Analytical model selection framework for asset failure prediction

Over the years, asset-intensive industries like energy, utilities and manufacturing have witnessed several service failures and safety incidents around machines and structures - without warning. Consultants estimate that typically manufacturers miss 5% to 20% of their productive capacity due to downtime[1]. Even though organizations understand the cost implications of downtime, fewer than 24% of operators use a predictive maintenance approach based on data and analytics to handle asset failure proactively[2]. Shifting from calendar-based maintenance to data-driven asset management can help anticipate problems based on asset health condition, enabling optimal usage of asset life and increased reliability.

Rigid physical laws govern assets that make inherent patterns, which are repetitive in nature and easy to decipher using machine learning algorithms. However, the patterns and failure behaviors are specific to asset type. Hence, a single predictive model cannot solve the issues of multiple devices used in these industries, which will own completely different characteristics and would demand exclusive treatment. The proliferation of failure detection systems for thousands of assets in large organizations has imposed an increasing burden in terms of cost and effort. Lack of availability of a generic framework is thus a major shortcoming in the current state-of-the-art failure prediction systems in large enterprises.

This paper will judiciously provide the business with an expansive guideline to select an appropriate analytical framework to predict asset failure based on the component type, failure modes and asset failure information.

Asset types and failure modes

It is critical to understand the similarities and distinctions of failure patterns and their sources across asset types. Firstly, we would begin with asset classification followed by analysis of key failure causing parameters across different asset types. Further, we drill down to component level failure modes to comprehend the pattern of the root cause. Lastly, we would arrive at a logical methodology to choose an appropriate analytical framework to build a model for asset failure prediction.

Asset classification

Figure 1 depicts the detailed arrangement.

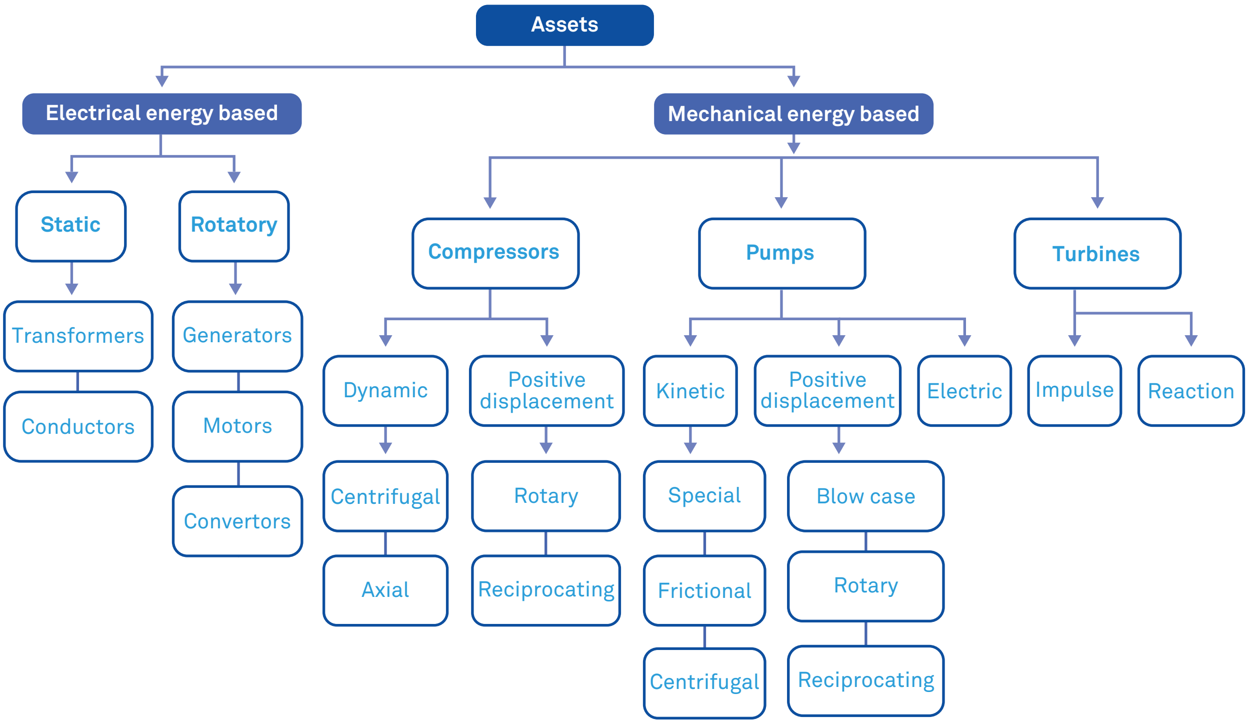

Figure 1: Asset classification basis energy type

Asset-specific failure parameters

To create a robust technique applicable to multiple asset failure scenarios, it is critical to understand the component failure modes in different asset types and corresponding parameters viz. pressure, temperature, moisture etc. Figure 2 highlights some of the key parameters causing major failures in transformers and pumps.

Failure parameters

Transformers

- Electrical disturbances
- Thermal stress
- Mechanical stress
- Fault in voltage
- Foreign objects
- Humidity
- Moisture
- Sun radiation
- Overheating of relays

Pumps

- Operating speed
- Cyclic stress
- Rotor spacing
- Temperature
- Radial thrust
- Vibration and noise
- Flow rate
- Contaminants
- Improper pressure

Figure 2: Asset specific failure parameter

Asset-specific component-level failure modes

To understand the impact of failure parameters, we performed a detailed sample analysis of the different types of component failures in Transformers, Centrifugal Pumps and Progressive Cavity Pump (PCP) systems. It was noted that while causes of failure is a function of operational parameters in case of static assets, it is a function of time in case of rotary assets. Hence, a failure-time distribution model is more relevant than a cross-sectional event prediction model for the rotary class. Thus, mechanical behavior plays a significant role in defining the model framework. Table 1 enunciates the systematic procedure of the analysis performed.

Category	Asset type	Failure mode	Component	Causes for failure mode	Failure function
Static	Transformer	Winding failure	Windings	Faults in dielectric, thermal or mechanical stress.	f(Operational parameters)
Static	Transformer	Bushing failure	Bushing	Overheating of conductors, sudden high fault voltage, seal breaking of bushes, not replacing old oil for long-time.	f(Operational parameters)
Static	Transformer	Protection system failure	Protection system	Overheating of relays, moisture, heat and corrosion.	f(Operational parameters)
Rotary	PCP pump	Abrasive wear	Rotor/ stator	Hard chrome plating becomes worn, high operating speed.	f(Time)
Rotary	PCP pump	Fatigue failure	Rotor	Material undergoing cyclic stress resulting in failure.	f(Time)
Rotary	PCP pump	Hysteresis	Stator	Pump's pressure above rated pressure, improper rotor spacing.	f(Time + operational parameters)
Rotary	Centrifugal pump	Radial/Axial thrust	Rotor/Shaft axis	Dynamic cyclic component, which is superimposed onto a steady state load.	f(Time)
Rotary	Centrifugal pump	Shaft deflection	Shaft	High radial thrust on pump rotor.	f(Time + operational parameters)
Rotary	Centrifugal pump	Bearing failure	Bearing	Contamination of bearing oil, high heat caused by bearing overload or by excessive lubrication.	f(Time + operational parameters)

Table 1: Major component failures in transformers, centrifugal pumps and PCP pumps

Framework for analytical model selection

According to Jerald F. Lawless, two sets of choices in analytical models are whether to use discrete or continuous-time models, and whether to use parametric or nonparametric assumptions[3].

The model should effectively capture features of the lifetime distribution that are seen from empirical data. Large samples are often required to substantiate the superiority of one model over another in terms of goodness of fit. Censoring schemes are extensively used for comparison of models and their usability. This leads to use models that are computationally useful, and to an extensive use of Weibull, log-logistic, and log-normal models. As the number and complexity of fixed covariates increases, the emphasis on distributional shape reduces, the primary focus being on location and dispersion aspects.

Nonparametric and semiparametric methods are more robust with respect to assumptions than fully parametric methods. It allows more information to pass from the current set of data to the model at the current state, to be able to predict any future data. Several models may provide a description of the observed data. However, use case objective and actionable insights help explain characteristics of data much better.

Thus, the generic framework for asset failure modeling takes into consideration the asset type and failures as a function of time or operational parameters. Environmental parameters have a snowballing impact over time, which helps determine the probability of occurrence of failure by analyzing how particular circumstances or characteristics increase or decrease the probability of survival. However, on the other hand, numerous other operational parameters could trigger asset failure. For these scenarios, causal modeling is required for the identification of lead indicators instigating failures. Figure 3 illuminates the comprehensive approach to choose an analytical framework in case of asset failure modeling.

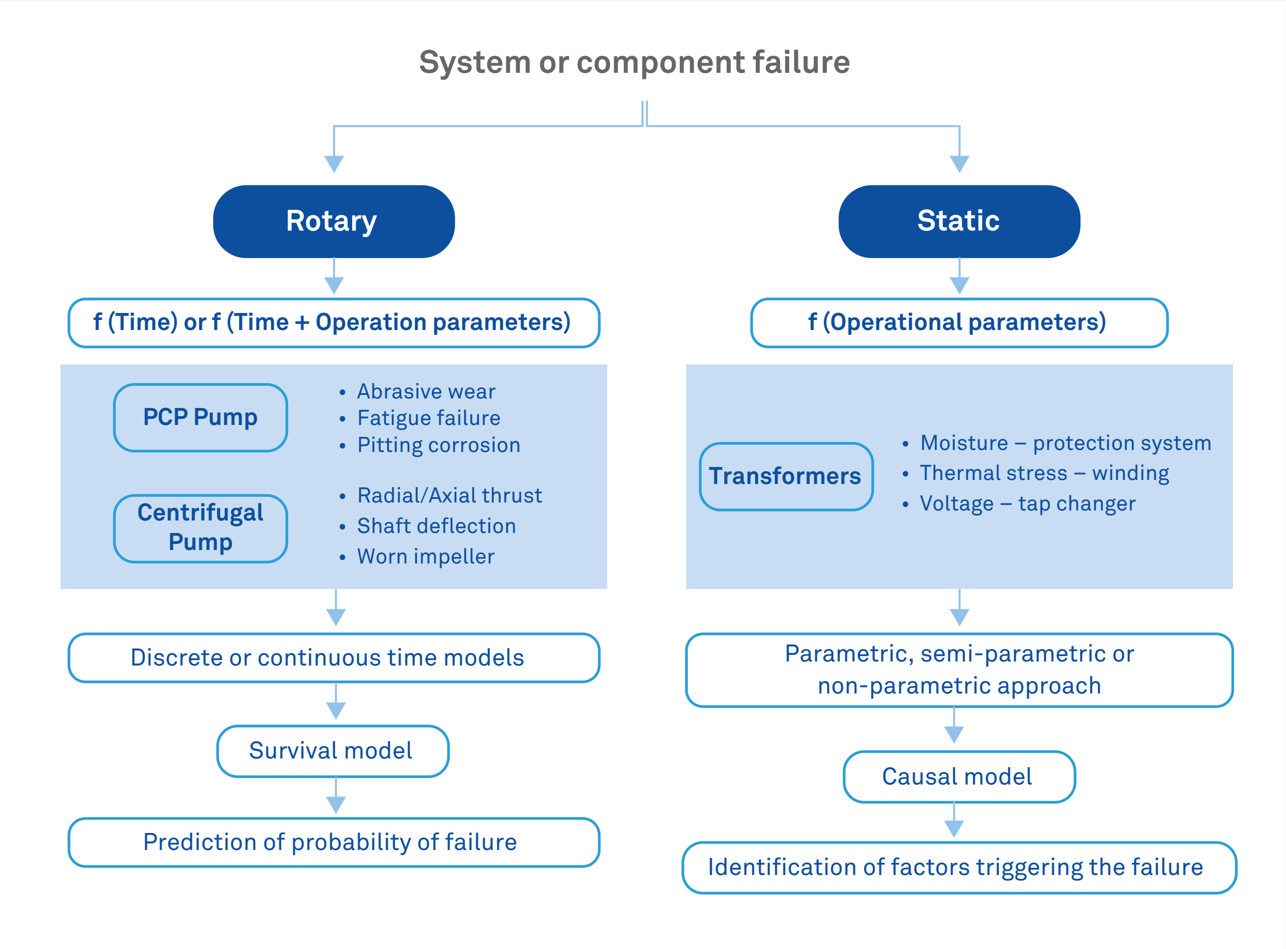

Figure 3: Generalized approach to choose analytical framework for asset failure prediction modeling

Real-life application of analytical framework

A leading Oil & Gas major based out of Australia enabled PCP pump failure prediction by leveraging this analytical framework.

The challenges the organization faced included inconsistent view of assets and their operational status. Also, manual intervention was slowing down preventive maintenance and leading to inaccuracy. The analytical framework enabled the prediction of the expected time for pump failure through the insights gathered by identifying influential parameters with survival analysis.

Table 2 showcases additional issues that were addressed using the analytical framework.

Issues	Asset failure Type	Component type	Model used
Sequence model for asset failure (Mining equipment)	System failure	Static	Logistic regression
Conductor failure analysis	System failure	Static	Logistic regression and decision tree
Predictive asset maintenance of turbo machines	Component failure	Rotary	Survival model
Predictive asset maintenance of centrifugal pumps	Component failure	Rotary	Survival model

Table 2 – Framework application in resolving real-life business challenges

Use of Bayesian methods as future trend

With the advent of sophisticated computational capability and integration of analytics in key business processes, Bayesian models are going to be the need of the hour for the future of reliability analysis. They have a very important advantage of using information from different studies, prior information based on previous experience and engineering knowledge alongside the appealing Machine Learning (ML) characteristics of versatility and statistical properties. Advancements in the implementation of Bayesian paradigm and computer hardware have opened the doors of a new horizon in front of analysts to marry the engineer's knowledge with statistician's theory.

About the authors

Dipojjwal Ghosh,
Principal Consultant, Wipro Ltd.

Dipojjwal is currently involved in the development of analytical apps for consumer and utility domains on Data Discovery Platform (DDP), Wipro's proprietary Insights-as-a-Service offering. He has around 10 years of research and analytical experience in manufacturing, energy, natural resources, and retail domains. He received his M.Tech in Quality, Reliability and Operations Research, from Indian Statistical Institute, Kolkata.

Bavya Venkateswaran,
Consultant, Wipro Ltd.

Bavya is currently responsible for solution design and implementation of advanced analytics & Artificial Intelligence-based use cases on Wipro's DDP. She has been instrumental in handling go-to-market initiatives and delivering turnkey solutions in Energy & Utilities, Human Resources, and Healthcare domains. Bavya holds an MBA degree from Goa Institute of Management, Goa and B.Tech in Electronics and Communications Engineering from SASTRA University, Thanjavur.

Anindito De,
Lead Architect, Wipro Ltd.

Anindito has 19 years of experience as Data Analytics professional. He is currently leading technology implementation of large scale automation programs for Wipro's global clients leveraging AI, ML and Cognitive technologies on Wipro HOLMES artificial intelligence platform. He received his M.Tech in Quality, Reliability and Operations Research, from Indian Statistical Institute, Calcutta and BE in Mechanical Engineering from Jadavpur University, Calcutta.

References

1. https://www.isa.org/standards-and-publications/isa-publications/intech-magazine/2006/January/channel-chat-when-true-cost-of-downtime-is-unknown-bad-decisions-ensue/

2. Study by Kimberlite, an international oil and gas market research and analytics company (http://phdsoft.com/category/phdc4d/)

3. Lawless, Jerald F (2011). "Statistical Models and Methods for Lifetime Data", John Wiley & Sons, ISBN 978-0471372158

Wipro Limited
Doddakannelli, Sarjapur Road,
Bangalore-560 035,
India

Tel: +91 (80) 2844 0011
Fax: +91 (80) 2844 0256
wipro.com

Wipro Limited (NYSE: WIT, BSE: 507685, NSE: WIPRO) is a leading global information technology, consulting and business process services company. We harness the power of cognitive computing, hyper-automation, robotics, cloud, analytics and emerging technologies to help our clients adapt to the digital world and make them successful. A company recognized globally for its comprehensive portfolio of services, strong commitment to sustainability and good corporate citizenship, we have over 175,000 dedicated employees serving clients across six continents. Together, we discover ideas and connect the dots to build a better and a bold new future.

For more information, please write to us at **info@wipro.com**