SymphonyAI

WHITE PAPER

Asset Maintenance Variation Management

Machine Learning Limitations in Maintenance

Over the past few years, machine learning (ML) has emerged as a favored technique for managing asset maintenance data. Previous methods involved collecting historical asset data and creating rule-sets based on threshold criteria. Due to data volume and complexity, this approach did not scale, resulting in arbitrary predictions for when to perform maintenance procedures. ML's first benefit to maintenance practitioners is freeing them from the management of these rule-sets.

However, this solution created a new problem. By training models based on existing data, especially with deep neural networks, the practitioner loses explainability, leading to some undesirable consequences. First, black box models and predictions that are difficult to explain or interpret lead to diminished trust in the recommended actions. Secondly, it creates more work for data scientists—tweaking, experimenting, etc. Thus, traditional ML approaches result in models that are harder to maintain and cost more to sustain.

A bigger problem emerges from the modeling approach many practitioners use when analyzing maintenance data: they treat it as a supervised learning problem. The hypothesis assumes with enough failure examples, you can predict future failures. In practice, the data never contains enough failure samples for these supervised approaches, so the resulting models are brittle and unreliable.

Typically, experienced practitioners then pivot to unsupervised approaches. Based on the lack of failures in the data, this essentially becomes anomaly detection. While valuable, this is typically narrowly focused on one particular type of data: sensor data, maintenance records, supply chain, logistics, etc., and lacks the ability to surface the continuous transitions between normal and failure states, when maintenance needs to occur.

This is occasionally combined with supervised learning models, but requires significant effort to generate a model for each asset, which doesn't scale, and introduces an entirely new problem of managing and maintaining a large library of models that continuously need to be tuned/retrained. Now organizations have transitioned from managing rule-sets to managing models or mini-models for various aspects of the maintenance life cycle. Models to predicts failures, other models to predict supply chain issues that impact the maintenance process, and still more models predicting operational readiness and asset utilization. Complexity ensues.

Maintenance Optimization is the Problem

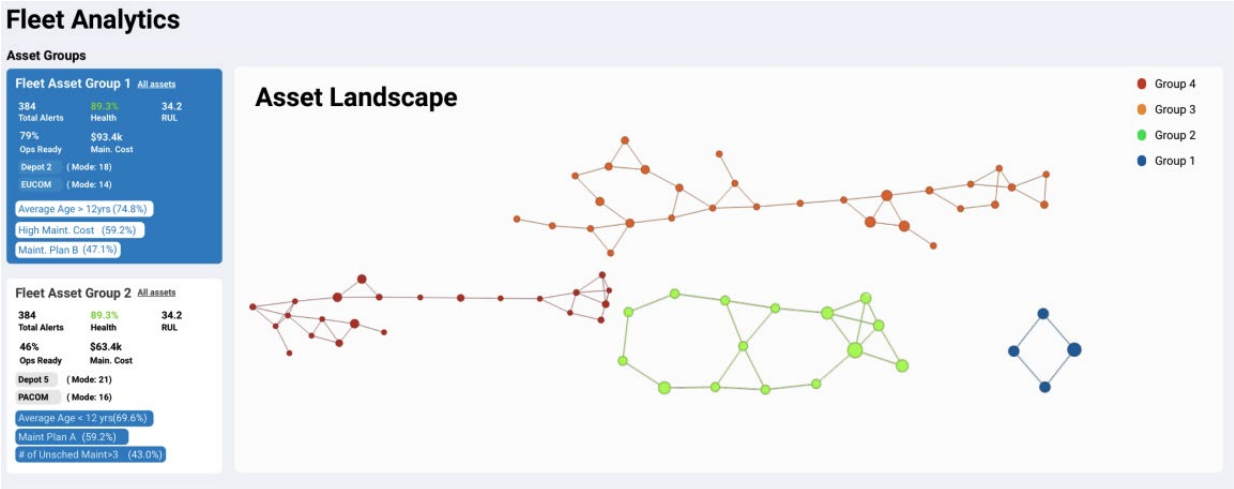
It is a fundamental tenant of science that complex problems are best tackled by breaking them up into smaller, more manageable problems.

This often maps directly to the limitations of certain underlying technology. For example, in unsupervised learning, traditional clustering algorithms have underlying assumptions which are likely not valid for the complex datasets in this domain, limiting the effectiveness of these algorithms.

To optimize complex systems like a maintenance life cycle, you need to assemble complex datasets from all related domains—in a way, it is a starting point that excites data scientists, but but also instills fear. To do it well, you require a fundamentally different underlying methodology.

Symphony AyasdiAI's maintenance optimization technology combines traditional ML algorithms with topological data analysis (TDA), which has proven successes analyzing complex, high dimensionality datasets in life sciences, healthcare, finance, cyber and complex process optimization.

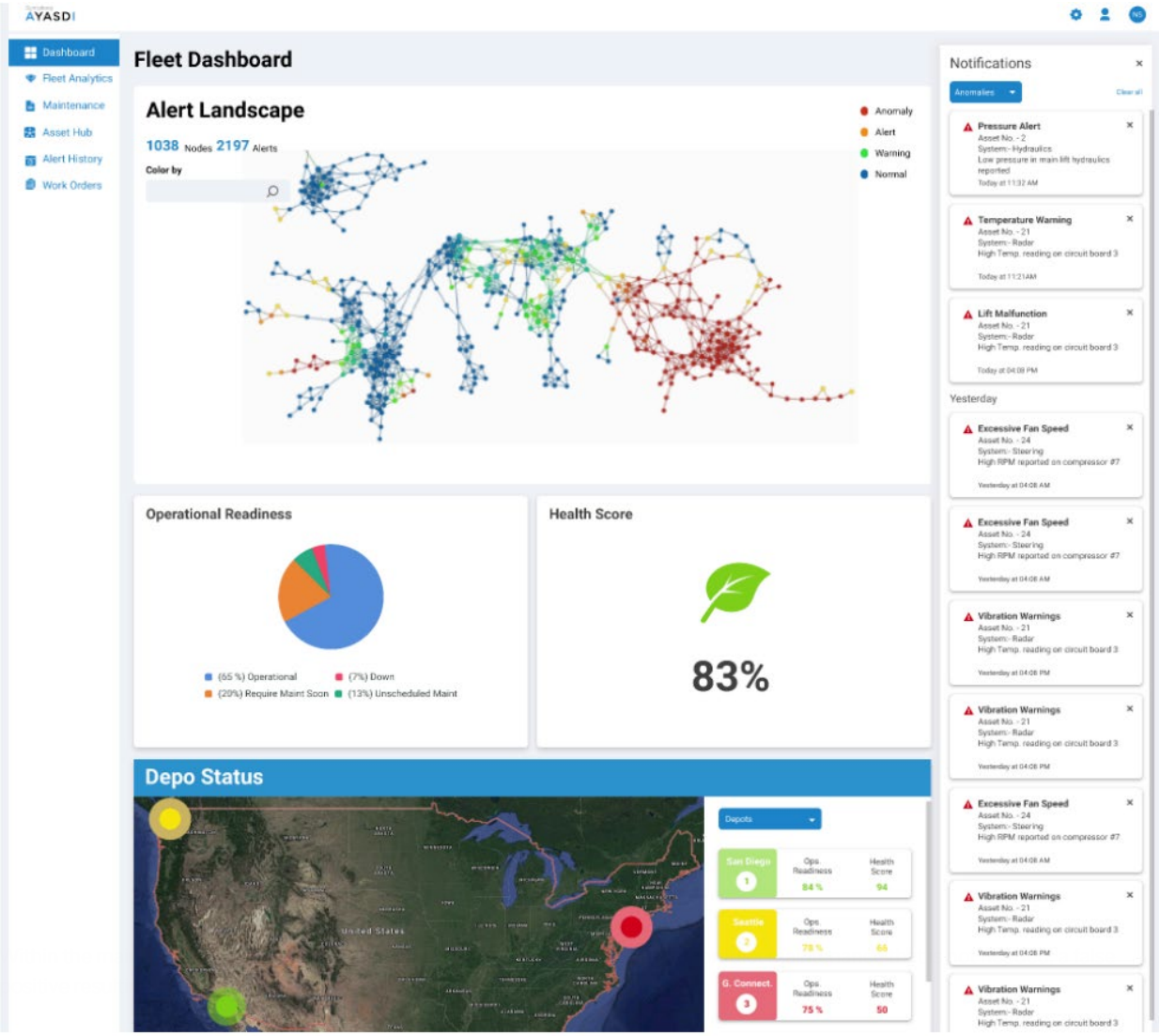
TDA was invented by Stanford mathematicians with funding from DARPA. TDA represents a fundamental change of relationship between algorithm and data. With other machine learning algorithms, the practitioner needs to have a hypothesis about the shape of the data, and an underling assumption that this shape applies across the entire dataset. With TDA, the shape of the data emerges without the dependency on a prior held hypothesis.



This novel approach is able to build one mega-model for a fleet of assets and their subsystems. It is capable of using both structured and unstructured data from disparate sources.

The model allows for segmentation and localization of shape/behavior, and this TDA shape allows for the quick recognition of significant groups within the dataset. In the maintenance domain, this translates into identifying best and worst practices.

For example, in a fleet of assets, which sub-population of those assets are best maintained from a cost standpoint, from a cost-plus usage standpoint, or whatever is your proxy for success? Among these, which maintainers worked with them, using what sequence of routines given a variety of usage patterns? The goal of optimizing maintenance is to deliver the right maintenance at the right time to optimize for cost but also maximize safety. This is the challenge for complex data analytics or TDA.



Second, it will fail to predict needed maintenance; resulting in safety issues and increased cost associated with an unscheduled maintenance action. To avoid these issues, the models must make highly accurate predictions, datasets should be analyzed to identify multi-dimensional patterns—usage, process, cost are all factors of keen interest to analysts or data scientists. How do you combine all this data into mega-models, encompassing all that is known about a particular maintenance operation? Traditional techniques are not able applicable. TDA and Symphony AyasdiAI's maintenance optimization technology is the answer.

About SymphonyAI

SymphonyAI is building the leading enterprise AI company for digital transformation across the most important and resilient growth verticals, including life sciences, healthcare, retail, consumer packaged goods, financial services, manufacturing, and media. In each of these verticals, SAI businesses have many of the leading enterprises as clients. SAI is backed by a $1 billion commitment from Dr. Romesh Wadhwani, a successful entrepreneur and philanthropist. Since its founding in 2017, SymphonyAI has grown rapidly to a combined revenue run rate of more than $300 million and over 2,200 talented leaders, data scientists, and other professionals.

Palo Alto, CA HQ | 3300 Hillview Ave. Palo Alto CA 94304 | +1 650 250 4777 | sales@symphonyAI.com | symphonyAI.com