WHITE PAPER

PREDICTING ASSET HEALTH AND THE ROOT CAUSE OF FAILURES USING SMART FAULT TREES

Abstract

In asset-heavy industries like oil and gas, mining, energy and manufacturing critical assets are usually operated over many years and sometimes even a few decades. The risk of these critical assets operating with invisible degradation is enormous on the end-users. Moreover, many end users are forced to have a shortened preventive maintenance schedule to ensure minimum downtime and keep the plant operations running. This further elevates the risks of unforeseen failures. With the advent of Industry 4.0 and Industrial Internet of Things, technology has opened many avenues for asset-intensive industries.

This paper presents an approach developed by Infosys using advanced technologies to solve the challenging problem of proactively identifying hidden Faults in assets to help plan the maintenance better and reduce unscheduled maintenance events. The solution uses a combination of Fault Tree Analysis for Failure Mode Evaluation and Analysis (FMEA) and operational data from plant systems to determine the current state of the asset and identify reasons for issues.

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Introduction

The maintenance and operations of large industrial plants are increasingly becoming complex, effort-intensive, and expensive over recent years. Many of these large plants have been operating for decades, and hence asset aging is a major problem. In Europe alone, the average age of nuclear power plants is more than 35 years. Almost 40% of power plants run on coal where the boiler repair costs account for 50% of the maintenance costs. Every boiler shutdown results in $200,000 of restart cost apart from the actual material and labor cost.

Similarly, in the oil and gas sector, many refineries globally have aged. While the number of operating refineries reduced by 30% in the last 20 years, the refining capacity increased by over 10%. This adds a significant load on the refineries. There were 1.3 incidents per day of unplanned downtime in the US, causing almost $20 billion worth of production loss in 2017. These challenges drive organizations to explore reliable solutions enabling them with more information on asset health, planning, and carrying out maintenance.

Several solutions based on data-driven analytics have been created in the past few years. With the advent of Industry 4.0, numerous solutions focus on determining the health of rotating assets like pumps, turbines and compressors, as indicated in Figure 1.

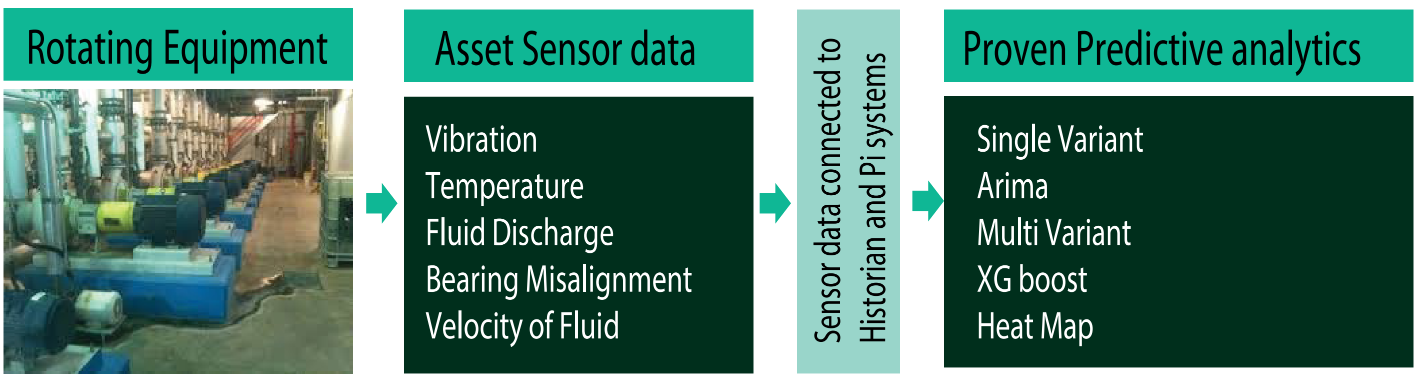

Figure 1: Predictive analytics for Rotating equipment

The non-rotary assets comprise more than 70% of fixed plant assets in power generation, oil and gas, mining and chemical industries. The non-rotary assets include boilers, heat exchangers, tanks, pipes, drums and reactors. Very few solutions are currently available that can significantly predict defects in these assets risking operations in the future. A key reason for the non-availability of a solution is the complexity of determining a solution for the maintenance requirement for non-rotary equipment. Unlike in rotating equipment, there is no direct online sensor to monitor the equipment status used in the models to predict any future failures based on anomaly detection.

Apart from non-rotary equipment, the industry is also struggling with the failure of assets to process alarms and define a proper approach to identifying and managing alarms. The organization's inability to federate the learning from one plant to another plant adds to the challenges.

Figure 2: Challenges in Asset intensive industries

Customers are demanding a common solution that can enable decision guidance on maintenance needs of both rotary and non-rotary equipment. The solution must consider all scenarios, including process alarms and their impact on asset health.

The solution covered in this paper, "Smart Fault Tree," takes a step forward in addressing the needs of the modern industrial world. The solution uses a multi-dimensional relationship of both design data and real-time plant data to forecast maintenance needs. It uses a combination of failure modes from the design depicted using Fault Trees and superimposes the different real-time alarms to identify the effect of the alarms on the overall life of the asset. The solution applies to both rotary and non-rotary equipment.

Fault Trees

Organizations use different techniques to capture learnings about assets and their different failure modes. A Fault Tree is one such method that organizations with large assets widely adopt. Fault Trees are physics-based models used for root cause analysis (RCA) of failures of different industrial assets for many decades. Organizations create a Fault Tree by placing the asset at the top and forming different Fault branches to define the multiple reasons.

As an example, an industrial boiler is analyzed utilizing the current approach. Industrial boilers are designed to generate steam from water, usually under high pressure and temperature.

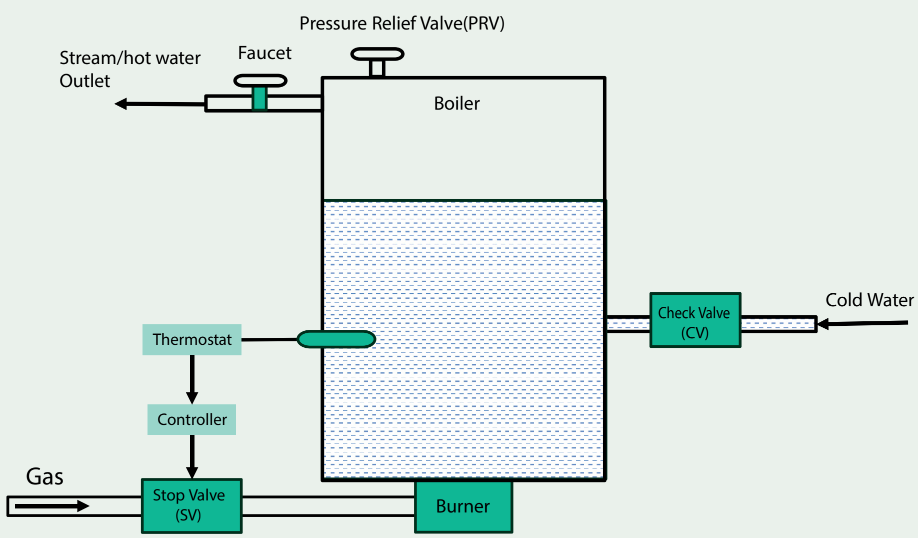

Figure 3: Schematic diagram of the Industrial Boiler and control system

Some of the common problems that industrial boilers face include

1. Tank rupture due to excessive pressure
2. Faulty or failed burners leading to insufficient heat generation
3. An improper mixture of gas and air leading to lower efficiency of heat generation
4. Leakage in tubes due to operation under high pressure
5. Faulty control system due to malfunction of sensors, probes, and valves can lead to a complete shutdown of the plant
6. Overheating of the boiler due to Faulty control system

A Fault Tree can be created for each of these Faults. In this case, a Fault Tree for a typical Fault like water tank rupture is created by understanding the design and operations of the boiler. From the hot water tank design, it is known that the tank can rupture due to high pressure. The high pressure is caused due to failure in pressure return valve (PRV) or high inlet water pressure, or high steam formation inside the tank due to overheating. The Fault Tree can be developed for hot water tank rupture using these design considerations and operations knowledge, as shown in Figure 4.

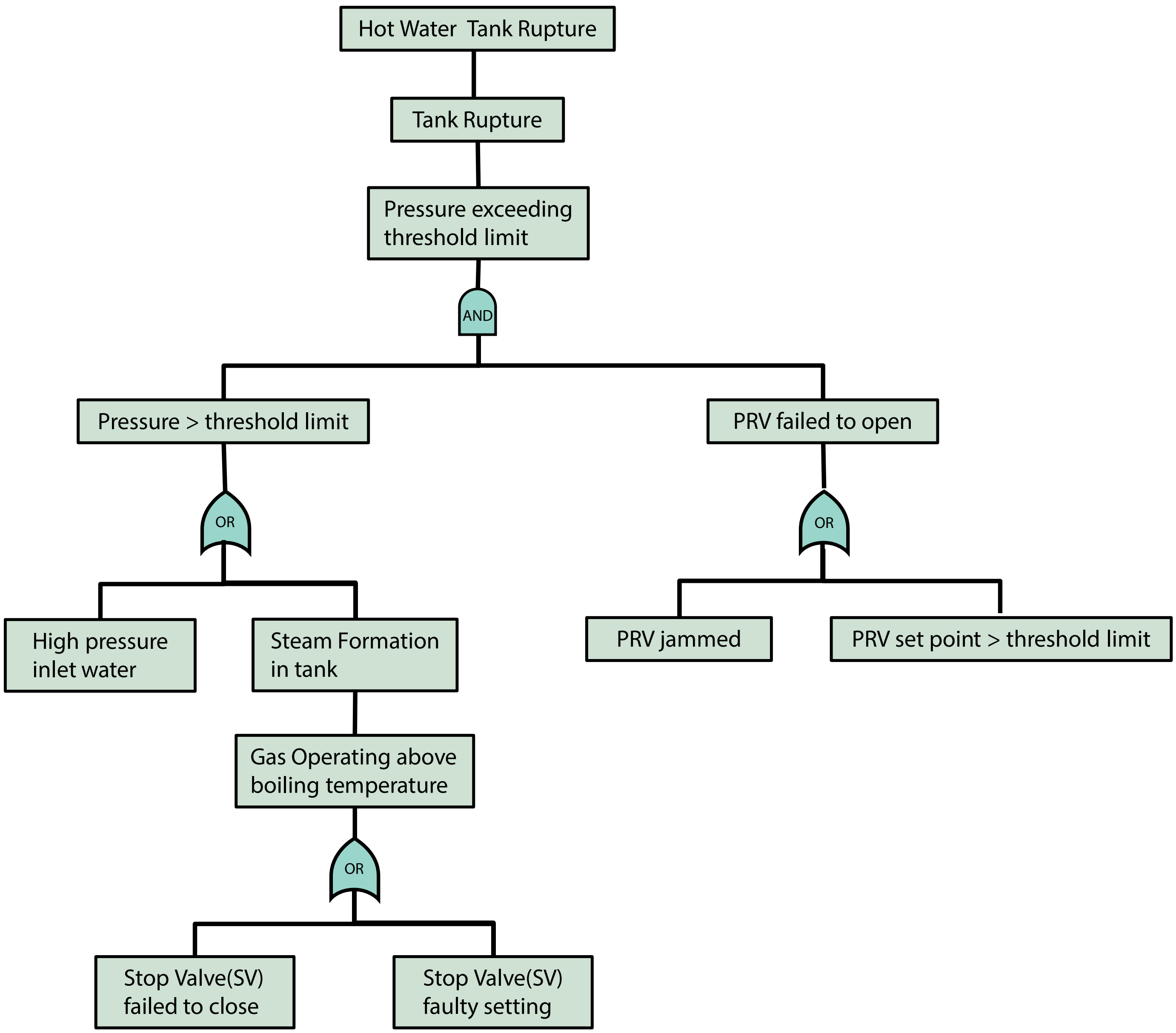

Figure 4: Hot water tank Fault Tree

The Fault Tree provides good visualization of the fault enabling easy understanding of the real-world situation. The data from the control systems can be linked to the events in the Fault Tree, which helps to identify the branch of the Fault Tree that can cause the water tank to rupture.

There are certain inherent challenges in widely adopting this methodology for day-to-day operations, including -

1. **Developing and managing the Fault Tree** – Currently, most of the Fault Tree creation is manual and paper-based. Few solutions are available for digitally developing and managing a Fault Tree. Off late, organizations are moving to use certain off-the-shelf documentation solutions for creating Fault Trees, but their distribution remains siloed. There is no centralized repository of the Fault Trees to take advantage of collective learnings at the organization level.

2. **Connecting Fault Tree to the real world** – the ability to connect the Fault Tree to the real-time operational environment to provide continuous insights on the asset health and failure causes for incident occurrence.

Creation of Smart Fault Tree for managing industrial assets

The "Smart Fault Tree" solution has been developed with two major components to make the Fault Trees more effective for day to day operations –

1. Fault Tree development and management workbench

2. Activating Fault Tree to dynamically indicate any asset-related anomalies and identify the most likely reason for failure.

Fault Tree development and management workbench

This workbench is primarily an integrated development environment that allows developing and managing Fault Trees for all assets across the enterprise along with different attributes for each asset. The environment is depicted in Figure 5.

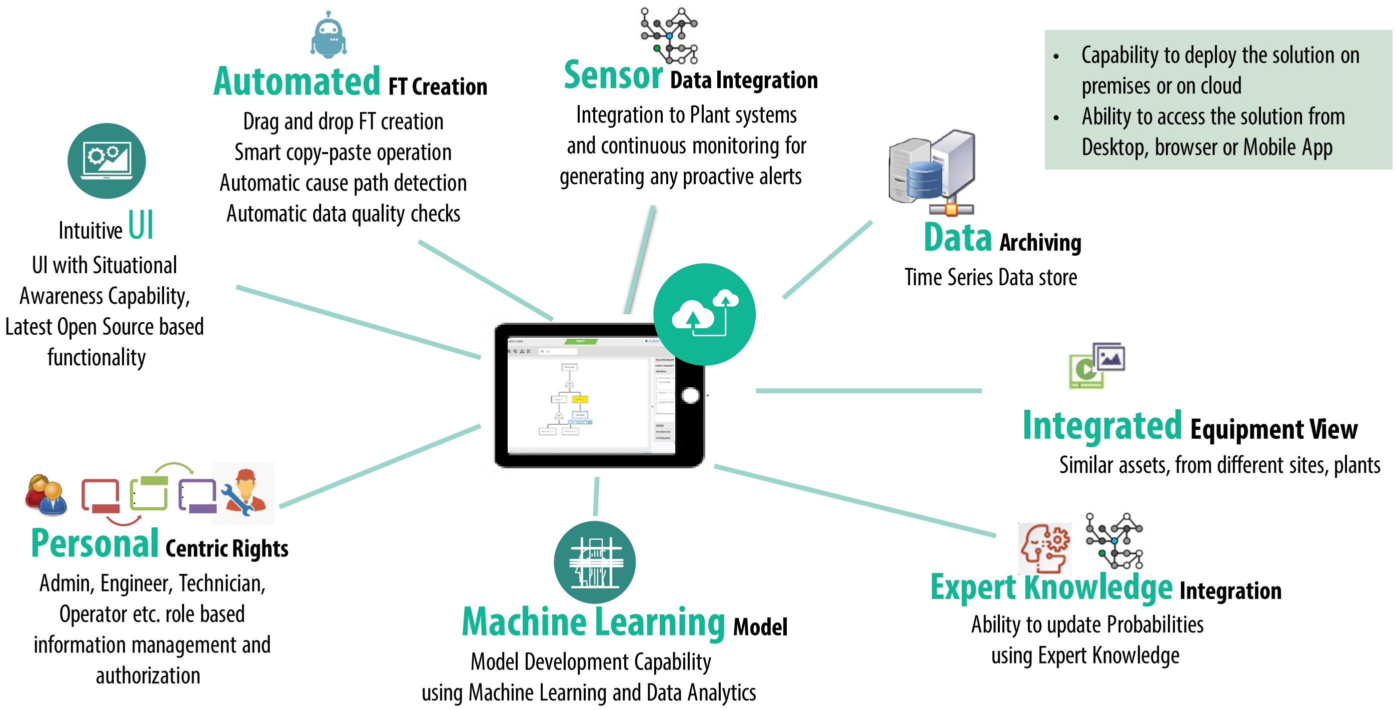

Figure 5: Smart Fault Tree Development and Management Environment

Activating the Fault Tree to become dynamic

For activating the Fault Tree, a model needs to be developed as part of the solution using historical data to establish a relation between alarms and asset failure, as explained above. The model would identify the impact of each alarm on different branches in the Fault Tree. It would also consider the aging of the asset along with the number of alarms generated during operation. In an industrial boiler, an alarm would be triggered each time the gas burner operates above boiling point. While this may not cause the tank to rupture, there is an inherent impact on the tank, and it is degraded. The degradation has a direct relationship with the number of times the alarm is generated and the age of the tank (which causes normal degradation as per design).

The solution uses different types of techniques like risk probability number (RPN) and artificial neural network (ANN) for developing the model

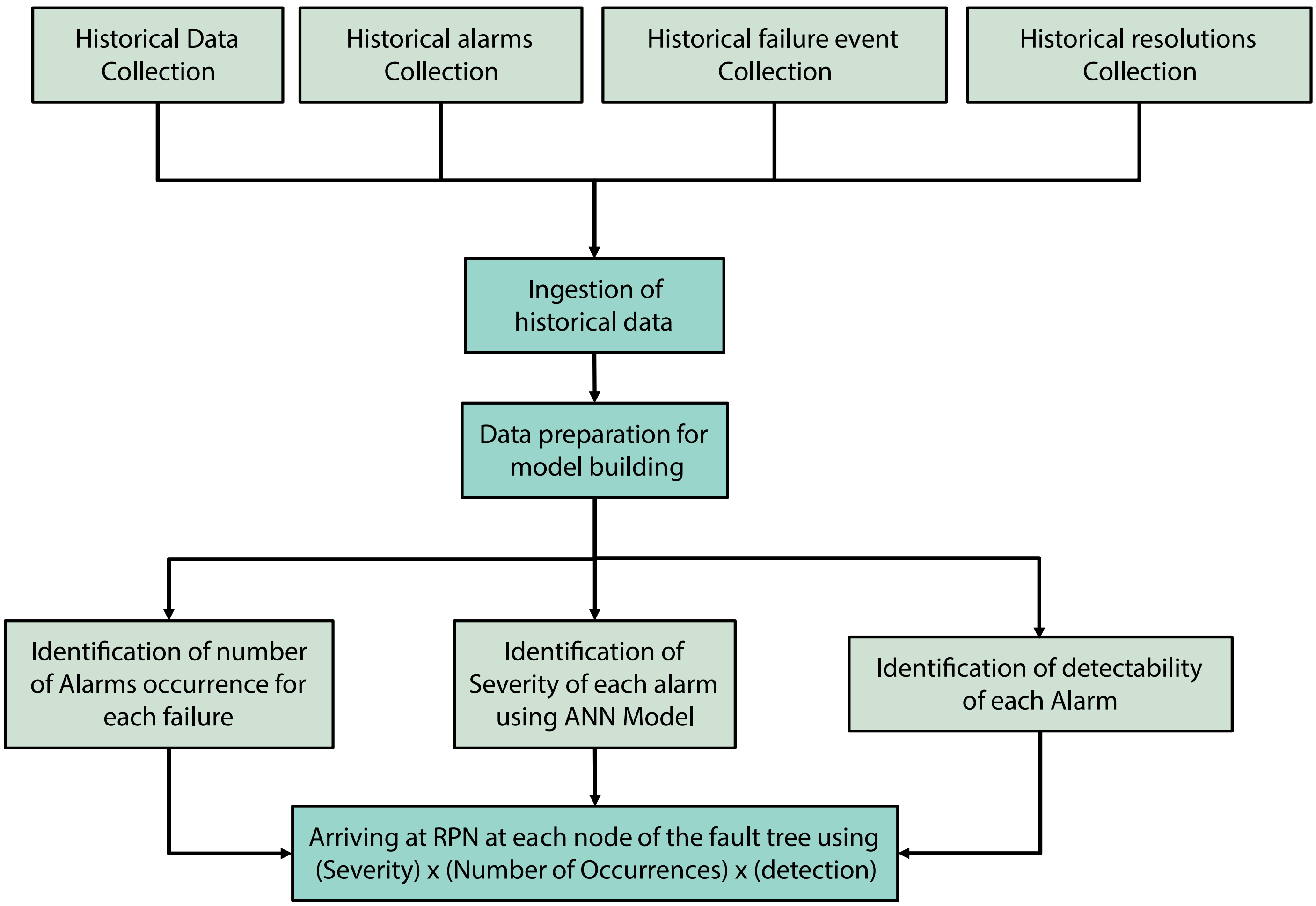

Figure 6: Building the Model for Failure prediction

The Fault Tree is connected to the live plant data using a standard industrial protocol interface to make the system live. Each alarm triggered in the plant now passes through the Fault Tree model to identify the impact on the asset and the probability of asset failure. In case of failure, the Fault Tree depicts the most likely reason for the failure.

The model will show the Fault Tree branches responsible for increasing the risks of the failure with probability.

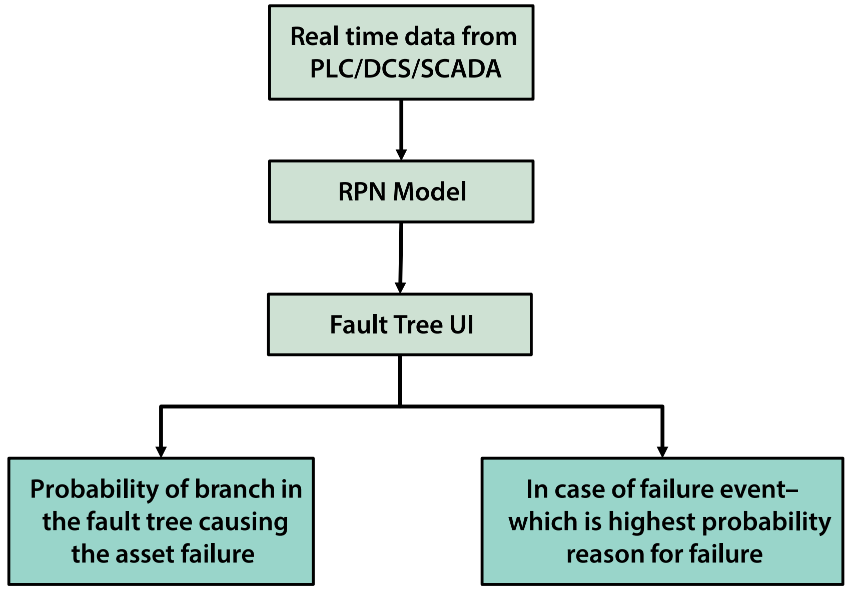

Figure 7: Connecting Smart Fault Tree to Plant live data

Smart Fault Tree in action

For any industrial asset, several measurements are made for the process and operating parameters of the assets, including flow, pressure and level. These parameters are defined with an ideal operating range, warning and alarm limits. Whenever the ideal range is breached, the protective logic in the control systems takes over with corrective action or shut down of the system. The operator resets the system, brings the parameters back to the normal range and restarts the operation. During this process, the impact of the alarm or warning on the asset goes unnoticed. For example, if there was turbulent flow into a tank, the impact of that flow on the life of the pipes and the tank is not estimated. In reality, there is a drop in the operating life of the tank and pipes due to this high flow rate. As these events keep occurring over a period, there is an exponential degradation in the life of the assets. The solution uses different techniques to identify the degradation of these assets and establishes the relationship between the process alarm and the impact on the life of the assets.

The "Smart Fault Tree" uses the RPN-based modeling technique.

RPN = Severity X Occurrences X Detection

Severity - This model uses the historical data and ANN-based weightage method to identify the severity of each alarm influencing the failure of the asset

Occurrences -The number of occurrences is available from the data set directly

Detection - Detection is considered as 1 for all the available threshold breach information.

Almost 80 percent of historical data is used as a training set, and the remaining data is used for testing and validating the trained model. As the equipment continues to operate under normal conditions, the initial warnings count will be zero, but over time as alarms are encountered, the count changes. Thus, the warnings profile can be fed to the trained neural network to get a score of the equipment's health which indicates chances of failure. The match of predicted failure risk with actual risk is indicated in Figure 8.

- Number of warnings on failure dates is taken as 100% and prior 200 rows' warning counts are normalized.
- Historic data is split in to training and test sets and a ML model (ANN) is created.
- Model is deployed for run-time prediction after suitable testing.
- The model predicts failure risk .(e.g., 70%-95%)

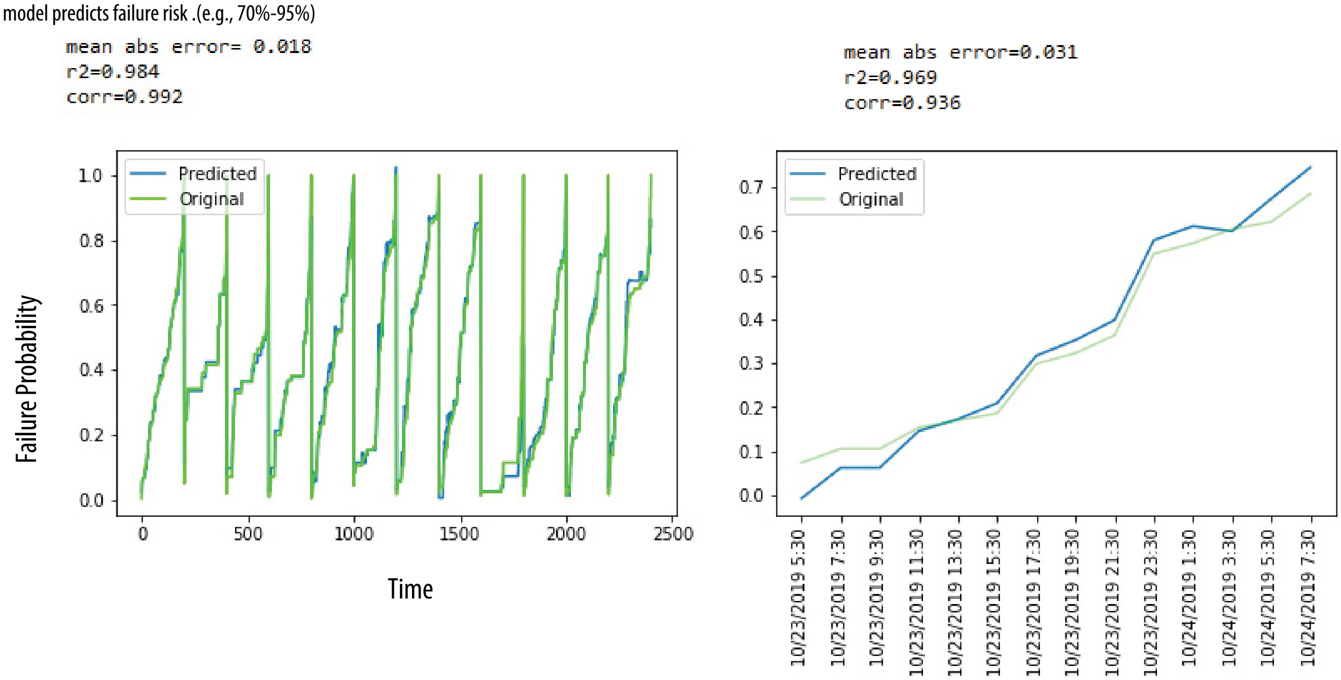

Figure 8: Failure risk prediction vs. Actuals

Depending on the criticality of the equipment, low risk scores (less than 30 percent) can be ignored, but a high score (85 percent and above) indicates that failure is imminent, hence mandating repair or maintenance. Thus, the model guides the operator as a decision enabling system for condition monitoring and maintenance, saving effort and monotony.

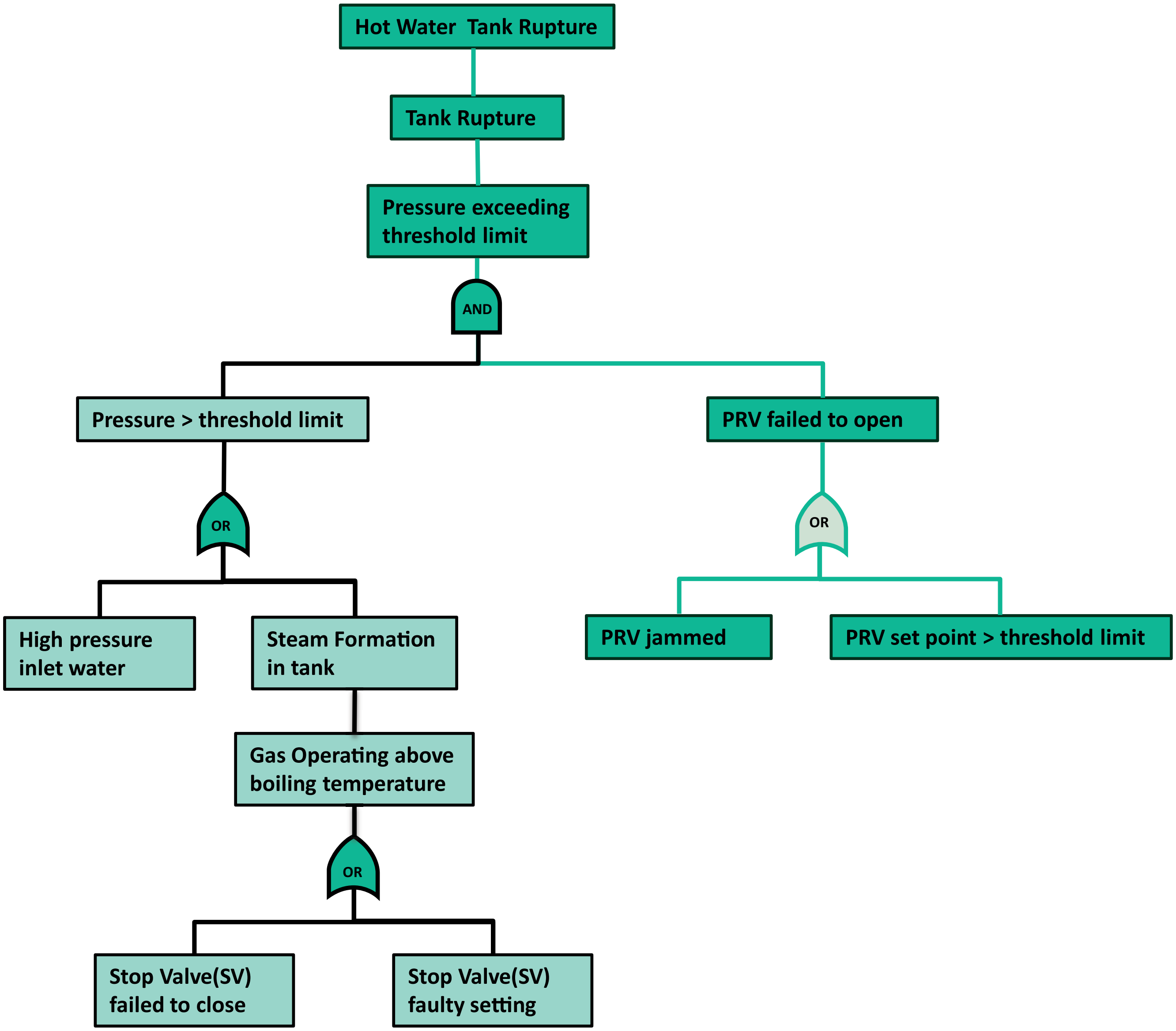

Figure 9: probable failure paths

The key outputs from the solution include –

1) Current risk for the asset to fail – It is a percentage value that is output from the model

2) Node or branch in the Fault Tree with most alarms and its influence on the asset failure risk – the number of alarm occurrences and their percentage contribution to overall risk

3) In case of failure, identify the most likely reason for failure – It is a percentage value that indicates the probability level for a reason being the prime cause for asset failure.

Indicative functional architecture

The application is developed to create the Fault Tree in drag and drop mode, attaching the parameters to various events and ingestion of data for building the models. The application will build the historical network model and predict failure based on ANN and RPN models. The functional architecture for the application is shown in Figure 10.

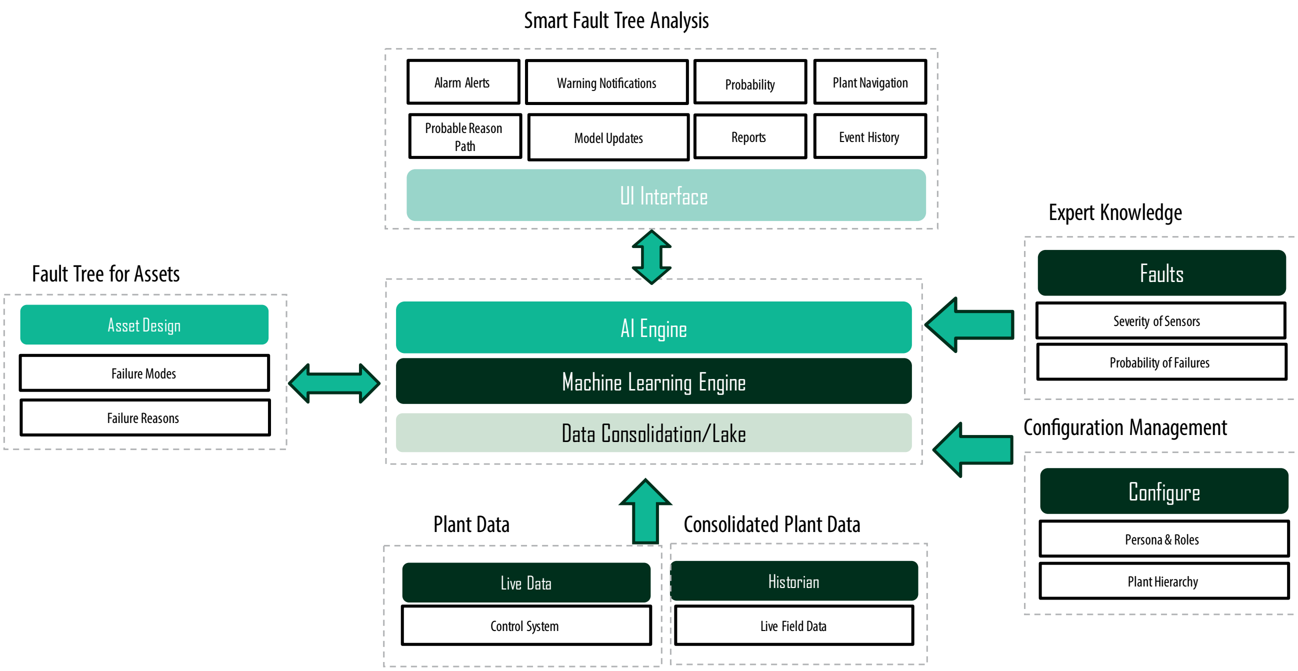

Figure 10: Functional architecture for Smart Fault Tree

Benefits to customers

This solution provides the customer with an opportunity to set up a remote surveillance system for monitoring the health of the assets and the operations teams for different sections of the assets at a distinct frequency (once a day).

This solution is focused on two key performance indicators –

1) Reduce the number of unplanned shutdowns for all assets, thus increasing plant availability for increased productivity. It also brings down the cost of maintenance both in terms of labor and spares.

2) Reduce time to repair in case of failure, a Smart Fault Tree would provide the route to the most likely reason for the Fault. This helps narrow down on the root cause and decide on the resolution much quicker than the normal process. It also reduces the overall downtime and improves productivity.

Conclusion

This solution is in the early stages and the accuracy levels in the 70% – 90% range. This solution serves as a starting point for organizations with little information on troubleshooting their assets. The solution will provide initial inputs on failure risk based on the learnings from the historical behavior of the asset. As the solution matures, this approach would provide a significant lifeline to aging assets currently not considered in the predictive maintenance scope. The important dependency for the organizations is to store data and knowledge related to failures. This repository would help build strong models that would be reliable and dependable over a period.

Acknowledgments

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