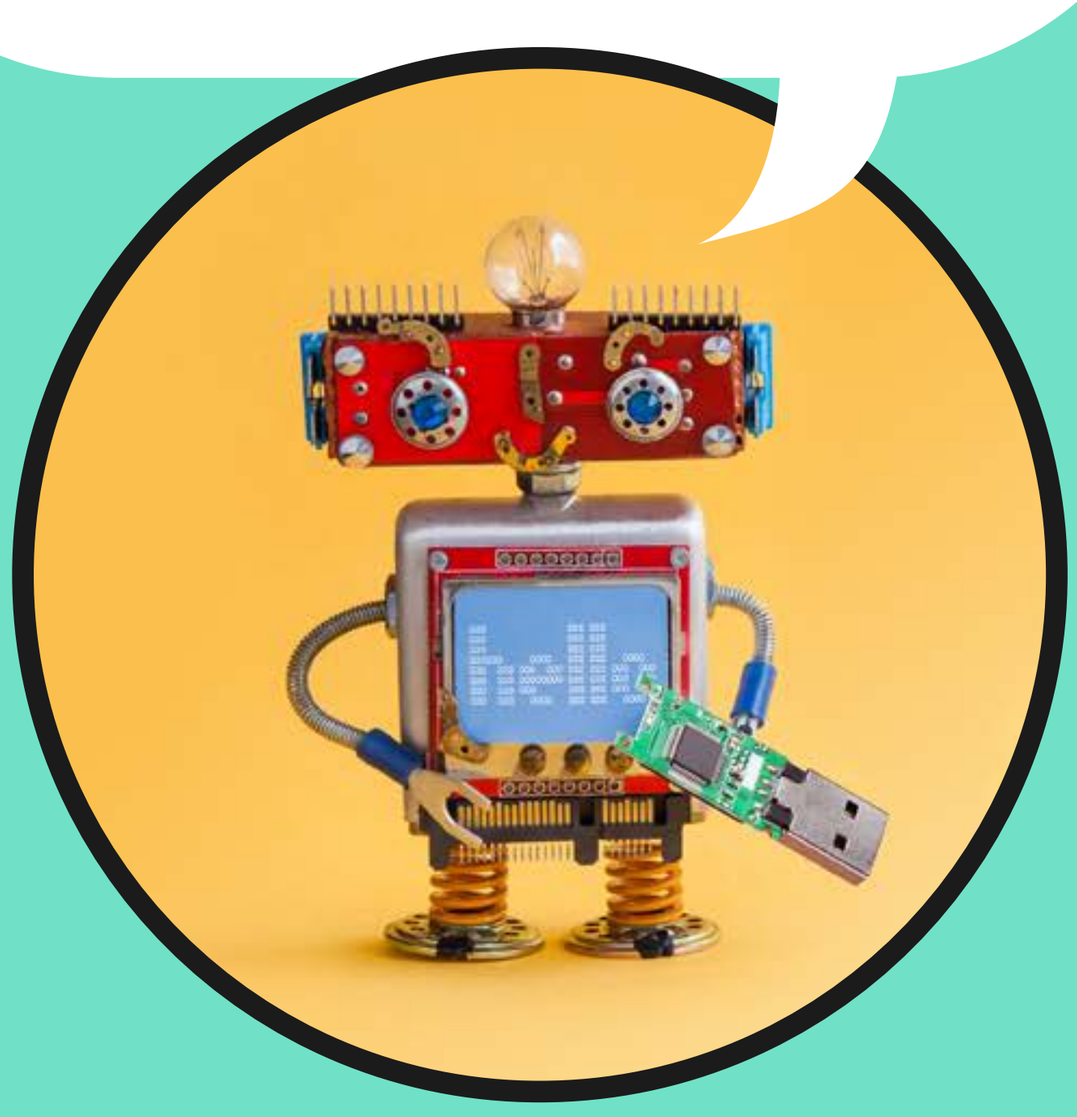
“Read it and get smarter” - Maurice Jilderda, Industry 4.0 Expert, Perfact

PREDICTIVE MAINTENANCE

FROM SCRATCH

Discover how to make your industry operation more efficient, sustainable and profitable

A Complete Guide for **Original Equipment Manufacturers**



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WHAT TO EXPECT

1. PREFACE

Rapid technological progress has boosted interest in predictive maintenance. Here, 'predictive' means maintenance that is performed on time, based on predictions of imminent failure or quality degradation, before these actually occur. In this way, quality problems in operation are prevented, and inconvenient and often expensive corrective maintenance, such as repair or replacement, is avoided. As a result – in line with the ultimate goal of predictive maintenance – overall equipment effectiveness is increased and downtime is minimized. So it's no surprise that interest in predictive analytics for maintenance is booming. Last year, Market Research Future projected that the predictive maintenance market will expand at a compound annual growth rate of 25% to reach USD 37 billion in 2025.

Original equipment/asset manufacturers (OEMs) and asset owners/operators alike acknowledge the potential of Industry 4.0 for making maintenance more efficient and effective. This involves the combination of digitalizing business and operational processes with installing Internet of Things (IoT) networks, and applying artificial intelligence (AI) technologies such as machine learning. While the focus is often on the technological opportunities and challenges, implementing predictive maintenance – like any other business activity – should start with getting the business case right.

"Don't focus on technological opportunities, but rather start with getting your business case right."

Frank den Ridder - Sensorfy

1. PREFACE

That's why Sensorfy and Perfact Group have joined forces: to better serve customers who are considering adopting predictive maintenance. At Sensorfy, we develop technological solutions for implementing predictive maintenance, thus building the world's most accurate predictive technology. At Perfact Group, we combine knowledge, people, and technology in order to help organizations and people to improve demonstrably. Together, we cover the strategic, tactical, and operational phases of predictive maintenance implementation.

To support our consultancy, we have developed a framework for predictive maintenance implementation. It addresses the complete process, from quick scan to scale-up, and divides it into three main stages: Connect, Predict, and Accelerate. In this guide, we elaborate this framework and illustrate its application in three concrete cases: one with an OEM and two with asset owners. All cases succeeded in reducing downtime and improving efficiency, thus capitalizing on the promise of predictive maintenance. Our framework provided them with an effective instrument for implementation.

The Sensorfy / Perfact team

"Our framework for predictive maintenance implementation addresses the complete process, from quick scan to scale-up."

Maurice Jilderda - Perfact

2. INTRODUCTION

When considering implementing predictive maintenance, the starting point should be an evaluation of how it would fit within the organization's business and maintenance strategy. What would be the purpose of such an implementation, and why should maintenance be organized according to a predictive model? And what about feasibility? Does the business currently have sufficient knowledge and organizational maturity concerning maintenance? Is the organizational culture in favor of or against embracing digitalization, and abandoning good-old planned or preventive maintenance? And last but not least, is management on board, showing leadership, bringing in the required specialists, providing ample budget, and aligning all the internal and external stakeholders?

This evaluation will be part of a business and feasibility quick scan, which is only the first step in the implementation process.

2. INTRODUCTION

2.2 Framework

Based on many years of Industry 4.0 consultancy and successful predictive maintenance implementations, we have developed a comprehensive framework covering eight steps, consolidated into three main stages:

Connect

1. Business and feasibility quick scan
2. Item selection and deeper problem understanding
3. Data selection, collection, and preparation

Predict

4. Algorithm modeling and design
5. Evaluation and validation

Accelerate

6. Real-time deployment
7. Integration into running business
8. Scale-up

2. INTRODUCTION

2.3 Cases

CASE	STEEL PRODUCER Lubrication effectiveness	MACHINE BUILDER Production-as-a-service	INSULATION PRODUCER Quality improvement
CHALLENGE	Revenue loss due to unplanned downtime	Business model shift toward production-as-a-service	Scrap and rework due to ineffective quality monitoring
MOTIVATION	A recent failure of a large gearbox due to a lack of lubrication revealed that the asset owner had no insight into the effectiveness of lubrication on its critical assets.	The OEM needed help to start its journey on the road to production-as-a-servic e, of which predictive maintenance would be a key element.	A high rate of external complaints due to leaking end-products confronted the asset owner with high costs for scrap and rework.
SOLUTION	Installing IoT sensors. Developing scalable algorithms. Gaining real-time in-sight into effectiveness.	Investigating failure modes. Defining maintenance strategy. Translating findings to Industry 4.0 elements.	Finding new quality measures. Incorporating continuous monitoring of seal quality into the production process.
GOAL	Reduce downtime. Improve efficiency.	Improve customer satisfaction. Reduce downtime and costs.	Improve customer satisfaction (fewer complaints). Reduce downtime and costs.

3. CONNECT

In the Connect phase, we make the connection between the problem at hand, concerning quality or asset condition, and the organization's business and maintenance strategy. When a business and feasibility quick scan yields a positive outcome, the first priority is to gain a deeper understanding of the problem, and select the items for which a predictive analytics approach could generate added value. Here, items refer to the defining quantities for the condition or quality problems; examples include temperature, load, vibrations, lubrication, specific material properties, etc., etc. For these items, the relevant data have to be identified. Depending on the specific problem(s) and the nature of the asset, this can be an iterative process in which the analytics potential of multiple items is assessed.

3.1 Business and feasibility quick scan

This starting phase comprises the business scan as described in the previous chapter, and a feasibility quick scan. This feasibility scan focuses on the added value that can be generated by adopting predictive maintenance. What added value can be expected, and will this be large enough to justify a significant investment? Also, we make a first conjecture about a promising business case, with a view to real-time deployment and integration, and the potential for scaling up.

3. CONNECT

3.2 Item selection and deeper problem understanding

With respect to predictive maintenance, the failure modes (and quality issues) of an asset are of primary importance. There may be hundreds of components or modules than can fail, many of them in different ways. What are the impact and frequency of all the individual failures, what are their root causes, and can we make predictions about their occurrence?

"From this we can deduce the impact a predictive analytics approach can have, and ultimately, the outcome of a business case."

This requires a deep understanding of an asset's nature and its mode of operation. From this we can deduce the impact a predictive analytics approach can have, and ultimately, the outcome of a business case. When multiple items are reviewed in this way, they can be ranked in a "3D" matrix of impact vs likelihood vs predictability, from which the most "promising" item(s) can be derived for predictive analytics.

3. CONNECT

3.3 Data selection, collection, and preparation

When the items have been determined, the relevant data that can provide information for the related problem have to be identified. Which data have to be selected, how can their collection/acquisition be organized, and what preparation (consolidation, pre-processing, filtering, etc.) is required? Data acquisition involves sensors (internal asset sensors and specific add-ons) and access to internal asset signals (for example, motor currents). This may require additional investments and thus contribute, adversely, to the business case. Then the sampling frequency has to be determined, ranging from once every hour or day to frequencies in the kilohertz range, with all the associated data bandwidth and storage issues. In addition, the need for synchronization between multiple data streams, time stamping, etc. has to assessed. In short, big data bring big challenges.

3. CONNECT

3.4 Cases

CASE	STEEL PRODUCER Lubrication effectiveness	MACHINE BUILDER Production-as-a-service	INSULATION PRODUCER Quality improvement
QUICK SCAN	The problem is urgent and real; unplanned downtime results in high revenue loss. The organizational maturity with respect to maintenance innovation is high. Conventional measurement technology is expensive and complex. A predictive approach fits in the overall maintenance strategy. Budget is available.	The high-tech machines lend themselves to servitization with respect to maintenance. The staff is highly skilled, but the organizational maturity concerning maintenance is low. The concept of servitization has been adopted, but the concrete business case is being questioned. Knowledge of failure modes required for making maintenance predictive has to be obtained. Budget is available.	The quality problem is urgent and has a high impact. The organization has a continuous improvement mindset. Budget is available.
ITEM SELECTION	Real-time asset health indicators have been obtained.	75% of failures can be detected with predictive techniques. The top three maintenance-related problems have been selected for real-life pilots.	An initial Lean/6Sigma approach combined with data science yielded no solution. After introducing new sensors, a correlation with the quality problem has been demonstrated.
DATA	A new concept has been developed for data acquisition via low-cost sensors.	The associated data have been identified for the three pilots.	The relevant data have been identified, based on correlations between data patterns and problem types. The corresponding measurements have been installed.

4. PREDICT

In the Predict phase, we develop the algorithms that can be used in a predictive maintenance approach. To prevent re-inventing the wheel, it is crucial to first assess the nature of the problem at hand with respect to the “installed base” of predictive solutions: is it standard, custom, or innovative? We select a suitable type of algorithm and then – with the extent of our efforts depending on the nature of the problem – we perform modeling to turn data into information, test the algorithm, and evaluate its performance in practice. If successful, this leads to validation of the algorithm for real-time deployment.

4. PREDICT

4.1 Algorithm modeling and design

In a straightforward case, a “standard” solution can be picked off the shelf and implementation will be easy. If a suitable solution appears to be available, even if it may need some testing and finetuning, we designate it as “custom”. For example, a solution for predictive pump maintenance will work for a fan as well, as both assets belong to the same class of rotating equipment, but will require tuning to the new application.

An “innovative” solution is needed if an analytics approach has never been applied to such a problem in the particular context at hand. Then, some real development and testing will be required first, for example regarding a physical quantity or a measurement method that has not been used before in an analytics context – it worked with temperature monitoring, but will it work with pressure?

“In many cases, rulings and first principles can already give good results, especially when they are smart (“if this, then that”) or based on multi-variable physical models, respectively.”

The next step is deciding on the type of algorithm to be used. Will “simple” rulings and calculations suffice, is a more elaborate first-principles approach (physics, thermodynamics, etc.) required, or do we have to invoke some sort of artificial intelligence (AI), such as machine learning (ML)? In many cases, rulings and first principles can already give good results, especially when they are smart (“if this, then that”) or based on multi-variable physical models, respectively. However, they tend to generate too many false-positive warnings. Nowadays, given the progress in computing power and data science, the real difference can be made with AI/ML.

4. PREDICT

Different types of AI/ML algorithms are available, each with their own application characteristics:

Anomaly detection:

This concerns relevant physical quantities identified by domain experts, such as temperature, pressure, flow, and frequency spectra of natural vibrations. Depending on the nature of the data, sensor readings are used for straightforward detection of an anomaly, or are fed into either standard statistics or a machine-learning algorithm that generates an output that is a measure of the (ab)normal functioning of the asset. If this measure exceeds a certain threshold value, then anomalous behavior is detected. Expert judgement may still be required to assess whether a detected anomaly is real, or just a (sensor) artefact.

Predictive analytics:

Future sensor data can be predicted based on their history: i.e. by processing time-series sensor data. This calls for a multi-variable algorithm. If the real sensor data differ from the predicted values, this may signal a potential malfunctioning, the source of which then has yet to identified. In the steel producer's case, this was used as one of the two techniques.

4. PREDICT

Prescriptive analytics:

This is the next level of predictive analytics, when not only the potential malfunctioning is signaled, but also the particular failure mode can be pinpointed. This can be compared to the working of the popular Shazam app, which is able to identify music based on a short sample. Prescriptive analytics can provide an “industrial Shazam” app, the challenge being that each industrial asset can make “music” that has never been heard before. In some specific cases, this is very valuable to apply, but often in other cases it does not lead to added value. In the insulation producer’s case, this technique was successfully implemented.

Forecasting:

The ultimate AI/ML application for maintenance is forecasting, often concerning the remaining useful lifetime of a component or module within the asset. Based on (condition) monitoring of the quantity or quantities involved, trends can be detected that are indicative of an approaching end-of-life, and a prediction can be made for the remaining useful lifetime. Based on this estimate, including a safety margin, component or module replacement can be planned. Using this technique requires a lot of data and understanding of the limitations and assumptions of the algorithm. An example of where it is used frequently would be an electric vehicle estimating its remaining travel time and battery life.

When the appropriate algorithm has been selected and geared toward the application, visualization and user interfacing have to be designed carefully in order to promote user insight and facilitate practical use.

4. PREDICT

4.2 Evaluation and validation

An essential element of the Predict phase is training. An ML model/algorithm usually comes with so-called weights: parameters that influence the output given a certain input. A model is first “trained” using historical data, meaning a set of known input and output data: sensor readings and the associated behavior, respectively. The set of weights, defining the model, is optimized to reproduce the known output. Then, the model uses real-life sensor data to generate new output data, i.e. predictions, and the real application of the algorithm can be tested, to evaluate its performance in practice. If successful, this leads to validation of the algorithm for real-time deployment.

4. PREDICT

4.3 Cases

CASE	STEEL PRODUCER Lubrication effectiveness	MACHINE BUILDER Production-as-a-service	INSULATION PRODUCER Quality improvement
ALGORITHM	A first algorithm concept turned out to be “high-tech” and complex. A new version was designed for better usability and scalability.	An analytics test program will be a combination of existing PLC data with new IoT data, all managed via the cloud and a web app.	A prescriptive algorithm including an operator dashboard generates operator-independent alarms, and flags proactive maintenance actions.
EVALUATION	The analytics scheme using the new algorithm proved to be effective.	For the top three failure problems, proven analytics concepts can be used. Therefore, the probability of success is high.	Using a prescriptive analytics approach, various insulation problems can be detected. Continuous production quality monitoring is now in place.

5. ACCELERATE

In the Accelerate stage, we shift to a higher gear, and get the predictive maintenance case really running. This starts with deploying the predictive model we have developed in real-life operation, and then integrating it in the day-to-day business. Ultimately, we can prepare for scaling up to other problems, other assets and other plants, turning our proven approach into a multiplier.

5. ACCELERATE

5.1 Real-time deployment

When changing over to real-life operation, numerous Industry 4.0 issues have to be addressed. To start with, data acquisition has to be real-time, in order to enable a real-time response in case of imminent failure. For that, reliable connectivity, both wired and wireless, inside and around the asset and with the outside world has to be organized. Wired PLC/DCS, edge solutions, Ethernet, Bluetooth, Wi-Fi, Zigbee, Wireless Hart, ISA100, LTE, long-range narrowband, 4G, 5G...; the communication technology options are endless. Then, communication and data security are the next, highly topical issues.

Computing and data storage also have to be considered. For computing, both edge and cloud solutions are available, and a trade-off has to be made. For example, edge computing for data pre-processing can prevent data communication overload and reduce complexity, but may require “smart” sensors or other local computing power. In a similar vein, either on-premise servers or the cloud can be used for data storage. These options each have their pros & cons, depending, for example, on internal IT maturity, external communication and storage costs, and data security criticality.

In real-life operation, users will include operators, service engineers, and other non-experts in the field of analytics and predictive maintenance. Therefore, user-friendly analytics engines, accessible dashboarding, and easily understandable alarm and warning systems have to be installed.

5. ACCELERATE

5.2 Integration into running business

Following successful real-time deployment, the predictive maintenance case then has to be integrated into the day-to-day business, and hence in all the relevant management systems, whether available on-premise or in the cloud. These include:

- MES (Manufacturing Execution System);
- DCS (Distributed Control System);
- CMMS (Computerized Maintenance Management System);
- ERP (Enterprise Resource Planning);
- PDM/PLM (Product Data/Lifecycle Management);
- APM (Asset Performance Management).

This integration comes with the familiar data and communication compatibility and security issues, and therefore should not be taken lightly.

5.3 Scale-up

When all the deployment and integration issues have been dealt with, the logical next step is scale-up. After all, a considerable investment has been made to come this far, and real revenue will come from repeating this exercise with a smaller investment. The first place to look for scale-up opportunities is the asset at hand, which can have multiple operational and maintenance issues that have not been addressed yet. Here, the knowledge and experience gained in a predictive maintenance context will most likely pay off. The developed approach can also be followed for other assets, either identical or related to the original asset. However, a 100% “copy-paste” is hardly ever possible, depending on local conditions and differences between individual assets. Lastly, in larger companies, scale-up to other plants is a viable option, but here cultural / international differences will also come into play.

The larger the scale, the more critical usability (integrated dashboarding), security and sustaining (of algorithms, maintenance methods, etc.) will become. On the other hand, the potential benefits will also be greater.

5. ACCELERATE

5.4 Cases

CASE	STEEL PRODUCER Lubrication effectiveness	MACHINE BUILDER Production-as-a-service	INSULATION PRODUCER Quality improvement
QUICK SCAN	The complete solution includes over 200 IoT sensors, cloud storage, and analytics and web dashboards.	The pilots for testing the three concepts are fully based on IoT and cloud deployment, and are therefore easy to start.	100% inline inspection has been realized.
ITEM SELECTION	The next step is integration into the customer's applications, ERP and CMMS.	Integration of the existing "operations cloud" with the new "maintenance cloud".	The detection algorithm is used to identify faulty products for automatic ousting from the production line.
DATA	Other asset issues can be addressed easily, due to profound algorithm development. This locally initiated approach can be adopted by other plants in the global company.	Due to the multiplicity of failure modes, extension to other failure modes is labor-intensive. Scale-up to other, related machines is relatively easy.	After an individual learning phase, the new algorithm can be used on each related machine. Recently, the solution has been "copied" to a plant in Canada. There is now an opportunity for OEM of this machine.

6. CONCLUSION

Implementation of predictive maintenance requires a structured approach as laid down in the framework described in this guide. In the three cases presented here, it has helped the OEM and the asset owners to establish well-founded predictive maintenance schemes that have resulted in reduced downtime and costs, increased efficiency, and improved customer satisfaction. The three main stages of the framework, Connect, Predict, and Accelerate, have to be addressed with due attention to the various sub-stages, and no shortcuts can be taken. This calls for following a disciplined way of working and investing in stakeholder engagement. When these conditions have been satisfied, the benefits can be great.

"You can decide to avoid beginner's mistakes or common pitfalls, and instead, accelerate by engaging the specialists."

If you have enjoyed reading this guide, discovered value in the framework-based approach, and identified an urgent problem calling for predictive maintenance, do not hesitate to contact the Sensorfy / Perfact team. Of course, you could try to learn everything yourself, maybe with the occasional help of readily available students from digitalization & AI university programs. Eventually, you may well succeed, but at the expense of going through an extensive learning curve, all the while losing valuable time and money. Or you can decide to avoid beginner's mistakes or common pitfalls, and instead, accelerate by engaging the specialists.

Ready to talk about predictive maintenance for your business? Contact us:
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