demonstrated in [35]. The study illustrates how it balances the trade-off between simplifying the model for better generalization and retaining sufficient features to capture the complexity of the underlying phenomenon, thus significantly improving the accuracy of RUL predictions. The visualization of the selected time series features, based on high monotonicity and trendability values for the next prognostic modelling, is presented in Fig.8(b).



a) monotonic and trendable features b) time series of selected features

Fig. 8. Selected features

V. CONCLUSIONS

Selecting useful features are essential for prognostics models. In most cases, the data are noisy and high in volume and required a feature extraction and selection process to avoid uncertainty in the prediction. This research primarily contributes to improving feature extraction and selection methods in order to reduce data uncertainty. It highlights the importance of data pre-processing and feature selection, using techniques such as normalization, smoothing and fitness analysis to identify the most relevant features to improve model prediction. The proposed framework is applied to the CMAPSS dataset from the NASA Ames Prognostics Data Repository. Results indicate that the processed data showed improvements in trendability and monotonicity, which facilitated the selection of useful features to improve the accuracy of prognostic models.

However, a critical consideration in this process is the risk of over-smoothing, which can eliminate essential prognostic features. Therefore, it is crucial to carefully adjust the smoothing parameters to achieve an optimal balance between noise reduction and the preservation of key data features. Furthermore, in cases with limited data, smoothing methods can lead to overfitting and unreliable conclusions. The analysis shows that while these methods reduce noise, they are sensitive to sparse data. This emphasizes the need for more data to confirm trends and ensure reliable results. For future research, it would be beneficial to explore the application of this framework to various mechanical systems, such as bearings and gears, to evaluate their effectiveness across a wider range of data sets.

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