# Enhancing Machine Reliability in Industrial Plants: A Diagnostic and Prognostic Approach Using Reliability Growth Models


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## ABSTRACT

In the dynamic and demanding environment of industrial plants, the reliability of machines is paramount. Ensuring that machinery operates reliably and efficiently is crucial for profitability of the plant. Reliability in industrial plants is beyond preventing failures, it is also about enhancing performance and extending the lifespan of equipment. By focusing on the most failure-prone components or systems, maintenance teams can prioritize their efforts and resources effectively, leading to significant improvements in overall reliability and total cost of ownership. This abstract delves into the critical role of reliability in industrial environments, emphasizing the importance of employing reliability growth models to systematically validate the effectiveness of solutions implemented to address machine reliability issues.

For every sudden unplanned shutdown event (also known as "trip" in the Oil & Gas industry), remote real-time data gathering and analysis are conducted to identify the components or systems responsible for the trip. All the events and contributors are tracked and trended to identify top offenders. Top offenders are deeply investigated to find the solution and the opportunity to develop automatic diagnostic and prognostic tools based on remotely acquired time-series data. In fact, the identification of the degradation pattern of an equipment is key to develop and tailor diagnostic and prognostic tools. Once a malfunction is identified, we look for the root cause(s), extract learnings, and develop targeted improvements. These improvements are first validated in controlled environments (e.g., lab or test bench), then implemented incrementally across the fleet. Each implementation cycle is tracked using reliability growth models to statistically measure the change of event (trip) rate and validate the effectiveness of the solution over time.

This process allows us to diagnose and isolate malfunctions using real-time analytics, to generate and refine new analytics based on observed failure modes and their signature and finally to quantify the reliability growth.

The growth of the reliability can be quantified using multiple metrics and statistical tools.

In the Oil & Gas industry, amongst the most disruptive events there are the sudden automatic production shutdown events (trips). They deserve a special attention and a lot of care is put for their prevention and avoidance. Although in multiple industry standards, such as [1] and [2] and in the reliability theory the rate of occurrence of failure events can be calculated using the MTBF (Mean Time Between Failures), when special attention is dedicated to the reduction of trips (more than to any generic type of failures), there is the need to define another metric, that is the MTBT (Mean Time Between Trips) and to focus to its change over time.

By integrating reliability growth models into our reliability process, we ensure that each improvement is measured and also we can predictively estimate the reliability improvement on any other unit in the fleet.

This methodology has already demonstrated success, with a MTBT improvement of more than 10 times, from the initial years of new projects to their stable operation after few

years, showcasing the power of structured reliability growth modelling in complex, distributed systems.

## 1. INTRODUCTION

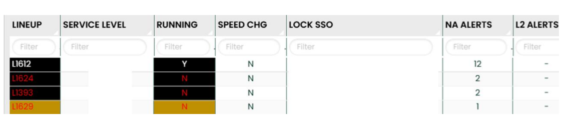
Industries often rely on various key performance indicators (KPIs) to monitor the quality and performance of their products. Common KPIs include the cost of quality, defects and warranty claims.

Baker Hughes Trip Reduction Program (TRP) approach is more comprehensive. Machines are monitored throughout their entire lifecycle. This begins with the design phase, where it is ensured that the product is designed to meet quality and performance standards. Once the machine are commissioned and running, performance is tracked remotely and with various machine parameters under real time live monitoring. Huge historical database is maintained to understand and identify the top issues and provide solutions. These solutions are extended across the fleet wherever applicable.

In Oil & Gas industries, where complex systems can fail or degrade for many reasons, a prognostic and diagnostic approach helps to monitor machine performance, detect analytics-based anomalies, provide solutions and leverage these insights at each stage to continuously improve the product. Ultimately enhancing the overall system reliability and customer satisfaction. By emphasizing cross-learning, we ensure that insights gained from one machine or system are applied across the entire fleet, leading to continuous improvement

## 2. MACHINE MONITORING

Thousands of machine operational parameters are remotely connected with Baker Hughes iCenters (multiple Monitoring & Diagnostic centers across the globe), with a 24 hour x 7 days monitoring and diagnostic service [Fig 1]. The iCenter team employs a comprehensive approach to monitor machines, which includes dynamic sampling of thousands of signals. This process involves the use of trip logs (capture at very high sampling rate of key signals across the instant of trips) for fast data collection and remote data transfer, supported by a server to store the vast amount of historical data. The user interface, available through the iCenter web portal, makes this data accessible for further analysis to a vast population of engineers and data analysts in the company.



| LINEUP | SERVICE LEVEL | RUNNING | SPEED CHG | LOCK SSO | NA ALERTS | L2 ALERTS |
|---|---|---|---|---|---|---|
| Filter | Filter | Filter | Filter | Filter | Filter | Filter |
| L1612 | | Y | N | | 12 | - |
| L1624 | | N | N | | 2 | - |
| L1393 | | N | N | | 2 | - |
| L1629 | | N | N | | 1 | - |

Figure 1. Continous monitoring of fleet under iCenter

### 2.1. Process to Analytics and Customer Interaction

The iCenter team monitors data continuously, using available analytics to detect degradation patterns or malfunction events and at the same time develops new analytics to understand better the issues and provide more insightful recommendations to plant operator. This involves the detection of events to identify anomalies. The process map includes several steps:

1. Event occurs in field
2. Event identification through analytics with date, time and type of signature
3. Prompt notification to Customer for adoption of corrective and preventive actions, including prioritization categories based on criticality of the event and recommendation for predictive measures. [Fig 2] & [Fig 2(a)]
4. Collection of further data from site and information related to event
5. Engineering investigation using data from remote sources, including pictures and unstructured data
6. Solution development and implementation
7. Monitoring of solution effectiveness.
8. Extend the lesson learnt and solution across the fleet in service and new products in development, as a continuous improvement process.
9. Develop new analytics for predictive maintenance based on product knowledge and lesson learnt.

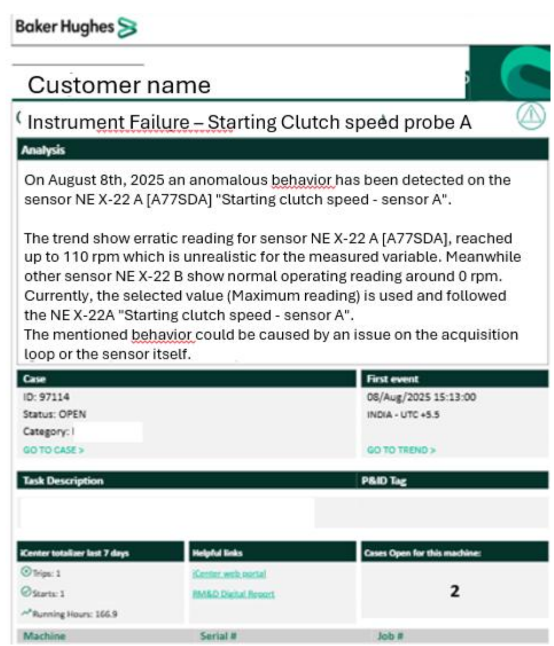


Figure 2. Template for notification to customer

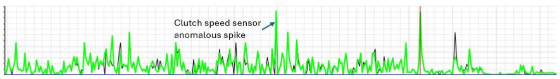



Figure 2(a). Clutch speed anomalous spike behavior

## 3. CROSS LEARNING

The TRP (Trip Reduction Program) team monitors the Mean Time Between Trips (MTBT) across the fleet to identify the rate of issues. This involves live monitoring to identify recurring events. Data is collected on daily basis to calculate MTBT and Starting Reliability Rate (SR) [Fig 3]. The focus is on specific fleets, and cross-learning helps identify repetitive issues and monitor them in specific projects.

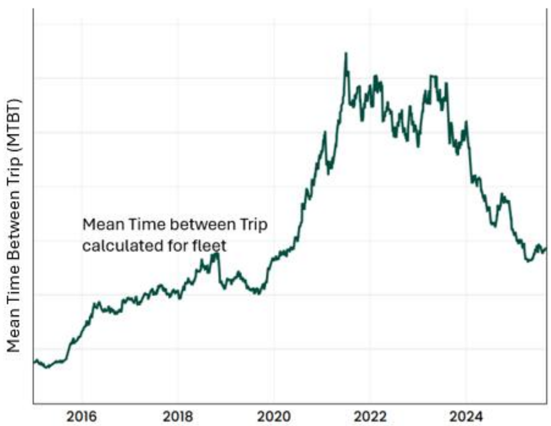



Figure 3. MTBT trend over the years for specific machine type under iCenter monitoring

Each event occurring in the field is meticulously identified and labelled through an engineering breakdown structure down to the component level. This detailed approach ensures that every aspect of the system is accounted for, allowing for precise tracking and analysis. Diagnostic analytics are employed to pinpoint the most repetitive issues within the fleet and to identify similar issues in new units. By leveraging advanced data analytics running in backend in iCenter, we can detect patterns and trends that might otherwise go unnoticed.

Once insights are gained, they are incorporated into design improvements for the new standard product. This process, while time-consuming, ensures that the lessons learned from field data are translated into tangible enhancements. For new units, we verify if the identified issues occur or may occur and implement the appropriate solutions, if for time constraints they could not be implemented during the project development phase. This proactive approach helps in mitigating potential problems before they escalate.

Our primary focus is on the fleet improvement and product improvement. For instance, with a certain number of units in the fleet, we continuously monitor Mean Time Between Trips (MTBT) and Starting Reliability (SR). These metrics provide valuable insights into the reliability and performance of the machines. Cross-learning is utilized to identify repetitive issues, which are then monitored in specific projects and, as applicable, implemented across the fleet. This systematic approach ensures that improvements are not isolated but are shared across all units, leading to overall enhancement.

Once a solution is identified for a specific cause and implemented across at least a portion of the fleet, we apply statistical models based on the Non-Homogeneous-Poisson-Process to measure the rate of change of trip rate, such as for instance the Crow-AMSAA model. This model is used to analyze the trip rate trend, to measure and confirm the effectiveness of the identified solution in the field and finally to predict the future performance of systems, based on the new rate of occurrence demonstrated by the portion of the fleet where the solutions were implemented already.

| Id | Event Date | Ebs | System | Group | Component | TRP in same project | TRP in other projects |
|---|---|---|---|---|---|---|---|
| 103378 | 2016-05-23T11:42:00 | Centrifugal (xMCL) | System 1 | Group 1 | Component 1 | NA | Project 1: TRP 01 |
| 104147 | 2016-06-09T19:19:00 | Centrifugal (xMCL) | System 2 | Group 2 | Component 2 | NA | Project y: TRP 0x |
| 104797 | 2016-06-22T18:16:00 | Centrifugal (xMCL) | System 3 | Group 3 | Component 3 | NA | |

Figure 4. Learning from different projects are tracked and implemented as cross learning across the fleet

### 3.1. Fleet-wise trend of KPIs

The team captures fleet-wide trends of Key Performance Indicators (KPIs)[Fig 3]. These trends provide a view of the fleet's performance, highlighting areas that require attention and those that are performing well. The Crow AMSAA model is applied to specific causes from projects to the fleet, ensuring continuous improvement. The team monitors specific issues, extends the monitoring to the fleet, and ensures ongoing enhancement of system reliability.

In summary, our approach involves a meticulous identification and labeling process, advanced diagnostic analytics, proactive implementation of solutions, and continuous monitoring and improvement. By focusing on cross-learning and leveraging models like Crow-AMSAA, we ensure that our systems are reliable, efficient, and continuously improving. This comprehensive strategy not only enhances customer satisfaction but also reduces costs associated with product failures and warranty claims.

## 4. CASE STUDY

In aeroderivative gas turbines, the starting system is connected to the turbine shaft through an overrunning clutch. The input side of the clutch is connected to the starting system, while the output side is connected to the gas turbine shaft. The speed of the input side of the overrunning clutch is continuously monitored to detect possible re-engagement events of the clutch once the gas turbine is running autonomously at a speed higher than that for which the starting system is designed for, and consequently to shut-down immediately the turbine shaft in order to prevent further damages. Magnetic passive speed pick-up are selected for this use. These sensors generate output voltage proportional to the rotational speed of the pole wheel in front of which they are mounted.

The amplitude of output signal is related to the distance between the probe face and the pole wheel, the geometry of teeth and the rotational speed of the wheel/shaft to be measured. The output signal from the sensor is also affected by the sensor geometry and the impedance in the signal acquisition system.

In the fleet of aeroderivative gas turbines served with the Trip Reduction Program, some trips were recorded due to the high readings of the overrunning clutch input shaft speed, when the clutch was actually supposed to be disengaged from the starting system and therefore to have its input shaft at standstill (zero speed).

The investigation was focused first on confirming that the signals generating the trips were generated spuriously and then in understanding the causes of such malfunction.
In the laboratory, a test bench was setup with the assembly of a sensor and clutch toothed wheel, trying to reproduce the anomalous readings from the magnetic speed pick-up which had caused the gas turbine trip.

A test campaign was performed for different models of speed sensors with different geometry and sensitivity. The probes considered for test have similar geometry which can easily be interfaced with available connection on clutches and represent a set of probes able to cover most of applications.
To carry out the test following test bench was used [Fig 5] and [Fig 6], with the appropriate safety and protection features.

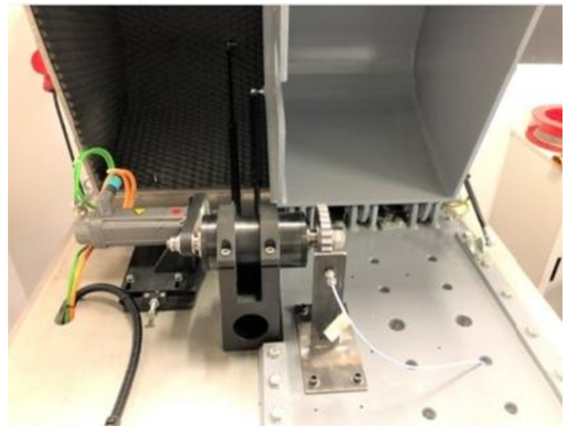


Figure 5. Test Bench

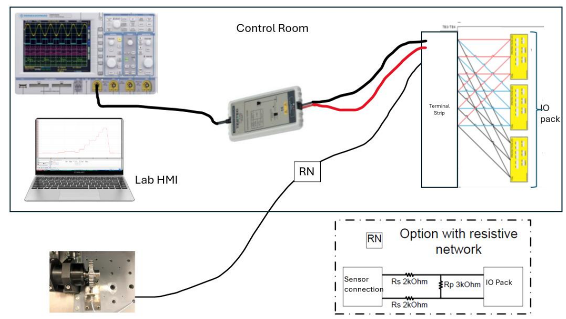



Figure 6. Test Setup

Test goal was to verify the correct working of probes under installation and to reproduce the generation of spurious signals by altering some setting parameters, such as the air gap between the sensor pole and the toothed wheel, the impedence of the entire signal acquisition loop and definitely the speed of the wheel. Finally, the aim was to get a correct and reliable reading from the assembly, enough robust and tolerant to the conditions of use, such as vibrations induced by the application on a gas turbine.

We tested two different models of passive magnetic speed pick-up, with the same arrangement of the test bench. The acquisition chain was replicating the one in the sites where the issues were identified.

An oscilloscope was used to monitor the signal amplitude (Vpeak-to-peak), with different settings of the air gap between the sensor pole and the toothed wheel at different speed.

As in site the air gap cannot be directly measured with filler gauges, due to the fact that the parts are not directly accessible, also in the lab the air gap was adjusted by changing the degrees of rotation of the speed pick-up body in a threaded support in front of the target toothed wheel. This was done on purpose, trying to replicate the difficulty of adjusting the air gap of the sensor in the overrunning clutch body in field.

The test was carried out with the sensor connected to the acquisition board, starting from a speed of 50rpm and increasing the speed up to 6000rpm, that is the typical range of speed for the input shaft of the overrunning clutch.

An oscilloscope was connected to monitor the signal amplitude (Voltage peak-to-peak) and the frequency.

### 4.1. Sensor Model A

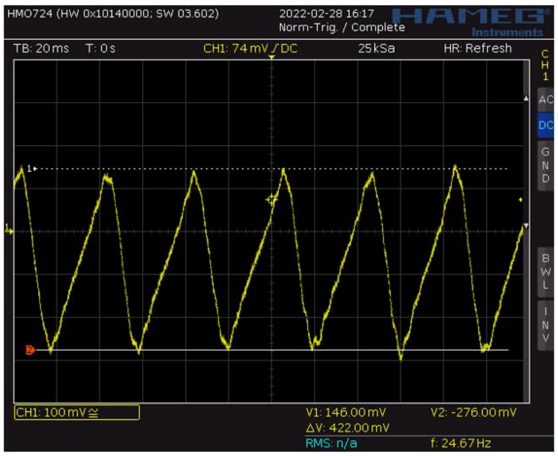



Figure 7. Test at 50 rpm speed with air gap of 0.7mm

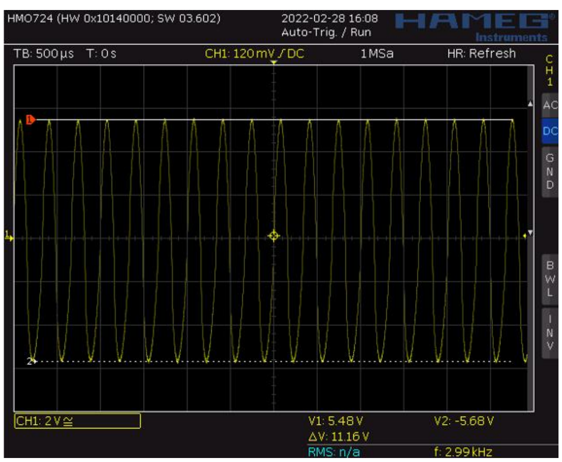



Figure 8. Test at 6000 rpm speed with air gap of 0.7mm

Figure 9 and 10 show the effect of an increased air gap [Fig 9 and 10]

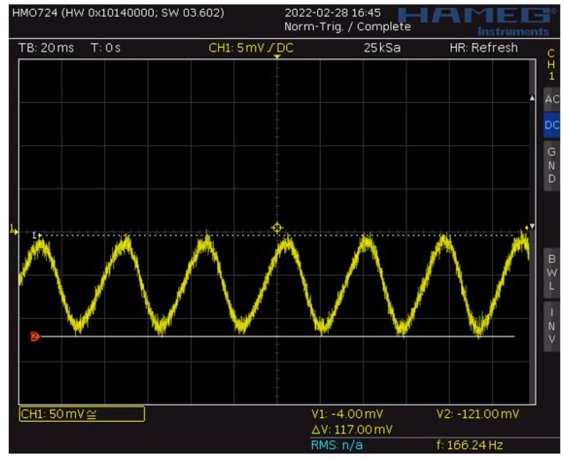



Figure 9. Test 2 with increased air gap at 50rpm

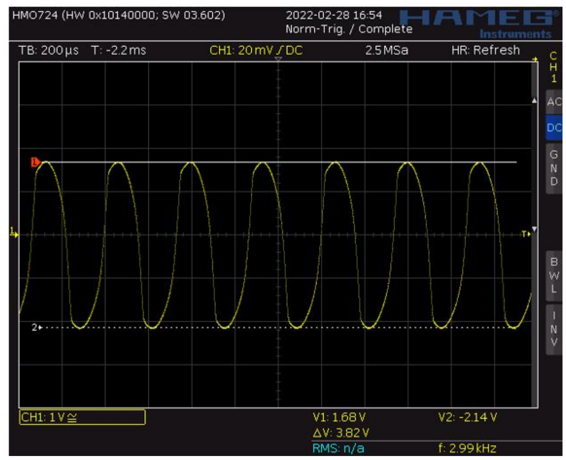



Figure 10. Test 2 with increased gap at 6000 rpm

We can see how by increasing the air gap the signal is generally weaker, but the shape of the waveform is improved. At 50rpm the signal is still strong enough (in terms of SN ratio and in terms of amplitude) to correctly detect the pole wheel speed.

A larger air gap improves also the reliability of the measurement, being the loop less sensible to spurious signals generated by pole wheel vibrations.

### 4.2. Sensor Model B

In this case we have tried to set the gap closer to the values indicated by the manufacturer of the overrunning clutch, that is nominally 0.12 mm, very difficult to be actually set up in the field [Fig 11 and 12]

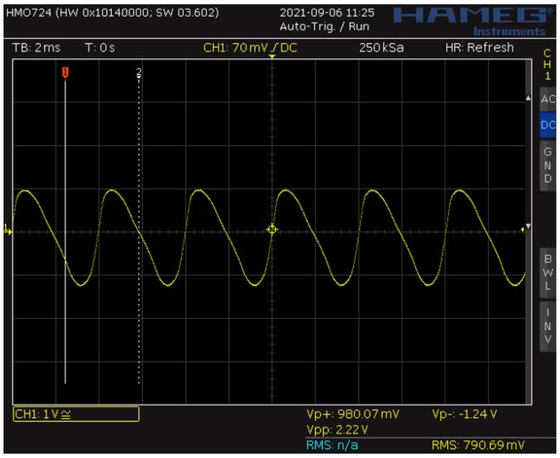



Figure 11. Sensor model B test at 500rpm with air gap of about 0.12mm

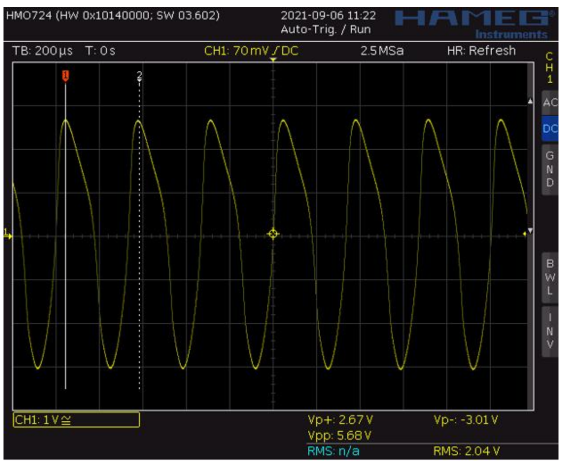



Figure 12. Sensor model B test at 6000 rpm

The overall trend is similar to the one obtained with the sensor model A

By comparing the results of the test, we want to find a correlation between the Voltage output and the air gap for sensor model A

We can approximate the correlation as a quadratic relation between air gap and output voltage Vout. [Fig 13]

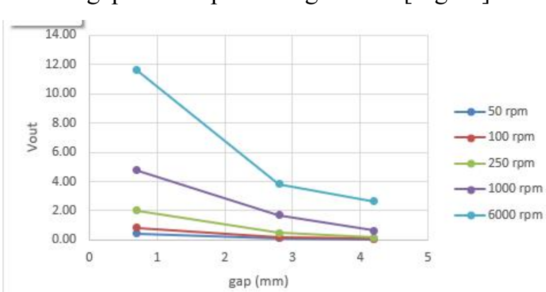



Figure 13. Correlation between air gap and Vout

From the above, we see how the trend of the sensor model B speed pick-up sensor when considering 0.33 mm air gap is close to the absolute values of the sensor model A with a 2.7mm air gap in terms of absolute Vout values.

Since the optimum choice of the sensor model A air gap has been based on the Vout values, we can conclude that we can extend the same consideration to the sensor model B when the air gap is 0.45mm

This allow us to conclude that both sensor models are suitable for the applications but the air gaps are different in the two cases: the optimum Air gap is 2.7mm for sensor model A, while it is 0.45mm (in line with the clutch manufacturer instructions) for the sensor model B.

During the tests, there was the possibility to reproduce some spikes of the speed signal at low speed values, that is when the output signal from the speed pick-up has a lower amplitude and therefore a lower signal to noise ratio.

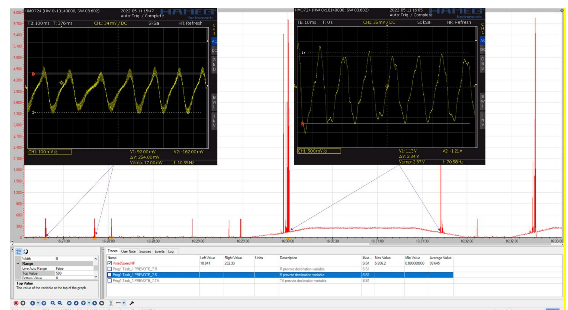


Figure 14. Trend with 0.68mm gap setting without resistive network

Finally, the tests were targeted to identify a balance between the degrees of freedom for the test bench: the sensitivity of the specific sensor model, the air gap, the impedance in the acquisition loop, given the target toothed wheel in the overrunning clutch.

Once defined the optimum air gap for the specific sensor model, the fine tuning of the gain in the entire acquisition loop was setup in field, by adjusting the values of some variable resistors in series and in parallel between the input wires to the acquisition board, acting as a voltage divider.

## 5. RELIABILITY GROWTH

In this case study, after having defined the optimum setup for the installation in site, we applied a Reliability Growth (RG) model, not only to evaluate the effectiveness of corrective actions implemented at a production site but also to investigate the root causes of suboptimal effectiveness over time. We observed variations that are beyond our direct control, such as personal adherence to engineering procedures and operational decisions influenced by human factors

### 5.1. Application of Reliability Growth and initial result

We applied the RG to analyze the effectiveness after a targeted modification campaign on a specific set of units . The initial results, right after implementing the corrective actions, showed an effectiveness level of 71% (in terms of reduction in the occurrence of the events) over approximately 0.2 million cumulated operating hours, if compared with the previous phase of plant operation (approx. 0.6 million cumulated operating hours).[Fig 15]

#### 5.1.1. Continuous monitoring and plot degradations

Over the following years, continuous monitoring of RG plots allowed us to observe a gradual decline in performance for the same type of event (spurious reading of the speed of the input side of the starting system overrunning clutch). Data showed an increasing number of events, even though operating conditions remained largely the same.

At this point, we tried to understand deeper why the situation did not remain stable.

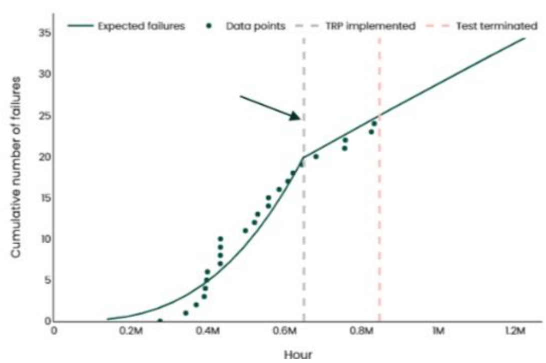



Figure 15. Applying RG to analyze the effectiveness after modification

Our investigation revealed that:

- Engineering drawings and technical specifications were not systematically updated to reflect the actual changes made at site.
- The human factor played a significant role, in particular personnel accustomed to established procedures. In particular, when gas turbines are removed from service for the periodic preventive maintenance, the starting system overrunning clutch is temporarily disconnected, including the speed sensors. Afterwards, when the clutch is reinstalled back and connected to a new gas turbine, the procedure for the careful installation of the speed sensors was not always followed.

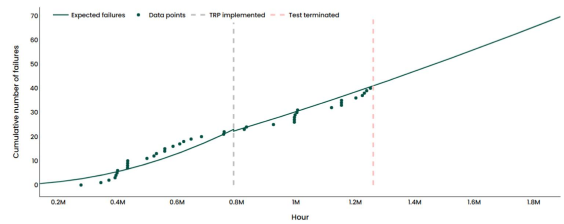



Figure 16. Continuous monitoring of RG curve

The continuous monitoring of the RG curve proved to be a crucial tool not only for measuring short-term effectiveness but also for interpreting degradation behaviors over time, thus enabling proactive approach towards continuous improvement in production sites. This allowed to focus the attention on other important organizational aspects, such as the need to have solid procedures for execution in site and above all a continuous training to operators, including the lessons learned.

## 6. CONCLUSION

The iCenter team's approach to prognostics and diagnostics involves comprehensive monitoring, data analysis, and continuous improvement. The iCenter play a pivotal role in this process, providing 24/7 monitoring and diagnostic services. The dynamic sampling of thousands of signals, coupled with advanced data analytics, enables the detection of patterns and trends that inform preventive and predictive measures. The engineering team further investigates and develops solutions, ensuring that lessons learned are extended across the fleet.

A cornerstone of the TRP is its emphasis on cross-learning. This approach ensures that insights gained from one machine or system are applied fleet-wide, leading to continuous improvement. By identifying repetitive issues and implementing solutions across the fleet, the TRP enhances system reliability and reduces costs associated with product failures. The use of advanced diagnostic analytics and models like Crow AMSAA further supports this process, ensuring that lessons learned are effectively utilized to improve overall system performance and customer satisfaction.

Ultimately, the TRP's meticulous identification, advanced diagnostic analytics, and proactive implementation of solutions create a robust framework for continuous monitoring and improvement. This comprehensive strategy not only enhances customer satisfaction but also ensures reliability.

## NOMENCLATURE

*MTBT* Mean Time Between Trip
RG Reliability Growth

## REFERENCES

[1] ISO3977-9: *Gas turbines — Procurement - Part 9: Reliability, availability and maintainability*
[2]: IEEE 762: *IEEE Standard Definitions for Use in Reporting Electric Generating Unit Reliability, Availability, and Productivity*

## BIOGRAPHIES

**Pranay Mathur is** a Principal engineer and turbo machinery reliability and control expert at IET Gas Services at Baker Hughes, Bengaluru, India. He received his bachelor's degree in electronics instrumentation and control engineering from Global Institute of Technology, Rajasthan. Pranay has 15+ years of experience in control and instrumentation for Heavy duty and Aeroderivative Gas Turbine. In his current role, Pranay connects with customers for field issues resolutions, investigations, driving product reliability improvement through domain expertise & digital solutions. Key contributor in trip reduction program, driving fleet reliability with monitored data

**Carlo Michelassi** is a Senior Principal engineer, reliability and maintenance expert at the IET Gas Service at Baker Hughes, Florence, Italy. He received his master's degree in electronics and reliability from Florence University, Italy. He has 20 years of industry experience in design for reliability and reliability improvement. In his current role, he serves as senior principal engineer for the reliability and maintenance of heavy duty and aeroderivative gas turbine auxiliary systems and instrumentation, leading a global team of experts.

**Gilda Pedoto** is a Lead engineer and experienced in Trip Reduction Program (TRP) service at Baker Hughes, Florence Italy. She received her master's degree in automation engineering and the Ph.D. in Information Engineering from University of Sannio, Benevento, Italy. During the Ph. D, she spent fifteen months in Johns Hopkins University in Baltimore, MD, USA working on predictive modeling based on biomedical data. Gilda has 10 years of industrial experience, working in aeroderivative and heavy duty gas turbine reliability improvement for Baker Hughes customers with the TRP service active. In her current role, she's the front line for several LNG plants, collecting issues from field and working with experts to solve them.

**Leonardo Vieri** is an Engineering Manager for Turbomachinery Control & Automation at IET Gas Services, Baker Hughes, Florence (Italy). With 30 years of experience in the Oil & Gas industry, he has held a wide range of roles, from field installation to various technical support positions for installation and commissioning within the organization. Since 2014, he has been leading the international Control & Automation Customer Support team, a group of experts operating in more than 10 countries, providing post-sales support across all Baker Hughes Gas Services technologies.