

Our point of view

# Data Science for Predictive Maintenance

## A New Way to Save

Predictive maintenance influences planned and unplanned downtimes. Conventional run-to-failure methods lead to prohibitively high repair costs and downtime once equipment does fail. Conversely, obsessive preventive maintenance work often leads to unnecessary high costs. Predictive maintenance leveraging Artificial Intelligence (AI) allows industrial operations to thread the needle between those two extremes. AI anticipates the imminent need for repair and identifies the right remedial action before an actual failure.

## Useful Approaches

We have identified several proven success factors for applying AI to predictive maintenance.

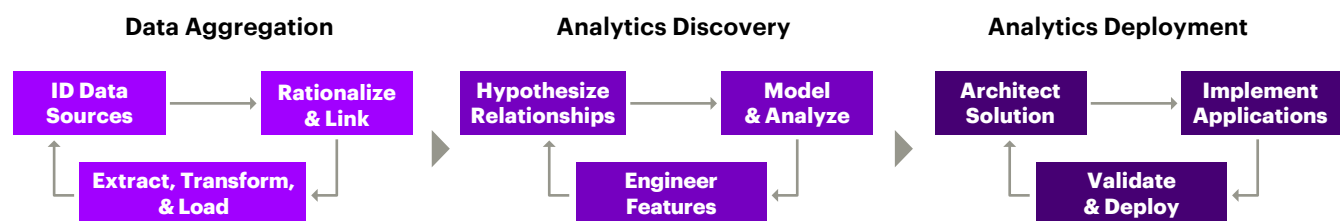
### Focus on an application

Total Productive Maintenance (TPM) may be your overall goal. However, AI solutions work best when purpose-built. Focus on improving a specific business process such as planned maintenance, then address others as needed.

### Phase analytics and modeling

Most firms lack an effective framework for deploying predictive analytics. Start with analytical discovery, iterate rapidly on feature engineering, then move forward with final modeling and deployment. **(Figure 1).**

**Figure 1 - Iterative Process to Deploy Analytics**



## Define criteria for success

Decide early if success means better uptime, cost reduction, or another KPI. Include the cost of false positives when looking at confusion matrix or F1 scores. An objective target will help the team develop the right model.

## Align analytics to the business problem

Different AI techniques solve different problems. Predicting failure is a classifier problem; predicting when a part will fail calls for regression. Categorized root causes from failure testing or returns suggests supervised learning. Unlabeled machine usage or log data will lead to an unsupervised learning approach.

## Unite relevant information

Leverage at-rest and in-motion data sources to unify the most relevant features from sense-and-respond environments. “Digital twins” may help improve operational efficiency.

## Integrate user views

Early critical thought about using AI to assist, augment, or automate will aid strategic use case development. Iterative checkpoints with users help ensure adoption.

## Maintain model interpretability

Successful projects evaluate dependencies like data size, cleanliness, training, and testing time to ensure meaningful results at scale. “Black box” complexity of advanced AI techniques can work against user acceptance.

## Avoid bias

Issues like population sampling, disparate impact, and class imbalances can compound over time. A “monitor the monitor” strategy ensures ongoing quality control.

## Case Study

A mobile phone manufacturer suffered high rates of “no trouble found” for returned phones and poor customer satisfaction.

Phone IOT data (Terabytes/day), support cases, and past repair records were aggregated and aligned. Failure mode analysis targeted hardware issues and battery failures to determine repair likelihood. A Gradient Boost model proved the most effective classifier (AUC of 83%; Figure 2)

Repair tech dashboards were updated to include relevant probabilities when servicing calls. Repeat phone returns (“bounce”) fell 69%. No trouble found rates dropped 44%.

Figure 2 - ROC curve shows good predictive power

