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# White Paper: 6 steps to starting a successful Industrial Data & AI project

## Industry 4.0, Is it really all about data and what we do with it?

Driving value from Big Data through the application of Machine Learning (ML) and Artificial Intelligence (AI) has reached the industrial sectors.

Companies are now starting to recognise that there is huge value in the data they create and hold allowing them to start planning on how to capitalise on that value as quickly as possible. The manufacturing and engineering sectors are one of the largest producers of data and it stems from production equipment, machines, sensors and business operation data sources.

The challenge today with the rapid evolution of data technologies such as ML & AI, coupled with an incredible level of hype surrounding them, has led to "analysis paralysis" at many companies, large and small.

Questions of where to start and how to apply these new technologies, along with uncertainties at the potential scale of deployments, are preventing some companies from moving forward, especially with specific use cases seemingly so rare at this point in time.

## Statistics around Big Data and AI

- 90% of the world's data has been created in the last two years alone.
- Most companies only analyse 12% of the data they have.
- By 2020, there will be more than 50 billion smart connected devices in the world, collecting, analysing and sharing data.
- AI's impact on marketing is growing, predicted to reach nearly $40 billion by 2025.
- IoT will save consumers and businesses $1 trillion a year by 2022.

This practical, “how to get started” guide gives industrial companies a much-needed blueprint for evaluating and implementing Data and AI technologies.

Quick Take

- For industrial companies, operational insight is often masked by huge siloed process and industrial data flowing from machines, sensors, automation systems, supplier databases and other data sources
- In effect, the production facility holds “secrets” related to data correlations, trends, anomalies, deviations, root causes, and other key operational information. This lack of insight leads to lower quality rates, production inefficiencies and competitive disadvantage
- True insight requires real-time reporting, deep dive analytics of historical trends and ML applications. These capabilities reveal production and supply chain patterns, anomalies, quality and root cause issues and other meaningful trends, in time for the operations and quality teams to take effective actions.

While every machine, scanner, robot and sensor output a steady stream of structured or unstructured data, companies can’t easily make sense of the volume, variety and velocity of data locked behind hard-to-use tools.

This is where technologies such as MAIO come to the rescue. Developed by Big Data and AI experts at Smartia, MAIO is designed to be used by non-experts to instantly see actionable insights in their data. By providing smart applications, users are informed through notifications if there is something of interest in the data and what action may be required. This is a change to the current time-consuming process of having to review data through dashboards and making sense of it before deciding on a course of action. Very often this process doesn’t take into account all the facts, as there is too much information to process for an individual in a given time. MAIO takes away this burden and provides the insights in a fraction of the time.

Typical challenges for today’s manufacturers:

“Our systems collect machine downtime metrics and other production data, but we don’t have the means to fully understand what’s important, or which metrics tell the full story of our operations in real time. In a way we’re working blind. We don’t have the ability to take corrective actions.”

“We have a scrap rate of 30%. We believe the problem is somewhere in the casting operation, but we can’t detect deviations and correlate results. What’s missing is our ability to use the scrap data to find the root cause, and take action based on real-time information.”

“Our operations manager walks from machine to machine with a thumb drive to gather the data he needs, then spends hours working on a spreadsheet to correlate and analyse the data manually, before finally distributing the output to teammates. This isn’t workable. By the time we get the data, it’s too late to fix what was broken.”

In each example, the problem isn't lack of data. The challenge is meaningful and real-time insight into that data. As one manufacturer put it,

> "It's almost as if our factory data holds secrets about key performance trends that we just can't get at."

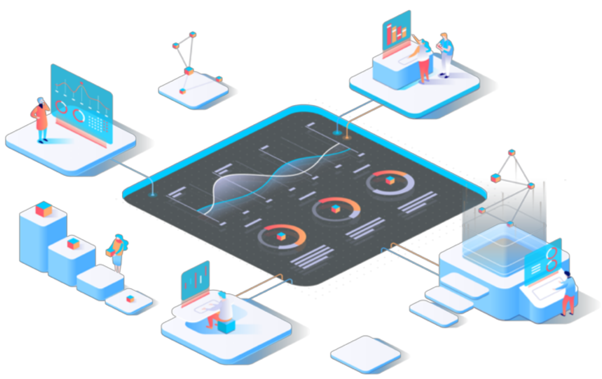
A recent article published by the Academy of Mechanical Engineers emphasizes the benefits of harnessing the constant flow of factory floor big data:

"Big Data requires management tools to make sense of large sets of heterogeneous information. In the case of a factory, sources of data include CAD models, sensors, instruments, Internet transactions, simulations - potentially, records of all the digital sources of information in the enterprise. The data bank is large, complex, and often fast moving, and so it becomes difficult to process using traditional database analysis and management tools. Industry stands to reap many benefits from Big Data as more sophisticated and automated data analytics technologies are developed. These technologies will help extract value and hidden knowledge from large, diverse data streams."

When discussing data, we really mean actionable data, which leads to knowledge, insights and any other form of data-driven intelligence and analytics. This is where artificial intelligence and machine learning starts coming into the picture.

There is no question that artificial intelligence holds the key to future growth and success in manufacturing. In a recent Forbes Insights survey on artificial intelligence, 44% of respondents from the automotive and manufacturing sectors classified AI as "highly important" to the manufacturing function in the next five years, while almost half (49%) said it was "absolutely critical to success."

The Manufacturer's Annual Manufacturing Report 2018 found that 92% of senior manufacturing executives believe that 'Smart Factory' digital technologies, including Artificial Intelligence, will enable them to increase their productivity levels and empower staff to work smarter.



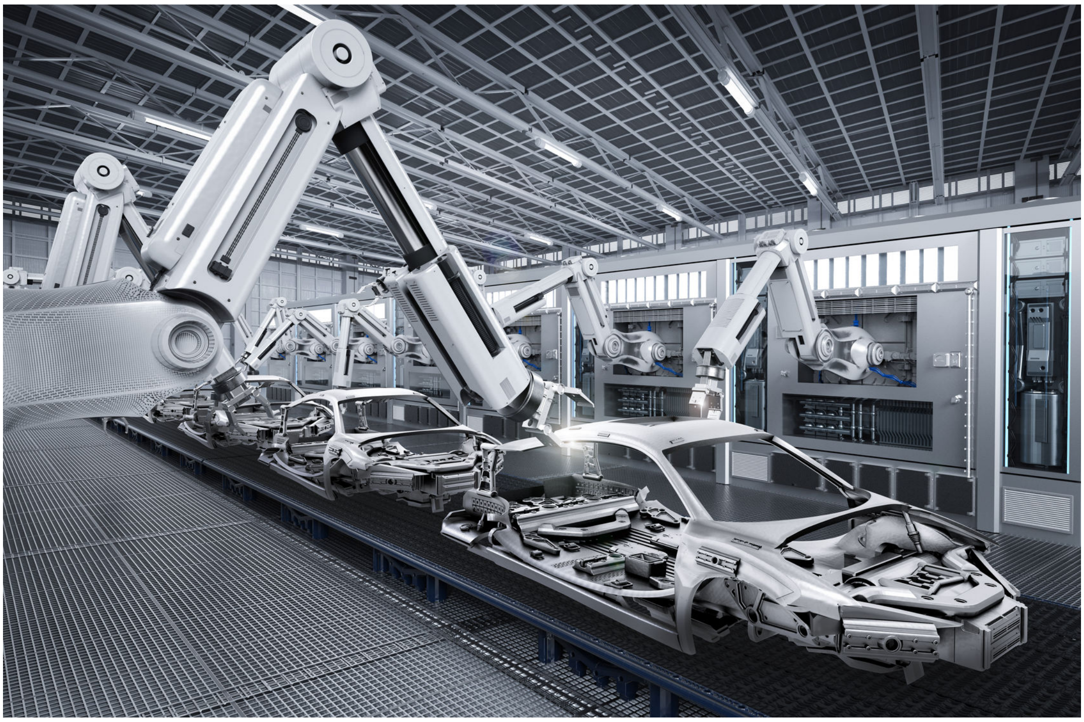
## Benefits of a good Data & AI project

AI and ML brings various benefits to production as well as maintenance and quality.

- In Production. AI enables machines and units to become self-optimised systems that adjust their parameters in real time by continuously analysing and learning from current and historical data. Already, some steel producers are using AI to enable furnaces to autonomously optimize their settings. AI analyses the material composition of iron intake and identifies the lowest temperature for stable process conditions, thereby reducing overall energy consumption. In another important use case in production, robots enhanced with intelligent image-recognition capabilities will be able to pick up unsorted parts in undefined locations, such as from a bin or a conveyor belt.

- Maintenance. AI supports predictive maintenance, for example, avoiding breakdowns by replacing worn parts on the basis of their actual condition. AI will continuously analyse and learn from data that the machines generate.

- Quality. Producers can use AI to help detect quality issues as early as possible. Vision systems use image recognition technology to identify defects and deviations in product features. Because these systems can learn continuously, their performance improves over time.



# 6 steps for starting a successful industrial Data & AI project

1. **Assign an Ops Manager as Project leader:**
The best project leader for industrial driven Data and AI projects is someone in manufacturing, engineering or operations management with authority over the operations being analysed. Their expertise in the operational and quality challenges, their pragmatic view of the goals of continuous improvement, and their focus on solving a specific industrial challenge facing the company is invaluable in driving the project to success.

2. **Target a specific challenge to address:**
Where to start is often the most difficult challenge a company faces when considering a Data and AI project. In successful projects, a clear trend emerges, focus on a well-known quality issue, throughput issue, or process issue (e.g., machine downtime) in a particular place among your operations. Solving a specific problem offers multiple advantages: clearly defined data sources, easily measured success, and easily calculable ROI. A common scenario is to focus on a machine or line that is experiencing high scrap rates or low output. Then use Data and AI technologies to find the root cause. Once the problem is corrected and the process is improved, it is then easier to find support from other groups within the organisation for a wider rollout.

3. **Determine the required data sources:**
Companies require a change in outlook when considering a Data and AI project. What data can we add to the mix? Data directly from sensors and PLCs, product data such as serial codes pulled from legacy MES/FIS and ERP solutions, images from cameras, worker IDs, shift codes from scheduling systems and supplier data, all of this should be considered if it in some way contributes to the process being analysed. In most cases, companies own or control the data sources, and their IT teams will need to be involved. Be wary of any solution that requires a rip and replace approach or requires major upgrades to existing systems.

4. **Identify internal data/process experts:**
Identifying the internal experts on data and process is one of the key factors in determining the success of your project. If these skills are not readily available, seek external support and focus on companies that have expertise in data engineering, AI, machine learning and software development. Companies such as Smartia Ltd would be a good starting point.

5. **Trust the data:**
After a project gets up and running, it's not unusual for teams to be surprised by the results. Mistrusting the data is a mistake, and unfortunately a common one: Fortune Knowledge Group found that 62% of business leaders said they tend to trust their gut, and 61% said real-world insight tops hard analytics when making decisions. For a Data and AI project to pay dividends, the team must be ready to trust the data, even when it disagrees with their previous assumptions.

6. **Be ready to take action:**
In the end, data analytics and AI can take you to the cause of a problem, but it cannot solve the problem on its own. Project teams must be ready to take action based on the output from the system, and to correct the root cause of a problem once it has been identified. The AI application developed can then be used to confirm that the problem has been resolved.

## Final Thoughts

All in all, by analysing and presenting data for actionable use, companies improve business decisions.
An industrial AI platform such as MAIO reveals patterns, trends, and data correlations and flags issues. MAIO was designed to cover the entire spectrum of data analysis needs, so users can move effortlessly from the data source to understanding what it is indicating. With it, users can uncover the secrets hidden in their industrial processes.

# Case Study: National Composite Centre (NCC)

## Application of Machine Learning to Autoclave Failure Prediction

### Problem

Autoclave processing is a key step in producing composite structures but comes with a large cost in terms of duration and energy consumption. When the process fails the structure being cured may have to be scrapped at a significant cost. The financial loss is further increased when the wasted energy and time is factored in.

### Business Case

Potential savings from using an early warning system for curing failure could be significant. For this particular project, with data spanning 5 years, 15 curing runs failed leading to part scrappage. Assuming that costs associated with each failed run could be up to £100k, the total potential savings would be in the region of £1.5m.
These estimates are for a single autoclave and for a relatively small production volume. Larger manufacturers with a larger number of autoclaves and higher production volumes would benefit from potential costs savings several orders of magnitude above this value.

## TOTAL POTENTIAL SAVINGS WOULD BE IN THE REGION OF £1.5M

### Solution

**The Data:** We were provided with a relatively small dataset of autoclave runs that had been manually extracted from the machine software. An extra challenge was the imbalance of the dataset (number of failed runs was outnumbered by successful ones).

**Domain Expertise:** The NCC has a wealth of knowledge and experience in autoclave curing. Consulting with these experts was crucial in generating our approach. One of the most important insights was the existence of a point of no return, beyond which the part being cured becomes unsalvageable; any prediction system would need to work on data available before this point to be useful.

Data Cleaning and Preparation: Initial data processing included:

- Redressing the imbalance: we used several resampling techniques for improving the balance between successful and failed runs.
- Discounting certain sensor readings: Invalid data due to dropped connections and other system errors were identified using NCC's domain expertise and removed

## The Approach

We split the analysis component into two phases. The overall system would then give two ratings for failure.

### Phase 1 – Machine Learning: Before the process starts

Considering only data available before a cure starts (scheduling information and control profiles) we were able to create a classifier to correctly predict a failed or successful run about 90% of the time.
Furthermore, from this model we could highlight certain features that contributed most to the prediction. Interestingly, amongst the top 5 features were two metrics relating to the scheduling of a run (day of the week and hour ended).

### Phase 2 – Machine Learning: During the curing process

Using the time series data from the thermocouples and pressure sensors we trained a neural network capable of predicting a failure before the point of no return with up to 92% accuracy.
Combining thermocouple data with the temperature control profile significantly improved the accuracy of the network.

### Further Work Ideas:

- Consider other data sources: our analysis seems to support the suggestion that upstream factors are important to curing failure.
- Improve data capture: Data for this project was manually acquired. Developing a more connected and automated method would significantly increase the volume of data available and improve the robustness of the prediction models.

## Your company could be next!

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