MANUFACTURING OPTIMIZATION: IMPROVE AND AUTOMATE DIGITAL TRANSFORMATION AT SCALE

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INTRODUCTION TO MANUFACTURING OPTIMIZATION AND MANUFACTURING OPTIMIZATION PLATFORMS

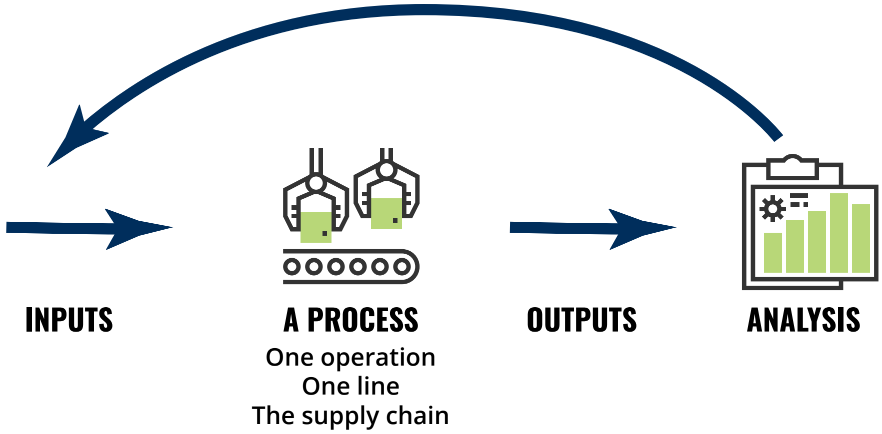
Manufacturers often adopt new technologies to reduce waste, increase margins, and produce better products. The pandemic emphasized and accelerated these aspects of operations as companies turned to technology to establish digital threads of production to better understand and alleviate staffing and supply chain challenges. As a result, many solutions not only became battle-proven, but are now here to stay. This includes cloud software that enables remote collaboration among distributed teams, and a more modern approach to Manufacturing Optimization (MO).

MANUFACTURING OPTIMIZATION

MO is a concept that evaluates the inputs and outputs for a particular process; determines what changes need to be made to the inputs to get a desired output; and then takes action to make the changes. The recurring process of analysis, action, and improvement forms an "optimization loop." The result is an optimized prototype-to-mass-production process.

There are two main approaches to classical MO: 1) employ an outside consulting firm to conduct analysis, identify efficiency improvements, and facilitate or execute the changes; or 2) adopt a Kaizen/continuous improvement strategy, optimizing production to reduce waste and redundancies.

FIGURE 1: CLASSICAL MANUFACTURING OPTIMIZATION



(Source: Instrumental)

Manufacturers everywhere are using both approaches today, but neither is overly efficient. Impactful consulting projects are expensive and eventually come to an end; and the Kaizen method, though effective, takes considerable time for the many incremental improvements to make a big impact.

MODERN MANUFACTURING OPTIMIZATION

Modern MO centers on scale and automation. Industries like electronics manufacturing move fast—a new product might go from Engineering Validation Test (EVT) to Mass Production (MP) in 4 to 18 months—and engineering and operations leaders need new ways to both speed up production and get better visibility into the process than classical techniques can support.

There are three main levels to conceptualize the progression from basic to advanced MO (see Figure 2). Basic MO deals with unit-level optimizations: for example, putting the structure in place to conduct failure analysis on an individual unit, determining the root cause, introducing a solution, and monitoring for the issue on additional units within the population. Accelerated MO deals with population-level optimizations. These optimizations use technology to identify correlations across multiple datasets to solve defective inputs before they propagate into mass production. Advanced MO is the next level and deals with generation-level optimizations. These optimizations combine population-level optimizations from multiple programs as well as the supply chain to reduce costs and accelerate timelines across generations of products.

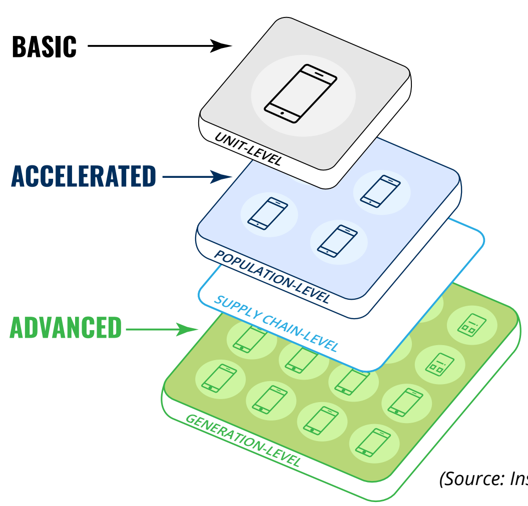
FIGURE 2: BREAKING DOWN MANUFACTURING OPTIMIZATION

Fundamental manufacturing optimization: Unit-Level
Putting structure in place to be able to successfully conduct failure analysis on an individual unit with a problem, determine the root cause, introduce a solution and monitor for the issue in additional units within the population.

Accelerated manufacturing optimization: Population-level
Aggregating relevant datasets linked by serial number and using technology to identify correlations across multiple units to solve defective inputs before they propogate into mass production.

Advanced manufacturing optimization: Generation-level
Combining population-level optimizations from across multiple programs and aligning partners across the supply chain in order to reduce costs and accelerate timelines and tackle harder problems across generations of products.

Bonus: Supply chain-level optimization requires (contractual) alignment across suppliers, CMs, and brands which weights structural, institutional optimizations over cost-cutting shortcuts for particular programs.



(Source: Instrumental)

MANUFACTURING OPTIMIZATION PLATFORMS

Manufacturing Optimization Platforms (MOPs) support modern MO needs. They are a collection of technologies designed to provide the benefits of an old-school, consultant-driven optimization project, but on a regular and recurring basis in machine-time. An MOP is essentially a continuous version of what global consulting firms like Bain and BCG would do for their clients on a one-time basis.

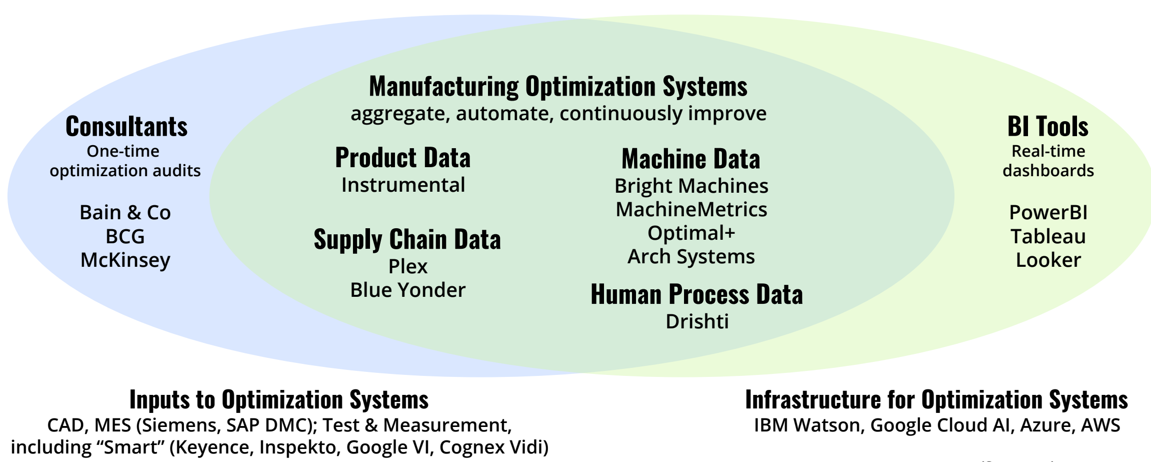
All MOPs have the following core properties:

- They **aggregate data from multiple places throughout the manufacturing process.** This could include only one dataset or multiple types of data. An MOP unifies and organizes these data in ways that are accessible and usable. An important outcome of the aggregation process is that data are quarriable and available for analysis on demand.
- They **automate the analysis of those data** to provide insights that enable optimization loops—opportunities to improve the process based on insights from the data. How the analysis is automated depends on the particulars of the system, but many engineering and operations leaders are leveraging big data, statistics, and machine learning techniques.
- They **deliver and present that insight to users who implement changes**. This can be done natively in their applications by pushing insights to other systems or through other platforms (text, Jira, Slack, etc.).
- They **close the optimization loop** by providing visibility and validation of the desired improvement after physical changes are made.

MOPs are often built as cloud-first systems to address the unique challenges of the supply chain, which tends to be distributed over multiple sites and vendors, leveraging infrastructures like Amazon Web Services (AWS) or Azure.

THE MANUFACTURING OPTIMIZATION ECOSYSTEM

FIGURE 3: MANUFACTURING OPTIMIZATION ECOSYSTEM



(Source: Instrumental)

The MO ecosystem exists between slow-moving, expensive one-time audits and rapid, real-time business intelligence tools. It encompasses many industries to address the different problems that need to be solved, as well as the different kinds of data used to solve those problems. For example, process-driven manufacturing has a lot of machines, so machine data are a key data source for optimization. Discrete manufacturing produces many individual items, so product data are a key data source for optimization. The supply chain works with supplier processes, availability, and order fulfillment, so supply chain data are a key source for optimization. Traditional manufacturing systems and domains like Computer-Aided Design (CAD), Manufacturing Execution Systems (MESs), and test & measurement serve as inputs.

This ecosystem exists because agile and proactive optimization techniques are needed now more than ever. While consultants remain well-suited for industries that do not change their production lines frequently, such as automotive and food and beverage manufacturing, they are used less frequently in most fast-moving industries like electronics manufacturing.

If consultants are at one end of the timing spectrum, Business Intelligence (BI) tools like Power BI, Tableau, and Looker are at the other. These are Do-It-Yourself (DIY) dashboarding tools used to deliver real-time insights. But unlike MOPs, the insights delivered by BI tools are not designed for manufacturing data. Engineers require dynamic data insights, advanced charting capabilities, and customizable alerts that empower users with the information needed to both find and fix the problem. Today, however, many optimization platforms still tie into external BI tools, which typically require at least one employee to implement and maintain, in addition to providing insights in their native environment.

FIGURE 4: MANUFACTURING OPTIMIZATION ECOSYSTEM VALUE DRIVERS

	Consultants	**MOPs**	**BI Tools**
Cost	$$$	$	$$
Reporting Frequency	Slow	Fast	Real-time
Time to value	Long	Short	Medium
Focus	Reported data	Manufacturing data	Business data
Industry applicability	Automotive, food & electronics	Fast moving	All
Impact	Large	Large	Small

(Source: Instrumental)

MAIN TYPES OF MANUFACTURING OPTIMIZATION PLATFORMS

There are four main types of platforms in the MO ecosystem, organized by the data they leverage for optimization and the result they are looking for: product, machine, human process, or supply chain. This segmentation is necessary because each industry benefits from different data sources that can be analyzed in different ways. For example, if you are in process manufacturing or the semiconductor industry, time-series machine data will help ensure machine health and uptime, which allows you to fine-tune your processes and brings improved quality and throughput. If you are in discrete manufacturing, you should be looking at discrete data, which means product data, to guarantee quality. If you are a process engineer looking at material routing and assembly optimization in hybrid scenarios involving people, human data are important. Generally, the more combinations of data being analyzed, the more robust and proactive the optimization.

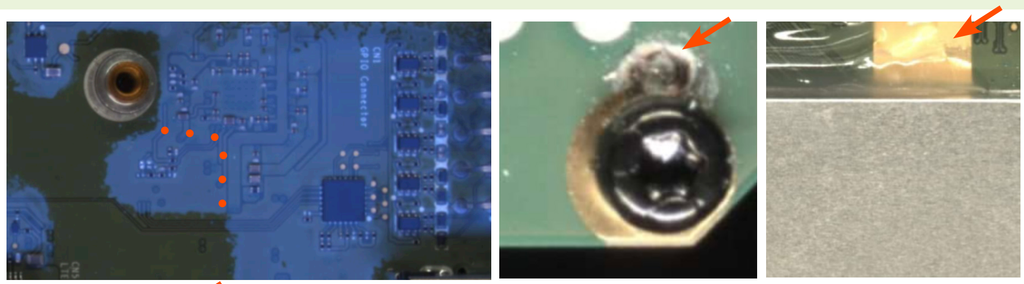
PRODUCT DATA-FOCUSED MOPS

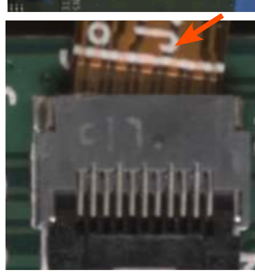
Product data-focused MOPs in this segment help by accelerating and automating optimizations at all stages of the New Product Introduction (NPI) process, from development through mass production. One example is using images and functional test data to identify product defects early, minimizing scrap, dark yield (products with defects that escape factory quality assurance processes), and rework. Importantly, these tools help manufacturers and brands understand the impact of changes to upstream processes on downstream performance to ship quality products on time. As a result, many companies are investing heavily in MOPs, which provides a measurable value that is distinct from Automated Optical Inspection (AOI) systems alone.

An important distinction between MOPs and smart AOI and vision systems like those provided by Cognex, Inspekto, and KEYENCE is that the latter are point solutions that serve as inputs to optimization systems. For example, a vision system may be able to perform defect detection when it knows what to look for or where to look, but not without being told where to look or what to look for, unlike an MOP.

Instrumental is a great example of a company focused on product data optimizations. Instrumental's platform allows customers to build a traceable digital thread of product data through their production processes, leveraging both images and functional test data. It offers commodity camera hardware and integrates with third-party/resident customer test station equipment, such as those supplied by Cognex, KEYENCE, and custom systems integrators. Electronics manufacturers use Instrumental to not only find and resolve their design and process issues faster, but also to expedite remote work.

Case Study: Discover and Failure Analysis in High-Volume Electronics NPI





Axon's global engineering team used instrumental to discover new issues such as improper conformal coat making, damaged parts, inconsistent glue, unmated connectors, missing screws, and more. This data enabled them to accelerate product maturity during NPI and justify investments earlier.

Axon builds mission-critical electronics for police and others who work in essential services. During the introduction of its new Fleet 3 police dash camera product, the team building the product was spread across two factories across two countries. Axon needed an MOP to keep everyone on the same page without stepping foot in the factory. Axon engineers used Instrumental's Discover Anomalies to unify the product data they needed in a shared workspace, leading to the identification of 20 new issues that could be worked into early design and process changes. This not only resulted in higher-quality products with fewer defects and returns, but also the subsequent enactment of a new process change using robotics to prevent downstream reliability issues.

MACHINE DATA-FOCUSED MOPS

Companies in this segment provide solutions that analyze machine data to identify optimization opportunities like line balancing and predictive maintenance. Examples are OptimalPlus and Seeq. Artificial Intelligence (AI) software and analytics tools from these companies can be used to automate and optimize predictive maintenance activities to avoid unplanned downtime. Solutions in this category are particularly well suited for process industries, such as oil & gas, which deal with very expensive capital equipment in continuous manufacturing scenarios because equipment is often large or has a long lead time for repairs due to the specialized nature of their features (e.g., an oil rig). As a result, it is incredibly valuable to have advanced visibility into current and future machine performance, not only for better reliability and business continuity, but also for safety and customer support. Ultimately, the idea is that these systems can be used to create self-healing, self-improving production lines.

HUMAN PROCESS DATA-FOCUSED MOPS

Human process data are slightly more niche than the other areas at this stage, but companies like Drishti use action recognition to provide data and insight into manual assembly lines. Traditional object recognition works by identifying a single frame in 2D. Drishti can register and analyze multiple frames of data over time, concurrently. For example, by monitoring a given environment, the AI can tell a user of the software which line associate installed and assembled the right components in the right order with a measure of how long each step in the cycle took.

In addition to optimizing manual assembly lines, these solutions can address well-known manufacturing challenges like bottlenecks and line imbalances, as well as minimize defect and scrap rates, and identify and address training needs. This creates new efficiencies and ways to optimize lines for engineering and operations professionals.

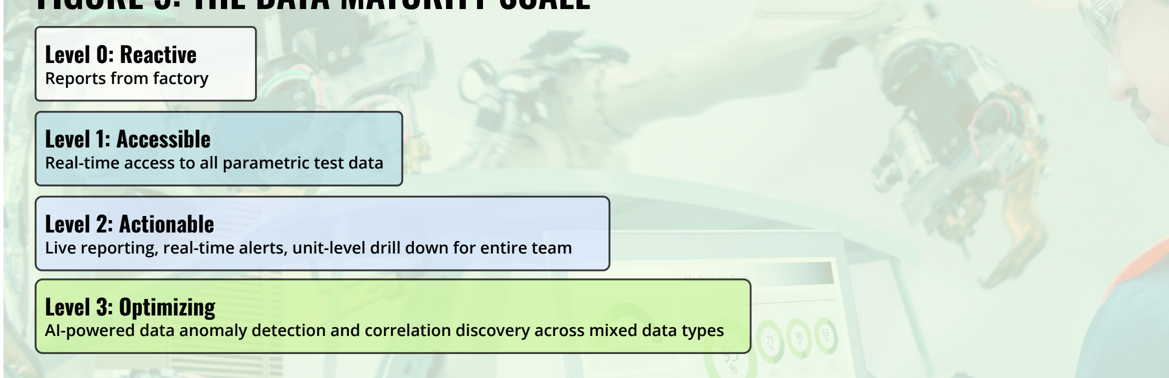
SUPPLY CHAIN DATA-FOCUSED MOPS

Supply chain MOPs focus on manufacturing process data, including throughput. They help companies predict, intelligently plan, automate, and execute optimizations, and they can take into account multivariate scenarios and their resulting impact, such as the impact of switching suppliers on Carbon Dioxide (CO_2) emissions, in addition to inventory forecasts. By putting these capabilities in the cloud, companies like Plex give stakeholders incredible visibility into the current state of operations without the need to involve additional colleagues or teams to pull reports. These cloud-based supply chain offerings are especially starting to take hold in high-volume, highly-repetitive discrete and process manufacturing sectors, such as automotive parts, metal fabrication, electronics, food and beverage, and aerospace. Part of their appeal is their ability to improve traceability by enacting a digital thread that can be leveraged to comply with regulatory requirements. They also ensure and appease consumer expectations in key areas like product quality, safety, and sustainability.

USE CASES FOR MANUFACTURING OPTIMIZATION

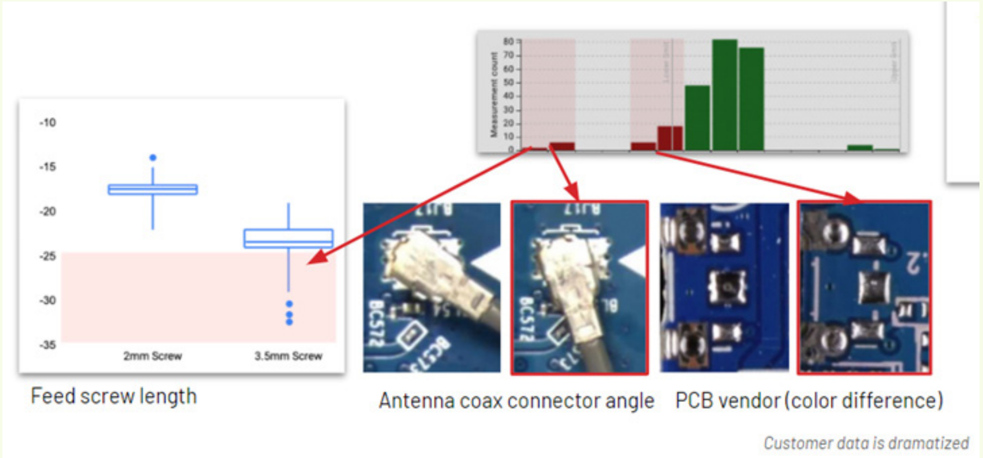
The lack of widespread automation in the manufacturing industry results in inefficiencies and waste. Scrapping defective parts or products, product returns, and brand damage are just a few examples of costly mistakes. In fact, according to research from Bain & Company, roughly US$0.20 of every dollar spent in electronics manufacturing is wasted, and roughly 5% to 10% of all products need rework. Putting the right data in front of the right people at the right time can significantly reduce this waste, especially in bringing new products to market. It is only recently that new manufacturing optimization tools have been available to address these challenges. As shown in Figure 5 the goal is to get from Level 0 (reactive) to Level 3 (optimizing). The following case studies depict the benefits of moving up the data maturity scale, including the impact of multivariate data correlations on business efficiency.

FIGURE 5: THE DATA MATURITY SCALE



(Source: Instrumental)

Case Study: Fortune 50 electronics manufacturer: automatic root cause analysis using data & image correlations



A Fortune 50 Electronics manufacturer was in EVT for a new consumer webcam product that, like all connected products, had an internal antenna. When manufacturing consumer electronics devices, antenna performance is always a challenge, which means there is always a need to figure out the root cause of any issues. The trouble is performing root cause analysis for antennas is difficult because they are geometry-dependent and many variables can influence an antenna's performance that you cannot even see. This is where the company found itself when a collection of functional antenna test failures occurred at the end of line test. It needed a product-focused MOP to perform automatic root cause analysis based on data collected from multiple places during the manufacturing process.

The company started by using Instrumental's Discover Relationships to analyze the failure units, which included looking at spectrum performance data alongside images. Using these data, the platform automatically identified three different root causes for the end-of-line failures, without taking apart a single unit. For the first one, Instrumental had information from the Bill of Materials (BOM) that showed all the failures were due to a feed screw length—a longer screw caused more failures. This led to a design change. For another, the same data were used with image data correlations to find that the antenna coax connector was being connected at the wrong angle. In the third instance, the AI picked up different color solder on the Printed Circuit Board (PCB). Given that different colors are used to indicate different vendors, this meant it was time to investigate the quality of the products provided by a vendor.

Case Study: Fortune 100 electronics company: failures & test station drift using data correlations

(Source: Light. Captured by the L16.)

During production, once you have ramped up and have multiple replicated lines, one of the core issues that test teams have is that there are many machines performing the same test. This could be multiple tests on a line and multiple lines in parallel. Ultimately, it means a lot of test stations. What happens when you have a lot of test stations is that there is drift. This means that the same unit tested in two different stations yields a different result. The implication is potentially shipping products that should not ship or not shipping products that should. As a result of this dynamic, test teams typically know which test station is the weakest in their network.

In this instance, a Fortune 100 electronics company was introducing a new Wi-Fi router, but was observing antenna failures at certain test stations. It needed an MOP to aggregate data from multiple places and automate the analysis of that data to understand the reason for the antenna failures. The company used Instrumental's optimization technology to discover that antenna failures were correlated with the test fixture, and not correlated with other functional tests or vendor configurations, by aggregating and automatically analyzing data from a patchwork of systems. This saved engineering and operations teams tremendous amounts of time in reworking products that did not need to be reworked and allowed them to instead address the testing issue. Before and without Instrumental, teams were not always able to get the data they needed for this kind of analysis, let alone be confident about whether a test result being in or out of spec would impact antenna performance.

CONCLUSION AND RECOMMENDATIONS

Manufacturing optimization is being adopted broadly in all areas, with leaders locking in multi-year engagements that improve their posture toward digital data and automated actionable insights. The newly added pressures of COVID-19 have only accelerated the need for tools that enable better business continuity and better utilization of companies' growing data sources.

Leaders in manufacturing agree that the future of the industry relies on increased utilization of manufacturing data to reduce waste and increase product margins as they bring products to market. It is a matter of when companies realize that manufacturing data are infrastructure, not if. Several points are clear: travel and ease of access to the manufacturing line are no longer guarantees or requirements. There has been an accelerated need for digital manufacturing data, which has been a core driver for adopting MO systems in the last 2 years; and now, more than ever, is not the time to fall behind.

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