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White Paper

Harnessing the Power of IoT in Manufacturing: Predicting Parts Failure with the Right Analytical Model

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Abstract

According to Gartner, the installed base of the Internet of Things (IoT) is likely to reach 26 billion by 2020.[1] Latest manufacturing trends also indicate that equipment manufacturers are increasingly rolling out more sensor-enabled products or connected products. Streaming data from the growing connected product base provides useful information that manufacturers can use to perform predictive maintenance by proactively identifying parts failure. Such an approach not only enhances the Overall Equipment Effectiveness (OEE) but also reduces costs associated with break-fix maintenance, leading to better product usage. There are various conventional and composite analytical models for parts failure prediction, and choosing the right one is crucial to achieving higher levels of accuracy. The choice may be influenced by multiple factors such as the nature of parts, product lifecycle stage, and data availability.

This paper highlights the importance of predicting parts failure and its role in the success of a product. It also offers an overview of conventional and composite analytical models and a framework for selecting the right model. Finally, the paper describes how an industrial equipment manufacturer was able to improve the accuracy of parts failure prediction through the use of a robust composite analytical model.

[1] Press release, Gartner Says the Internet of Things Installed Base Will Grow to 26 Billion Units By 2020, December 12, 2013, accessed August 2015, http://www.gartner.com/newsroom/id/2636073

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Exploring the potential of IoT: Extracting business value from sensor data

The past few decades have witnessed a massive surge in internet usage by industrial users and consumers. Every day, new sets of devices are connected to the internet and this is shaping the IoT. According to Gartner, there will be 4.9 billion connected devices in 2015, representing a 30% increase from 2014.[2] Manufacturers can extract immense value from connected devices that are embedded with sensors. This is done by interfacing physical machinery with sensors and software, and networking them through the internet. They can capture staggering volumes of data on machine performance from electrical and mechanical sensors, RFID tags, smart meters, and other devices, ushering in a new way of operating, maintaining, and managing equipment.

GE pioneered the 'Industrial Internet', and predicts opportunities valued at $1 trillion a year through best-in class asset maintenance.[3] The company's aggressive pursuit of intelligent machines has improved data storage and management as well as enabled real-time analysis. In 2014, GE generated $1.3 billion from analytics based on data from the Industrial Internet. CEO Jeffrey Immelt said he expects sales of as much as $5 billion by 2017.[4]

Preventive maintenance assumes that the probability of equipment failure increases with use and schedules maintenance based on calendar time, run time, or cycle count. However, data on failure patterns from four different studies show that (on average) only 18% of assets[5] have an age-related failure pattern; 82% exhibit a random pattern. This indicates that preventive maintenance provides a benefit for just 18% of assets. Analytics solutions help manufacturers take IoT to the next level by turning sensor data into actionable insights that can be used for predictive maintenance. Predicting parts failures will allow manufacturing organizations to achieve operational excellence and avoid high costs of equipment failures.

The importance of parts failure prediction in driving product success

Original Equipment Manufacturers (OEMs) and parts suppliers are constantly looking for ways to achieve superior product performance for greater market success. Periodic analysis of parts failure offers useful insights into product performance and provides the ability to predict failure, both of which are critical for product improvement. Customer claims and sensor data serve as major inputs for conducting parts failure predictions. Here are a few ways in which parts failure analysis influences product success:

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[2] Press release, Gartner Says 4.9 Billion Connected 'Things' Will Be in Use in 2015, November 2014, accessed August 2015, www.gartner.com/newsroom/id/2905717

[3] Forbes, GE Speaks on the Business Value of the Internet of Things, May 2013, accessed August 2015, www.forbes.com/sites/maribellopez/2013/05/10/ge-speaks-on-the-business-value-of-the-internet-of-things

[4] Bloomberg, GE Sees Fourfold Rise in Sales From Industrial Internet, October 2014, accessed August 2015, http://www.bloomberg.com/news/articles/2014-10-09/ge-sees-1-billion-in-sales-from-industrial-internet

[5] Industrial IoT/Industrie 4.0 Viewpoints, Optimize Asset Performance with Industrial IoT and Analytics by Ralph Rio, August 17, 2015, accessed Oct 2015, http://industrial-iot.com/2015/08/optimize-asset-performance-with-industrial-iot-and-analytics/

- **Parts failure trends drive manufacturers towards important design changes** that lead to superior performance in the field. This enables newer, improved versions to gain traction in the market.
- **Longer and extended warranties are crucial to stay ahead of the competition**. Parts failure trends and predictions derived from the existing equipment base help manufacturers estimate the maximum warranty period that they can safely offer.
- **Hassle-free warranty claims allow manufacturers to build goodwill**. Manufacturers usually provision a financial corpus called a warranty reserve to handle warranty claims with ease. Parts failure prediction is essential for estimating the optimal warranty reserve and mitigating the perils of over or under-provisioning.

The following section provides an overview of the analytical models that can be applied on the input data to predict parts failure.

Analytical models for predicting parts failure

The usage of analytical models for parts failure predictions has evolved over time. Statistical tools and techniques are critical components of these analytical models and can be applied depending on the context of parts failure prediction. For example, Schneider Electric indicates that predictive maintenance of building control system equipment almost halves the downtime in comparison to reactive maintenance.[6] These analytical models can be classified into two major categories:

Conventional analytical models: These models use the classification of repairable and non-repairable parts to predict failure based on usage period. A key feature of such a model is that it uses historical 'time to failure' data as the basis for predicting parts failure. These models predominantly use statistical distributions such as Weibull or Exponential. They have been very useful in the past, when manufacturers lacked rich information from sensor data.

Composite analytical models: With the evolution of technology, sensors are now inserted in some critical parts, enabling capture of data on the events that precede failure, as well as on occurrences of failure. For example, in an automobile, a worn out brake shoe or a tear in the brake lining can lead to brake failure. This is where composite analytical models can be used effectively. Composite models are essentially extensions of conventional models (classical reliability techniques complemented with advanced and data mining models), and are growing in usage. In addition to repairable and non-repairable parts and time to failure, composite models analyze the factors that lead to parts failure to improve prediction accuracy.

[6] *Schneider Electric, Predictive Maintenance Strategy for Building Operations: A Better Approach, accessed Aug 2015, http://www.schneider-electric.us/documents/buildings/wp-predictive-maintenance.pdf*

Table 1 summarizes the list of techniques used by conventional and composite analytical models to predict parts failure and the conditions in which they should applied.

Analytical Model Category	Type of Parts	Usage of Techniques	Analytical Models	Conditions Favoring Usage of the Model
Conventional Analytical Models	Non-repairable parts	Predominantly used techniques	• Weibull • Exponential	Flexibility of parameters for a wide range of failure rates associated with different parts
				Constant failure rates, conducive for the intrinsic failure period
		Rarely used techniques	• Extreme Value • Log-Normal • Gamma • Birnbaum Saunders Model • Proportional Hazards	Unique situations where time of failure can take positive and negative values
				Parts afflicted with failure degradation such as corrosion, erosion etc.
				Parts for which repair rates are estimated a priori with known substitutes
				Parts that undergo cycles of stress load lasting for a short period of time
				Parts that have a list of explanatory factors which influence failure
	Repairable parts	Predominantly used techniques	• Homogenous Poisson Process (HPP)	Repairable parts that are in the instrinsic period of their ageing stage
		Rarely used techniques	• Non-Homogenous Poisson Process (NHPP) • Exponential Law	A flexible model that can estimate the expected number of repairable part failures in a time period irrespective of the aging stage i.e., both increasing/decreasing failure rates
				Assessment of design improvements - an improved design ascribes to lower 'beta' values
Composite Analytical Models	Techniques used in conjunction with conventional models to explore and derive data insights		• Association Analysis • Clustering • Decision Trees • Machine Learning Algorithms	Situations where the database has a long history and is rich in many variables. A Big Data environment is ideal for composite models.

Table 1: Techniques used in conventional and composite analytical models

Top three criteria for choosing an analytical model

The choice of the right analytical model determines the predictive accuracy of parts failure. The wrong choice can bring about bias in critical business decisions – such as overstated future claims that result in sub-optimal provisioning of the warranty reserve. It is therefore critical to diagnose the following factors before zeroing in on the right analytical model to predict parts failure:

Failure behavior of parts during the usage cycle

Earlier, equipment units comprised of a large set of individual parts. Technology advancements have resulted in more sophisticated, modular, and complex parts. For simple parts, the usage life spans three stages:

- **Early failure period:** This is during the introductory phases of the parts lifecycle. Due to defects, design issues, and faulty assembly set-up, some parts may fail early. This stage is characterized by a decreasing failure rate (that is, the number of failures per unit of time).
- **Intrinsic failure period:** Among the units that survived the early failure period, a few of them may fail during the useful life period due to the stress caused by use. The failure rate is more or less constant during this period. This period aligns with the growth and maturity phases of the part's lifecycle.
- **Wear-out failure period:** The remaining units may be used beyond the useful life. This stage is characterized by an increasing failure rates of parts, and occurs during the decline phase of the lifecycle.

As shown in Figure 1, these three phases form a 'bath-tub curve'.

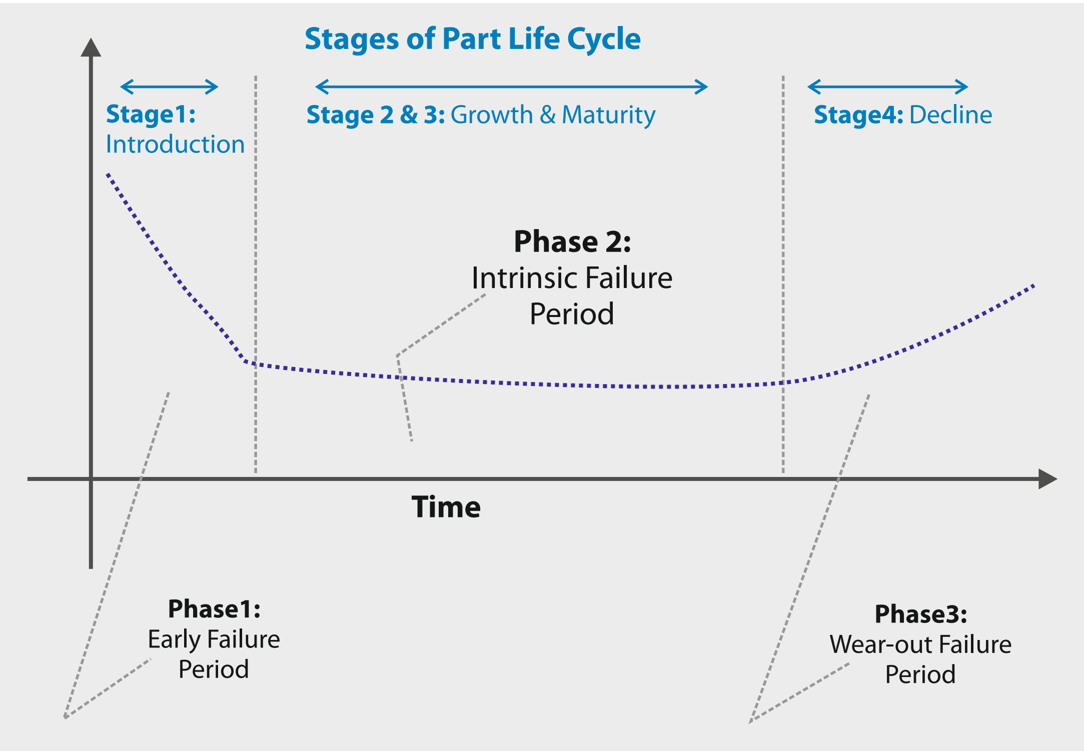

Figure 1: Failure rates across the parts lifecycle

It is important not to consider the entire installed base during prediction, since different sections of the installed base may fall under different portions of the bath-tub curve. For instance, warranty periods usually do not last beyond the intrinsic failure period of the product. If the product has a long usage cycle, it might end in the early failure period. Therefore, prediction of parts failure in an equipment base that is still in the warranty period requires different treatment as compared to a product that is nearing the end of its lifecycle.

Type of parts

Conventional thinking related to reliability theory suggests that different statistical models are required to predict failures depending on whether the part is repairable or non- repairable. A non-repairable part has to be replaced upon failure, while a repairable part can be restored to working condition. As a result, the failure of repairable parts is mathematically represented by repair rates, while non-repairable parts failure is captured as failure rates. The replacement of a non-repairable part ushers in a new part lifecycle. On the other hand, there are chances that a repairable part may fail again. Therefore, it is essential to treat both types of parts differently while predicting failure.

Data availability

The choice of an analytical model also depends on the extent to which data is available for the various factors that influence the accuracy of parts failure prediction. Data availability may be limited or sufficient to predict parts failure accurately. As stated earlier, recent advances in data technology assist in capturing events that lead to parts failure in addition to details on parts failure itself. Composite models are more useful when such data is available to attain more accurate predictions. Conventional models can be deployed if only claim data is available.

A framework for the selection of an analytical model

Figure 2 depicts a decision framework and various conditions for choosing the right analytical model to predict parts failure. It highlights data availability and the nature of parts as major influencing factors. The grey shaded area of the diagram represents the various decisions that need to be made after assessing data availability for a specific type of part. For instance, if the collected data for a repairable part has only claims information, an assessment of failure rates will help zero in on the appropriate conventional model (for instance, exponential or Weibull model). Composite models are more relevant when data pertaining to events leading to the part failure is available.

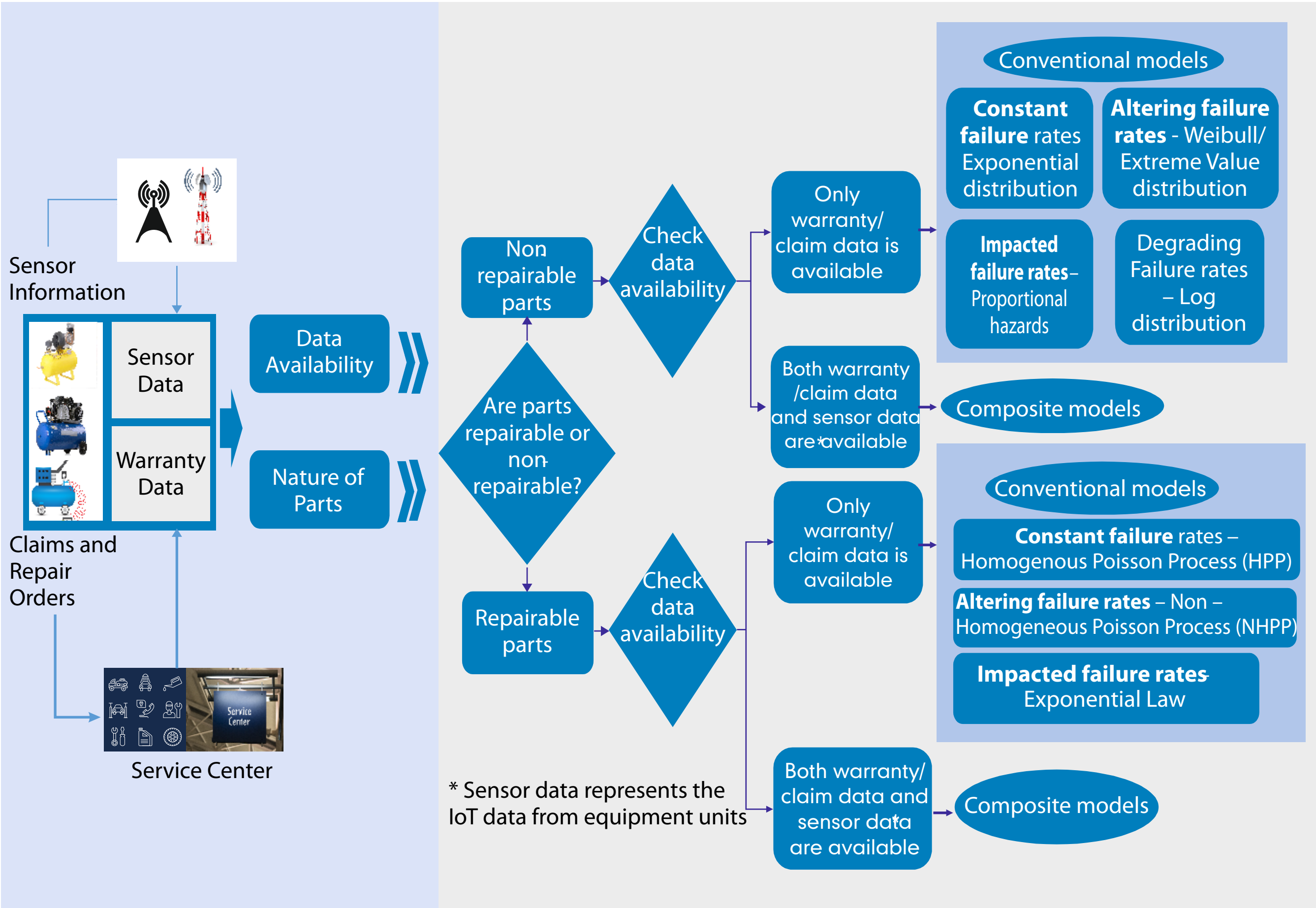

Figure 2: A framework for choosing the analytical model for parts failure prediction

Case study: Industrial equipment manufacturer drives growth in the replacement market, resulting into $25 million estimated cost savings

A well-diversified global industrial solutions company wanted to profitably manage and grow its parts business for the replacement market. Air compressors comprise the company's flagship products and the leadership realized that there was immense opportunity for its compressor parts in the replacement market. However, they first needed to address several challenges and complexities associated with the needs of a diverse market and user base.

The existing installed base had 85 different types of compressors with many parts that exhibited unique consumption patterns based on usage. For example, casing parts have different consumption patterns compared to rotary parts. In addition, the large number of individual parts complicated the parts failure prediction process. Addressing these challenges would require the company to estimate future parts requirements in a specific territory. Armed with the knowledge of territory-level parts consumption, the company could then decide how and where to stock the parts for hassle-free consumption.

A structured solution using a composite model simplified the parts consumption process through a two-stage execution framework as represented in Figure 3.

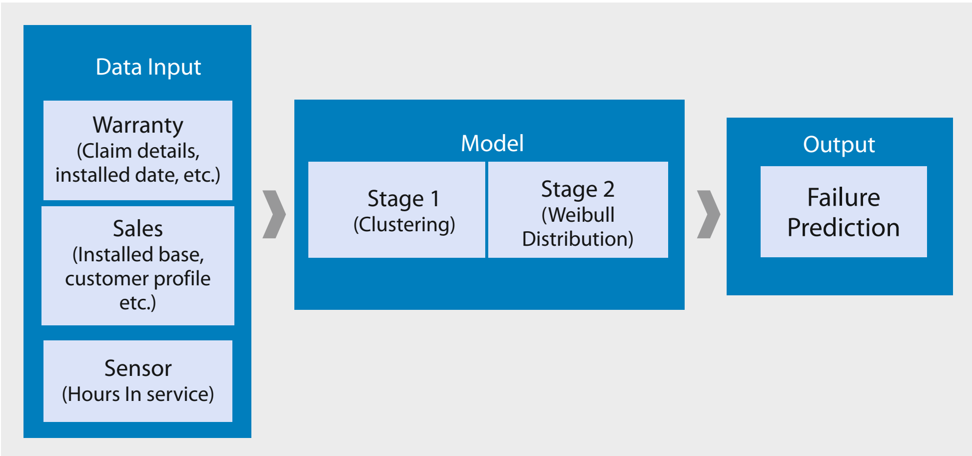

Figure 3: Two-staged composite model solution for predicting part failure

In stage 1, the company was able to profile the large number of parts and wide set of users, and create clusters of users for a product–part type combination. The service hours for each unit was the only sensor based data captured from equipment units. This information was used in conjunction with customer profile and usage information to create user clusters for each product–part combination. User clusters were created by applying the hierarchical agglomeration technique. The customers were then grouped based on parts usage by administering the K-means cluster. The result of clustering was crucial to the application of conventional models in the next stage.

In stage 2, the model enabled estimation of parts consumption for each user group identified in stage 1. The company was able to estimate the probability distributions for each user group based on historic parts consumption. The best fit distribution was then chosen to estimate future parts consumption by applying Bayes' theorem. Figure 4 illustrates a high-level representation of the steps in each stage and the links between the stages.

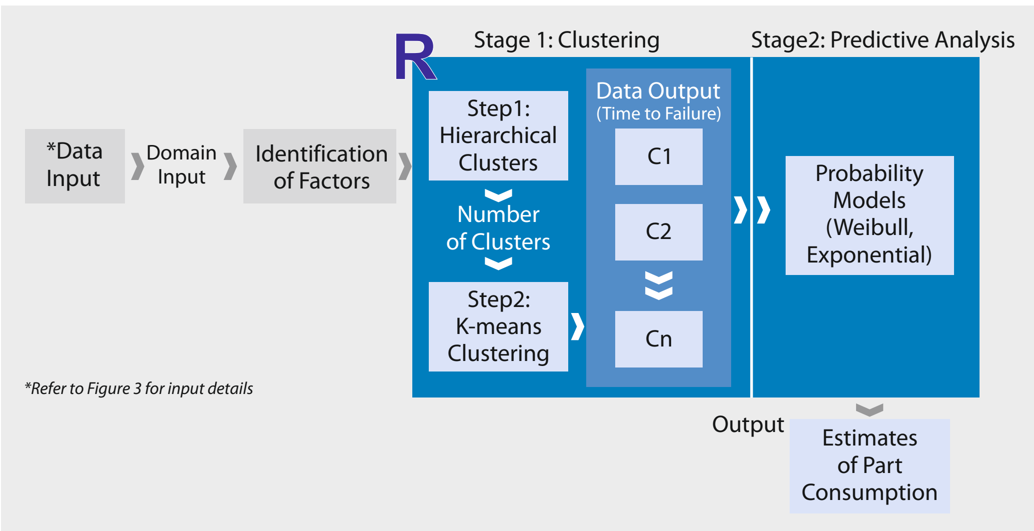

Figure 4: Links between stage 1 and stage 2 of the composite model

The composite model was tested with historical data from specific geographies that was bifurcated into a model and test set. In this case, a two year old dataset from connected devices and sales was divided into a model set comprising 1.5 years of data and a test set with six months of data. A composite model was applied on the model set to make predictions for the next six months, which were then compared with the actual sales on the test set. The difference between the prediction and actual sales reflects the accuracy of the model. During the test phase, the company was able to achieve 90% accuracy. To further improve the accuracy levels, the organization refined the model by capturing additional factors such as trouble codes. The solution yielded the following direct and indirect benefits:

- Accurate estimation of revenue generation from replacement parts, with **the revenue target set at $180 million** for the North America market
- Reduction in obsolescence by producing the right parts
- Assured parts availability for replacement markets, minimizing usage downtime
- Approximately **$25 million estimated cost savings** by preventing parts obsolescence, including lower licensing costs through the use of an Open Source statistical software program

Building a smarter manufacturing business

Manufacturing organizations need to collect, organize, integrate, and transform vast amounts of data. However, this is just the start of creating a data-driven business. Implementing analytics across the IoT-enabled installed base is the most crucial piece of the data puzzle. Analytical models support data interpretation, which in turn helps manufacturers uncover valuable operational insights for faster and more effective decision-making.

In addition to minimizing the equipment downtime, predictive maintenance offers numerous opportunities for manufacturers to improve operational excellence. Sensor-based data gathered from equipment units over long periods of time can also be used to analyze longitudinal data on usage. This offers several advantages, such as the ability to alert the user in real time in case of warranty compliance issues. Such analysis also helps manufacturers carry out design changes and differentiate the product across user segments. They can anticipate demand for onsite repair or field services to hire the right number of field technicians and optimize daily routing. Predicting parts failure also allows manufacturers to automatically re-order parts and maintain the appropriate replacement parts inventory for proactive servicing. As the IoT goes mainstream, analytics will be the key to building smarter, more efficient, and profitable manufacturing businesses.

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