A novel prognostics solution for accurate identification of degradation patterns in turbo machines with variable observation window

Unnat Mankad[1], Gabriele Mordacci [2], Aidil Fazlina Hasbullah[3], Fahzziramika Nadia Jaafar [4], Carmine Allegorico [5], and Gionata Ruggiero[6]

[1]*Baker Hughes, Bengaluru, 560037, India*
unnat.mankad@bakerhughes.com

[2,3,4,6] *Baker Hughes, Kuala Lumpur, 50400, Malaysia*
gabriele.mordacci@bakerhughes.com
aidilfazlina.hasbullah@bakerhughes.com
fahzziramikanadia.jaafar@bakerhughes.com
gionata.ruggiero@bakerhughes.com

[5]*Baker Hughes, Florence, 50127, Italy*
carmine.allegorico@bakerhughes.com

ABSTRACT

The degradation of a system is a time bound phenomenon, which leads to the deterioration of turbomachinery, in terms of performance and reliability. If undetected and not acted upon in time, this could also lead to sudden system failure, resulting in unplanned unit downtime and maintenance. Unplanned downtime of a turbomachine leads to severe production loss for the end customer and consequent economic damages. Early detection of a degradation pattern would provide the customer with the opportunity to timely carry out corrective actions, preventing an unscheduled down time. The paper evaluates degradation identification methodology currently known from literature and finds them not accurate enough for general purpose application required by the solution. The paper discusses a novel methodology which can accurately detect degradation patterns of timeseries data. Critical features of this methodology are novel time-based correlation enabled regression model with variable observation window, autonomous training, and automatic adjusting capability to incorporate operating behavior change or physical system replacement. This leads to high accuracy, high generalization, and domain agnostic application capability. Moreover, particular focus is given to achieving high probability of detection and a low probability of false alarm. The paper demonstrates the performance achieved by the methodology when applied to the field of prognostics and diagnostics of IoT connected turbomachines through 50+ real application cases.

1. INTRODUCTION

Rotating Turbomachines play a critical role in Industrial domain in Oil & Gas / Energy Plants serving various applications, such as Liquified Natural Gas (LNG), pipeline, fertilizers, refineries and power generation units. One of the most important aspects for the operators of these turbomachines are continuous availability and reduced downtime covering the entire life cycle. Iannitelli et al. (2018) highlighted that unscheduled shutdown of the turbomachines can have impact on the whole plant downtime with associated significant loss of production.

Baker Hughes is a leading Original Equipment Manufacturer of Rotating Turbomachines with a wide Product Range of Gas Turbines, Centrifugal Compressors, Pumps, Steam Turbines, Electric Motors, Axial Compressors, etc. These products have been operating in various Oil & Gas and Power Generation facilities around the globe covering all the segments of the entire value chain of Oil & Gas industry and have an unparallel operating history.

Baker Hughes has developed monitoring capabilities which are offered as a service, applied to a broad installed fleet of rotating equipment including gas turbines. Baker Hughes' iCenter ecosystem continuously acquires different sensor parameters of its deployed assets at customer premises. These large number of operational data from the everyday operation of turbomachines is usually collected and analyzed by means of analytics, component models and rules implemented by subject matter experts, as soon as new data is transferred to the monitoring center. Allegorico & Mantini (2014) indicated that anomaly detection rules and models are designed to scan through the data and notify the monitoring and diagnostic engineers, if any anomalies or emerging problems are detected. All alerts are analyzed by diagnostic engineers along with trouble shooting analysis and useful insights are sent to customers comprising set of recommendations.

With turbomachinery covering various applications and operating in different operational scenarios, Baker Hughes follows a hybrid approach consisting of physics and data driven methods, where strong OEM knowledge is further enhanced by state-of-the-art data science methodologies to create robust solutions. This approach can be applied to the entire fleet of operating machines, to bring economies of scale and help maximize the availability and uptime of the monitored units.

1.1. Degradation phenomena

In Turbomachines, degradation phenomena accumulate over a period of time. Zagorowska, et al. (2019) indicated that degradation in turbomachine is an unwarranted phenomenon which deviates from the expected behavior and that changes the behavior of the affected system. Few examples of degradation include clogging of filters, performance degradation of compressors, increase spread of exhaust temperature measurement of gas turbines, etc. If degradation is not detected early, this may lead to a gradual build up above the mechanical integrity of the system which can cause sudden failures, break down and consequent downtime of the turbomachine with production loss for the end customer. A typical example of degradation in turbomachinery systems concerns filters. A filter acts as a mechanical stop for contaminants, to make sure they do not pass through the downstream systems. Due to their nature, filters have a tendency to get clogged or choked after a period of operation with gradual buildup of contaminants, creating a higher resistance to the flow. To detect abnormal operating conditions, analytics could be built to observe the behavior of the component by monitoring physical quantities, such as the pressure drop on the filter. This can be analyzed to infer information on its actual defect state. The ability to promptly detect these deteriorating conditions could be useful for implementing corrective actions.

Generally, degradation phenomena cannot always be directly measured, however it is possible to make use of indirect information or calculated parameters to verify the level of degradation of a system (for example the level of fouling of an axial compressor can be determined indirectly through the analysis of its compression efficiency). In general, the presence of a degradation phenomenon is signaled by the fact that the timeseries of interest shows a drift over time. If the timeseries has an upward trend, it is considered a positive degradation, otherwise it is considered a negative degradation.

In the current study, authors have focused on univariate time series with a stationary behavior in the normal operating range of the system. In these cases, a monotonic signal trend is considered anomalous and possibly linked to an ongoing degradation phenomenon. In the event that this monotonic trend is accompanied by a similar behavior of other signals related to it, the event is considered non-independent and therefore not anomalous.

Figure 1 shows a typical behavior of a sensor going through a degradation trend. As the sensor value increases over a period, this is considered a positive degradation phenomena.

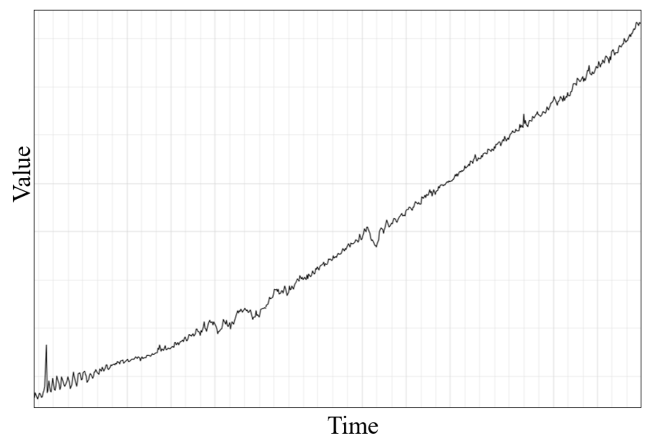

Figure 1. Example of a degradation pattern in a generic signal

In the analysis of degradation phenomena, another factor to consider is the observation time window. Figure 2 highlights the behavior of the same signal over a longer observation time.

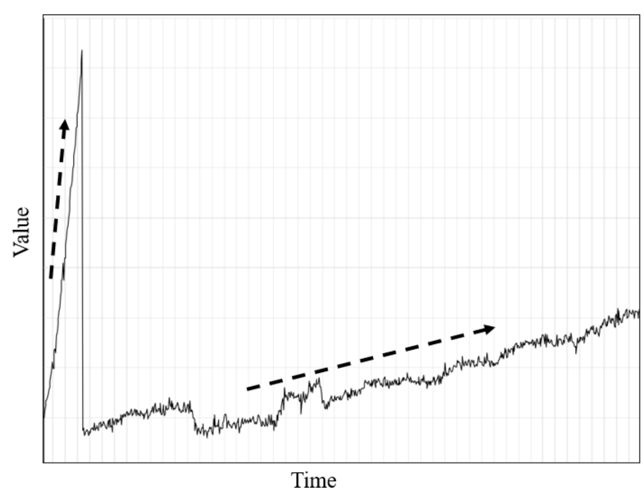

Figure 2. Example of multiple degradation patterns for the same signal

In this case, two different degradation profiles can be noted that evolve with two different time scales. The first degradation profile is quite sudden, while the subsequent one is rather slow and it build up over a longer period of time. The sudden drop down of the signal after the first degradation pattern is currently excluded from the current analysis.

2. Existing Methods for Trend Identification

2.1. Monotonicity Trend – Mann-Kendall Test

The purpose of the Mann-Kendall (MK) test (Mann 1945, Kendall 1975, Gilbert 1987) is to statistically assess if there is a monotonic upward or downward trend of the variable of interest over time. A monotonic upward or downward trend means that the variable consistently increases or decreases through time.

The MK method calculates test statistics as the count of positive and negative deltas in the dataset.

$$\boldsymbol{S} = \sum_{\boldsymbol{j-1}}^{\boldsymbol{n-1}} \sum_{\boldsymbol{i-j+1}}^{\boldsymbol{n}} \boldsymbol{sgn}(\boldsymbol{x_i} - \boldsymbol{x_j}) \qquad (1)$$

Where x is the observation value, i and j are time indices.

If number of observations, $n \geq 10$, Variance of S is calculated as follows.

$$VAR(S)_{MK} = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p-1}^{g} t_p\,(t_p - 1)(2t_p + 5)\right] \qquad (2)$$

where g is the number of clusters of data points having the same data value and t_p is the number of observations in the p th group.

For example, in the sequence of observation in time $\{28, 32, 34, 2, 29, 32, 2, 34, 32\}$ there are $g = 3$ tied groups. Tied group $t_1 = 2$ for tied value of 2, tied group $t_2 = 3$ for tied value of 32 and tied group $t_3 = 2$ for tied value of 34

MK Test statistics is calculated as follows:

$$Z_{MK} = \frac{S-1}{\sqrt{VAR(S)_{MK}}}\ if\ S > 0$$
$$Z_{MK} = 0\ if\ S = 0 \qquad (3)$$
$$Z_{MK} = \frac{S+1}{\sqrt{VAR(S)_{MK}}}\ if\ S < 0$$

A positive value of Z_{MK} indicates an increasing trend, while a negative value of Z_{MK} indicates a decreasing trend.

The MK test was applied on the generic signal in Figure 3, which shows a clear degradation trend in different periods of time. The points where the increasing trend is detected are highlighted in orange.

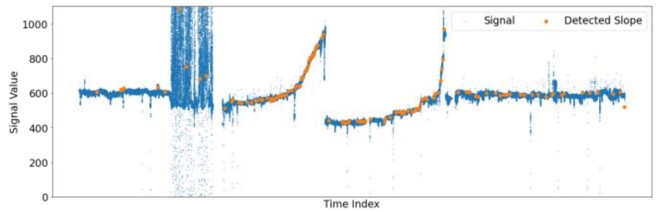

Figure 3. MK Test results

As observed from the Figure 3 for the given data set, the method was promising in terms of detecting the slope region, however it produced many false positives. To improve this manual threshold tuning is required, however this is not a practical and most effective solution for more general and scalable applicability of the methodology.

2.2. Theil Sen Slope Method

Theil (1950) proposed the median of pairwise slopes as an estimator of the slope parameters. Sen (1968) extended this estimator to handle ties. Sprent et al, (1993) indicated that Theil-Sen estimator is a regression method, robust to outliers.

Thiel-Sen estimator calculates the slope by taking the median of the slopes between each pair of points in the data. For a pair of points, $(x_i,\ y_i), the\ slope\ is\ calculated\ as$

$$slope = \frac{(y_j - y_i)}{(x_j - x_i)} \qquad (4)$$

An intercept between each pair of points, can be calculated as

$$b_i = y_i - m * x_i \qquad (5)$$

where m is the Thiel-Sen slope. Following the similar methodology of finding the median of each slope between each pair of points, median of intercept is calculated.

Theil-Sen Slope method was applied on the same signal of Figure 3 after setting an appropriate threshold to detect the degradation pattern. Figure 4 shows the results of the Thiel Sen slope method.

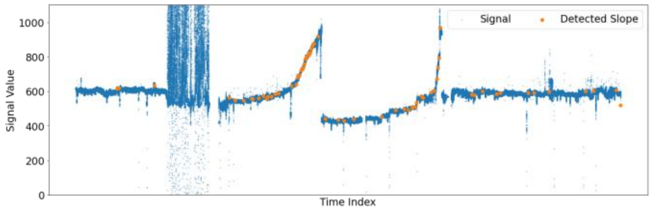

Figure 4. TS Test results

As observed from Figure 4 for given data set, Thiel-Sen method identifies trending patterns, however it still generates many false positives and is strongly dependent on the threshold value, which need to be manually adjusted based on the profile of the signal. This limits the general purpose and scalable applicability of the methodology.

3. Novel Methodology

Abernathy et al. (1973) indicated that sensor measurement are affected by noise and noise increase over a period of time as the sensor ages. Noise of the sensor measurement impacts the method development and it's ability to identify the degradation patterns. Furthermore, the degradation detection method must be easily scalable to other use cases and be able to work with different degradation patterns such as slow and fast degradations and presence of noise.

De Giorgi et al. (2023) have done an exhaustive literature review on detecting degradation phenomena as part of prognostic and diagnostics for jet engine health monitoring and have found that current literature degradation health monitoring techniques have certain gaps in terms of lack of standardization, lack of real world testing/comparative studies and limited consideration of multiple degradations.

Following the above analysis, it was concluded that current methods available in the literature may not effectively provide a generalized and robust solution. Furthermore, the existing methods are quite difficult to be fine-tuned in real application scenarios and are prone to generate a high rate of false positives.

As seen in Figure 3 & Figure 4, the degradation profile of a signal is a function of time. This could be caused by various factors, such as the intrinsic structure of the system, external interferences, natural aging and so on. In order to effectively capture degradation phenomena which evolves over a different time scale, authors had decided to distinguish 2 types of degradation profiles:

- Fast Degradation – These degradation profiles are quick with respect to typical behavior of the given signal/system.
- Slow Degradation – These degradation profiles slowly build over a period of time and may not show an obvious degradation behavior when the observation window is small.

Authors have then devised a novel methodology by filtering the signal into a High Frequency component and a Low Frequency component.

The High Frequency component of the signal is calculated as:

$$High\ Frequency_t = High\ Frequency_{t-1} * \alpha_t + Signal_t * (1 - \alpha_t) \quad (6)$$

Where α is the exponential smoothing average constant. As degradation phenomena are function of time and depends on past values, this constant has been selected to keep a balance between past observations and current values. After a careful analysis and various tests on real cases, this value was kept at 0.35.

The low frequency component of the signal is then calculated as

$$Low\ Frequency_t = Signal_t - High\ Frequency_{t-1} \quad (7)$$

Figure 5 shows the original signal and decomposition of the same into high & low frequency component of the given signal. Observing Low Filter, it is evident that, this features carries out the denoising of the signal.

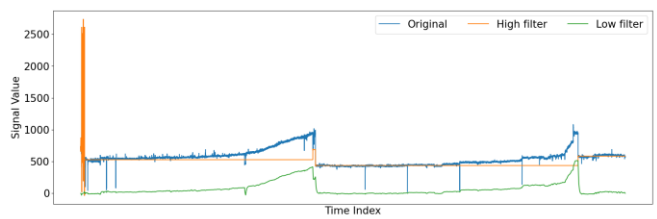

Figure 5. Signal decomposition in Low frequency

A novel time-based correlation approach was used to identify the degradation patterns of the low frequency component. The approach was based on the observation that if the signal is trending up or down over a period of time, it shall have a strong correlation with time, which will be positive or negative respectively.

The correlation coefficient was obtained by normalizing the covariance of the low frequency signal.

The covariance of the signal is calculated as

$$Covariance = E[XY] - (EX)(EY) \quad (8)$$

The variance is calculated as

$$Var_X = E[X^2] - E[X]^2$$
$$(9)$$
$$Var_Y = E[Y^2] - E[Y]^2$$

Then the correlation coefficient is calculated as

$$Corelation\ Coefficient = \frac{Covariance}{\sqrt{Var_X * Var_Y}} \quad (10)$$

A threshold of 0.9 was then applied to this correlation coefficient to detect sections of the signal with high slope, as showed in Figure 6.

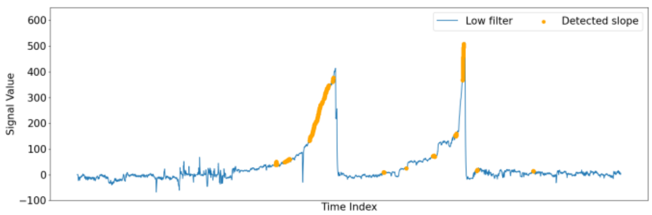

Figure 6. Time based correlation on Low frequency

As observed from Figure 6, the method is more robust and less sensitive if compared to previously discussed methods. It effectively captures the sections with high slopes; however, it is not capable of capturing the areas where degradation is slowest and it also generates some sporadic false alarms.

To overcome the limitation of the current method on the slow degradation patterns, the authors devised the dedicated approach described in the next paragraph.

3.1. Methodology for Slow Degradation

Verbai et al. (2024) applied linear regression method to identify and predict the degradation phenomena. Authors have further used the linear regression method to develop the methodology to capture slow degradation

The linear regression model is expressed as:

$$\hat{y}_i = b_0 + b_1 * x_i \quad (11)$$

Where $\hat{y}_i$ is the predicted value, b_0 is the intercept of the line, b_1 is the slope of the line, and x_i is the actual value.

The linear regression model is fit on 1 week of Low frequency data of the signal and further analysis is carried out on the line slope b_1, R^2 error and Root Mean Square Error.

R-squared (R^2) of the linear regression model is calculated as

$$R^2 = 1 - \left(\frac{SS_{residual}}{SS_{total}}\right) \quad (12)$$

Where $SS_{residual}$ is the sum of squares of the residual errors and SS_{total} is the total sum of the errors.

R^2 indicates the proportion of data points which lie within the line created by the regression model. A higher value of R^2 is desirable as it indicates a better fit.

To ensure a good regression model for subsequent analyses, a minimum value of R^2 score is required.

The Root Mean Square Error (RMSE) indicates the quality of predictions. It evaluates how far predictions are from the measured true values using Euclidean distance.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (13)$$

Where $\hat{y}_i$ is predicted value, y_i is actual true value and n is number of observations.

Above regression methodology was applied on low frequency of 7 days data. However in order to early detect the degradation phenomena, observation window considered was 1 day.

To further make sure that generated errors are within the typical operating range of the signal a threshold was applied on RMSE as a function of normal operating range of the signal.

To make sure, that only important degradation patterns are captured, a minimum threshold value was applied on the slope on top of already discussed threshold on R^2 and RMSE values. The proper value of the threshold was selected while doing an exhaustive testing to obtain a balance between False Positive and False Negative.

Results of Figure 7 shows the degradation pattern captured by the new methodology with high accuracy.

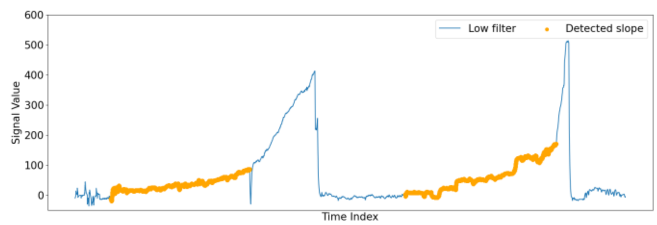

Figure 7. Detection by Slow Degradation Methodology

3.2. Time Window for Fast and Slow Degradation

Based on the extensive tests carried out and iteratively optimized, authors have specified 2 different observation periods, 24 hours and 7 days, which have proven to be effective on use cases that are common in our industry.

Table 1. Time Window duration

Degradation Type	Time Window
Fast Degradation	24 Hours
Slow Degradation	7 Days

3.3. Autonomous Training and Self Adjusting Capability

The developed methodology is intended to have a general-purpose application by covering various types of signals that are typically acquired on turbomachines. Moreover, it must be able to function correctly for signals that span in a wide operating range.

To meet the above requirement, authors have developed a methodology to characterize the “Normal State” of operation of a signal, namely its typical operating range known from the past.

In order to define an operation range of the signal and detection of potential anomalous behavior of the signal, authors have then developed a typical operating range of signal called as confidence band.

Confidence Band is a function of the following signal statistical indicators and is calculated dynamically:

$$Confidence\ Band = f(Mean, Standard\ Deviation, Quantiles) \quad (13)$$

Any sustained operation outside of the normal state could be considered as a potential degradation pattern.

The method continuously updates the above statistics and redefines the system normal state when needed. Other factors that influence the signal behavior are the maintenance events such as major inspections, repairs, replacements, etc. and other external contributors like the process load and ambient conditions, which can lead to different operating behavior of a given signal. The algorithm is designed to self-adjust when this change in signal behavior occurs.

4. TECHNICAL CASES

Authors have extensively applied and tested this methodology on a variety of turbomachinery signals acquired by Baker Hughes’ monitoring service. In the following section the authors reported some examples of real degradation events captured by applying this methodology on historical data. If not detected promptly, the progression of the degradation phenomenon could have caused the signal of interest to reach protection thresholds, causing alarms or even the trip of the unit. A trip leads to unavailability of the turbomachine and the loss of production for the end customer, with consequent economic damage.

The implemented methodology provides early detection of degradation of critical signals and provides the opportunity to perform corrective actions and increase the availability of turbomachinery.

This section captures few of the real technical cases captured from variety of signals acquired by Baker Hughes’ monitoring service. Few of these signals are part of Centrifugal Compressors Auxiliary systems, Gas Turbines, etc. Some of the examples of these signals are Filter Differential Pressure, Vent Pressure, Compressor Efficiency etc,. As discussed before, these signals are expected to be stationary with in the normal operating range of the system. Any independent monotonic trend identification is considered to be anomalous behavior of the signal.

The grey are highlighted in the figures represents Confidence Band of the signal, which is the expected range of operation. As discussed before, methodology keeps on dynamically calculate this confidence band. Anomaly events are generated when the signal exceeds this confidence band.

4.1. Example of Fast Degradation

This section describes the example in which underlying degradation phenomena is Fast in nature and happens with in time window of 24 hours.

4.1.1. Fast Degradation Profile 1

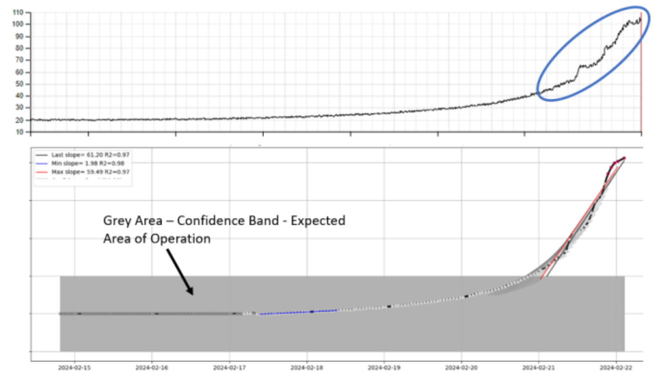

Figure 7. Detection of Fast Degradation event 1

4.1.2. Fast Degradation Profile 2

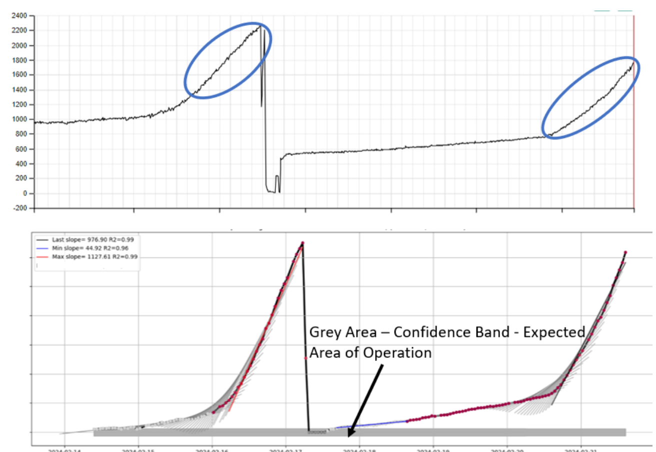

Figure 8. Detection of Fast Degradation event 2

As seen from Figure 7 & Figure 8, the methodology can effectively capture fast degradation of the signal, even when signal has high oscillation or a reset.

4.2. Example of Slow Degradation

This section describes the example in which underlying degradation phenomena is Slow in nature, accumulates over a longer period of time and happens with in time window of 7 days.

4.2.1. Slow Degradation Profile 1

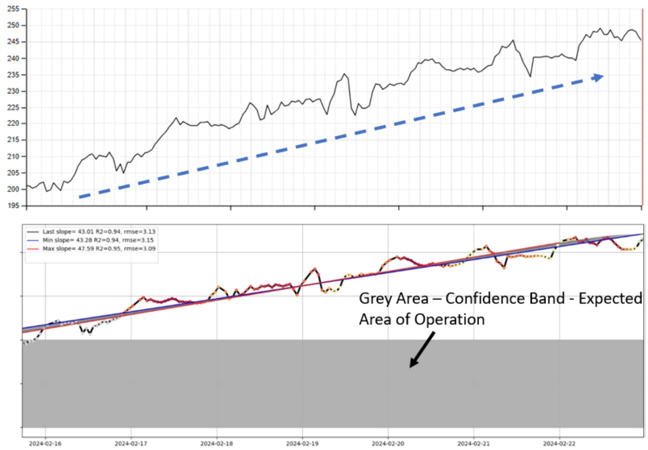

Figure 9. Detection of Slow Degradation event 1

4.2.2. Slow Degradation Profile 2

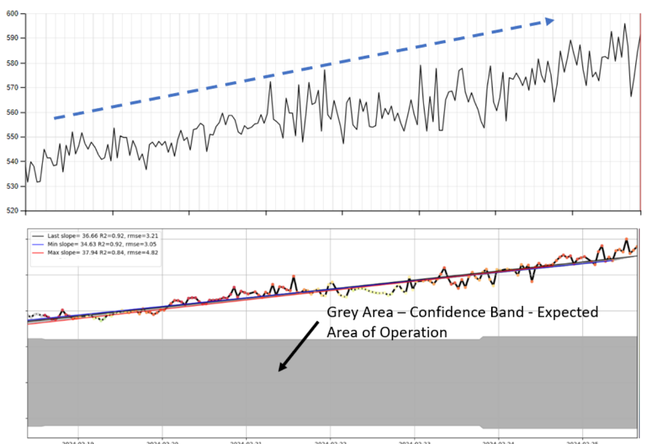

Figure 10. Detection of Slow Degradation event 2 – Noisy signal

In some cases, the monitored signal can be noisy and this may impact the detection capability of the algorithm. A such example is visible in Figure 10, where the raw signal is noisy, but at the same time shoes a slow degradation process. With the novel approach of the methodology, segregating low frequency of the signal, the methodology is effectively able to denoise the signal and accurately captures the degradation trend.

4.3. Timely Corrective Actions

The degradation patterns detected by this analytic could be associated to some specific failure modes of the system, thus mapping of this potential root cause with detected type of degradation phenomena is of high importance. Based on strong OEM knowledge, Baker Hughes has identified up to 8 root causes for degradation patterns. Some of these root causes are Instrument deviations, Clogging, Condensation, Process fluctuations, Fouling etc. With the given identified root cause, diagnostic engineers then propose a targeted corrective actions to the site service engineers. Implementation of this corrective actions eventually leads to improved uptime of the unit with no unscheduled shutdowns/repairs for the end customer.

5. Result Analysis

To summarize, the novel methodology proposed by the authors, separates High frequency and Low frequency component of the signal to effectively denoise the data and separate the rapid changes happening into the signal.

As the degradation profile is strongly dependent on the time interval, currently 2 observation windows have been considered. Results have shown that method is effectively able to capture the Fast and Slow degradation of the signal, whereas standard methods like Mann Kendall and Thiel Sen slope has not been very effective and accurate in either identifying the degradation trend or wrongly capturing the degradation. It is to be further noted that, analytic has quite good generalization capability as it is able to catch wide operating range of signal as observed from Figure 7, 8, 9 & 10.

In order to validate the methodology on a larger data set, the approach was applied on 600+ turbomachines being monitored by Baker Hughes's iCenter eco system. With extensive understanding of Turbomachines system, signals for validation were selected in such a way that signal show a degradation trend due to inherent malfunctioning of the system. Some of the examples of these signals are Filter Differential Pressure, Vent Pressure, etc. Methodology was tested in a Batch process where incoming data with a given sampling frequency of 1 minute was processed in a batch of 2 hours.

To calculate the key performance indicators of the methodology, a manual approach was used which required a great effort from the subject matter experts to analyze all the events generated by the algorithm. The methodology was also tested on a number of real cases of degradation that were already known to the monitoring service.

Table 2 shows the performance metrics of the method implemented.

Table 2. Performance of Method during Validation

Details	Value
Number of Assets on which methodology was applied	600+
Average processing time for 2 hours batch with 1 minute sampling	1.1 seconds / asset
Total Degradation events captured on multiple signals	50+
Probability of Detection	> 95%

False Positive Rate	< 5%
False Negative Rate	< 5%
Precision	> 95%
Recall	> 95%

6. Conclusion

In this paper, the authors discussed the problem of detecting degradation phenomena in the application field of turbomachinery and explained the importance of implementing early detection of such events in Baker Hughes continuous monitoring service.

Authors have also described degradation phenomena which accumulates with time scales of different duration, happening on different signals acquired on turbomachines. The existing methods for the identification of degradation patterns, already known in the literature, have not been deemed accurate enough for general purpose applicability required by the solution. A novel approach has been developed comprising strong features, like the extraction of low frequency component of the signal, the incorporation of time based correlation and linear regression model applied on multi time observation window. It was shown that these unique features empower the method with accurate detection rate, precision and recall. The proposed methodology also embeds autonomous learning and auto setting capability that enables generalized application covering multiple types of signals with wide operating ranges.

To validate the new methodology on a large data set, tests were performed on historical timeseries data from more than 600+ turbomachines being monitored by Baker Hughes's iCenter eco system. The signals were chosen on some families of mechanical systems which generally can present degradation phenomena during their life cycle. The paper then also discusses some real detection cases and explains the process through which the probable associated root causes are identified and the corrective actions are suggested to the final customers for field implementation. Finally, the performance matrix of the methodology is shown, which was found to comply with the stringent detection requirements followed by Baker Hughes.

Nomenclature

LNG Liquified Natural Gas
OEM Original Equipment Manufacturer
MK Mann Kendall
TS Thiel Sen
RMSE Root Mean Square Error

References

Abernathy, R. B., Powell, B. D., Colbert, D. L., Sanders, D. G., & Thompson Jr., J. W. (1973). *Handbook Uncertainty in Gas Turbine Measurements*. Fort Belvoir, VA, USA : DTIC.

Allegorico, C., & Mantini, V. (2014). A Data-Driven Approach for on-line Gas Turbine Combustion Monitoring using Classification Models. *Proceedings of PHM Society European Conference*. July 8-10, Nantes, France. https://doi.org/10.36001/phme.2014.v2i1.1461

De Giorgi, M.G., Menga, N., & Ficarella, A. (2023). Exploring Prognostic and Diagnostic Techniques for Jet Engine Health Monitoring: A Review of Degradation Mechanisms and Advanced Prediction Strategies. *Energies*, vol. 16. https:// doi.org/10.3390/en16062711

Gilbert, R.O. (1987). *Statistical Methods for Environmental Pollution Monitoring*. New York: Wiley.

Iannitelli, M., Allegorico, C., Garau, F., & Capanni, M. (2018). A hybrid model for on-line detection of gas turbine lean blowout events. Proceedings of PHM Society European Conference. July 3-6, Utrecht, The Netherlands. https://doi.org/10.36001/phme.2018.v4i1.405

Kendall, M.G. (1975). *Rank Correlation Methods*. London: Charles Griffin.

Mann, H.B. (1945). Non-parametric tests against trend, *Econometrica*, vol. 13, pp. 163-171. doi:10.2307/1907187

Sprent, P. (1987). *Applied nonparametric statistical methods. tatistical Methods.* New York: CRC Press.

Sen, P. (1968). Estimated of the regression coefficient based on Kendall's Tau. *Journal of American Statistical Institute*, vol. 63, pp. 1379-1389

Theil, H. (1950). A rank-invariant method of linear and polynomial regression analysis, 1-2; confidence regions for the parameters of linear regression equations in two, three and more variables. *Indagationes Mathematicae* , vol. 1, issue 2

Varbai, B., Wéber, R., Farkas, B., Danyi, P., Krójer, A., Locskai, R., Bohács, G., & Hős, C. (2024). Application of regression models on the prediction of corrosion degradation of a crude oil distillation unit. *Advances in Materials Science*, vol. 24, pp. 74-85. doi:10.2478/adms-2024-0005

Zagorowska, M., Ditlefsen, A-M., Thornhill, N F., & Skourup, C. (2019). Turbomachinery Degradation Monitoring Using Adaptive Trend Analysis. *12th IFAC Symposium on Dynamics and Control of Process Systems, including Biosystems*. April 23-26, Florianopolis, Brazil. https://doi.org/10.1016/j.ifacol.2019.06.141

BIOGRAPHIES

Unnat Mankad is a Staff engineer, Mathematics and Data Science, Service Engineering at Baker Hughes, Bengaluru, India. He received his master's degree in mechanical engineering from Birla Institute of Technology and Science (BITS), Pilani. In his current role, Unnat develops complex analytics for on-line prognostics, diagnostics, and predictive maintenance of Baker Hughes' iCenter covered turbo machines. As expert of time series sensor data analysis, he also supports data science and machine learning driven algorithm developments focusing on emissions, reliability, and availability improvements.

Gabriele Mordacci is the iCenter engineering Manager at Baker Hughes, Kuala Lumpur, Malaysia. He received his master's degree in Aerospace engineering from Universita degli studi (UNIPI), Pisa Italy, with a final thesis on the High speed gearbox diagnostic with microphone dynamic analysis. He worked in RMD developing the first analytics based on the fleet statistical for different type of technology and translating the field experience in digital application. As OEM expertise supports diagnostic and data scientist to prepare and validate the new analytics algorithm and output.

***Aidil Fazlina Binti Hasbullah** is a Diagnostic Engineer at Baker Hughes, Kuala Lumpur, Malaysia. She received her former tertiary education from Universiti Teknologi PETRONAS (UTP) in Electrical & Electronic Engineering major in Instrumentation and Control. In her current role, Aidil Fazlina focuses on remote monitoring and diagnostics of turbo machines of global installed fleet. She also act as focal point for onshore LNG plants for Malaysia and India fleet. Prior joining Diagnostic team, she has experience of working with LNG plant as Instrument engineer, leading Factory Acceptance test for instrument control system. She also actively collaborates with Baker Hughes' Data Scientists to support advanced analytics development to improve the reliability and availability of the turbo machines*.

Fahzzira Jaafar is a Product Service Engineer at Baker Hughes, Kuala Lumpur, Malaysia. She received her bachelor's degree in mechanical engineering from Universiti Teknologi Malaysia (UTM). Fahzzira has expertise in Balance of plant and a strong experience in monitoring, analysis and troubleshooting of different type of turbomachines covered by Baker Hughes's RMD services. Prior joining Product Services team, she has been involved in number of EPCC (Engineering, Procurement, Construction and Commissioning) and DED (Detailed Engineering Design) projects for Offshore and Onshore applications. In her current role, she is responsible for all activities relating to enhancing services technology integrating customer data, or capturing engines/products reliability, availability, maintenance, safety and other performance parameters.

Carmine Allegorico is a Senior Principal engineer and experienced data scientist at Baker Hughes, Firenze, Italy. He received his master ' s degree in mechanical engineering from University of Napoli Federico II. In his current role, Carmine is a technical point of reference for the analytics discipline providing engineering guidance to other teams, helping to train new engineers and keeping abreast of industry trends and issues. He provides consulting during the development and implementation of advanced solutions for the on-line diagnostic and predictive maintenance, coordinates the creation of internal processes and support the adoption of new platforms and technologies

Gionata Ruggiero is currently covering the position of Asia Pacific Service technology leader and he is currently based in Kuala Lumpur where he lives with his family. In his 20+ year of international experience having worked in Florence, Nigeria, Angola and India and covered several positions in the engineering organization: Subject Matter of expert, Project engineering serving different NOC and IOC, and Monitor & Diagnostic bringing innovative idea with an inclusive approach. Leader of a multicultural and multidisciplinary team, Gionata is responsible of the engineering support since the Installation and commissioning until the end of the life cycle included the IET iCenter in Kuala Lumpur. He is known as Customer focus engineering able to identify solutions and pioneering new technology injection mixing SME and digital domains. Gionata hold the Bachelor of Industrial Engineering and he recently completed advanced studied in Digital transformation and Clime Change Toward Net Zero Emission.