WHITEPAPER v1.3

Predictive quality

The future of quality in manufacturing

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CHAPTER 1

The future of manufacturing quality

The challenge

How quality is managed in manufacturing presents ample room for improvement. J.D. Power's research[1] found that, in recent years, for every 100 vehicles produced, there were around 93 quality problems found. This isn't news—despite the process improvements, quality checklists, tests and automation available, unexpected quality problems still occur.

Manufacturers must prioritize shipping good parts by detecting any defects, since defects can't always be prevented. It is time to admit that current methods of managing quality aren't that effective.

Not having a firm handle on quality inside the factory is a precarious situation. Out-of-control scrap rates put cost pressure on manufacturers. Warranty issues loom like a shark in the water—we know the danger is out there but not when it may strike.

The impacts of poor quality go deeper than scrap and warranty claims. Cycle times lengthen. Rework rates inflate. Dealing with these ongoing challenges results in poor productivity and low staff morale. The problems continue after production. Late delivery and inconsistent quality incur financial penalties and damages customer loyalty.

1 J.D. Power https://www.jdpower.com/business/press-releases/2023-us-initial-quality-study-iqs

Manufacturers need to keep costs lower

A research paper from the International Journal of Production Research[2] estimated that direct costs from quality-related issues such as scrap, rework, and warranties can equal 4% to 5% of sales for many automotive manufacturers. When considering the above tangential factors, which may be difficult to measure, this figure could even be higher.

This 4 or 5% is significant. With a dynamic macroeconomic environment, automakers and Tier-1 suppliers need to carefully consider the liabilities side of the balance sheet more carefully. Many factors threaten to inflate costs for manufacturers in the current environment, such as:

- Higher production, labor and shipping costs due to inflation
- Navigating inconsistent and volatile supply chains
- Putting programs in place to conform to tightening environmental regulations
- Retooling old lines and robotic automation
- Investing in net new EV production lines and greenfield facilities
- The developing technology of additive manufacturing

Production is becoming more costly

Changing consumer demands have forced manufacturers to embrace new and sometimes complex production methods. This manifests on the shop floor in a variety of ways, including:

- Power electronics test times are often longer than the time required for assembly, resulting in multiple test stations on a single line that are challenging to align and calibrate.
- Test systems' complexity has increased as they are often required to emulate complex vehicle systems before they are integrated at final assembly.
- Managing and controlling software and firmware revisions on hardware is a new challenge for manufacturing systems and plants that were not built for electronics assembly.

Not only do these electronic components require complex manufacturing methods, but reworking them is often too costly. Defective electronic parts end up in the scrap pile. Adding another layer of complexity to the manufacturing process is the trend of increased vehicle customization. More model types need to be created, which adds extra steps and cost to manufacture, test, and sort these similar-but-different parts.

2 Quality Innovation Prosperity https://www.researchgate.net/publication/312025228_The_Quality_Costs_Assessment_in_the_Aspect_of_Value_Added_Chain

The status quo

Quality management software (QMS) exists to help with quality control, but these tools often only help to organize documents, reports, and training. There is little connection between this sizable paperwork to the actual component being produced. The QMS does not directly measure whether it works properly, is durable and reliable, or will function once assembled with other components.

There is often a different view of quality when considering formal compliance versus what happens on the line day-to-day. Unique processes are often kept under control by long-standing and loyal lineside employees and engineers who have been around long enough to know how to get parts shipped, regardless of the state of the process. The aging workforce and skills gap in manufacturing presents a real risk to quality that cannot accurately be measured. Depending on human stores of information and knowledge is a fading practice.

When more objective methods are used, statistical process control (SPC) is one of the few tools available. SPC offers promising possibilities but is underused in practice. It isn't scalable enough on its' own to adequately control quality.

A primary goal of quality is to ensure that no defective products get shipped. The emphasis is on testing or inspecting parts at the end of the line to ensure that defects do not end up on the truck. Problems are not discovered until the end of the line, or at key waypoints in the process where in-process verification is performed.

Defective parts are often scrapped without much investigation into how to prevent the same issues from reoccurring. Scrap rates remain high. The shop floor is a place of reactivity, where engineers and quality teams are conducting post-mortems on failed parts, or simply accepting high levels of scrap instead of proactively managing quality.

The over-reliance on compliance and defect detection, limitations of tools like SPC, the aging workforce, and a lack of in-depth root cause analysis investigations are all critical limitations when it comes to improving quality. But what if manufacturers understood their process and the internal relationships within it well enough to find out why defects happen in real time? Or better yet, could they use the data they have available to predict these defects much earlier in the process?

The recipe for predictive quality

Automotive manufacturers have historically been on the leading edge of quality management and control methods. From Henry Ford's assembly lines to Toyota's kaizen and poke-yoke, automotive manufacturers are leaders in quality.

Now there is an opportunity for automotive manufacturers to pave the way for a new paradigm of quality control. Industry 4.0 has ushered in three innovations that set the stage for new predictive quality technology.

Ubiquity of data

Digitalization is transforming every process in manufacturing and business operations. Data collection is already integrated into every new operation on the shop floor. The volume and granularity of data continues to increase. It is no longer feasible to analyze this amount of data with the human eye alone.

ML/AI

Machine learning and artificial intelligence are now broadly usable and increasingly leveraged in industrial applications. Artificial intelligence is the backbone of predictive quality. It is necessary to process large volumes of data and extract valuable insight with minimal human intervention or guidance.

Cloud computing

Completing this technological hat-trick is cloud computing. Cloud computing provides a cost-effective, scalable, and flexible infrastructure for predictive quality. The cloud's combination of resources and tools processes data at the scale and speed needed to give manufacturing teams the insights they need before production is impacted.

An operationalized and actionable platform

The technology ingredients are a critical enabler, but the recipe that brings these together and to the users is no less critical to the adoption of predictive quality in real manufacturing environments. Today, many companies rely on data analytics consulting firms or a team of data scientists to analyze and extract insights from their data. These result in many one-off projects that are costly, developed too late, and result in investments that do not scale. By the time one problem is solved, many more may have arisen, or conditions have changed so that the analysis is irrelevant.

When downtime is so costly, engineers need a better way to solve problems fast. A predictive quality solution needs to be actively integrated into the shop floor ecosystem. It must react quickly to address the timely nature of manufacturing production. The platform needs to be user-friendly and be able to translate complex AI algorithms into understandable language for engineers and managers. The value of predictive quality diminishes if it is only usable by data scientists.

CHAPTER 2

Measuring the cost of poor quality

To propose a new framework for managing quality, a method to quantify it must be established. However, some of the costs of poor quality are hard to measure. Warranty rates can take time to manifest, and a single defect can vary in its degree of impact. Metrics like rework, productivity, and excess inventory can be easily tallied. Other measures like scrap, staff morale, reputation and customer satisfaction are harder to quantify.

Two metrics that we will dive into to demonstrate the point are customer satisfaction and scrap.

Customer satisfaction

Delivering shipments to customers on time and with sufficient quality is a non-negotiable activity for manufacturers. Supplier contracts are iron-clad with heavy penalties for breaching these contracts. Not only are these heavy penalties a direct cost to a Tier-1 supplier, but they may lose the opportunity to bid on future contracts with that customer. OEMs keep structured, quantitative quality scorecards that keep a running evaluation of their Tier-1 suppliers. The danger of scoring poorly on these scorecards puts future business for the Tier-1 supplier at risk.

The damages increase with the impact on the OEM's production. Shutting down an OEM due to a delayed or insufficient shipment of subcomponents can cause costly chargebacks for lost production. News of an event like this can travel by word-of-mouth and cause wider spread reputational damage.

Further complications arise when a major quality event is identified on the shop floor and threatens to endanger a supplier contract. To fulfil the contract, the Tier-1 may need to pay expedited shipping fees both from their own supplier to bring in new material, and to the customer. If the delay is large enough, it could result in the next order being delayed, causing a domino effect of extra shipping costs. One quality event could easily cause a six-month expedite chain.

Scrap

Of all the metrics used to measure quality on the shop floor, scrap rates are commonly used to measure quality over other metrics like long cycle time, overall productivity, and rework.

A scrap rate is calculated by dividing the amount of scrap produced in a given time period by the total amount of output in that same time period. This common measure can be unreliable because it fails to consider other unexpected and large sources of reported scrap.

These sources could include material damaged after receipt, material theft, and scrapped material logged at a time much later than it occurred to support achievement of quarterly management goals and performance-based compensation agreements.

Pressure to meet scrap targets can influence employees on the shop floor to take whatever actions they have available to them to make sure scrap numbers meet their targets. Scrap rate targets have good intentions, but they fail to take the whole picture into account.

CHAPTER 3

Lies that statistical process control (SPC) told me

Manufacturing teams that intend to reduce scrap focus on controlling processes, and Statistical Process Control (SPC) is the key tool used. SPC is the only truly data-driven method for controlling quality that most manufacturers are aware of.

SPC is typically used to enable sampling of a few pieces of manufactured material at a specific time interval to make conclusions about a population of parts. The limitation is that it assumes that the process variance and process center have not changed over time, and that the process has a normal distribution. In practice, 1.5 to 2 sigma changes in process center are not unusual. Moreover, when SPC is applied in production, there is rarely the time, head count, and manufacturing capacity available to react to the SPC signals as SPC was envisioned. SPC may not be offering as much value as expected— and more often only placates QMS requirements.

Predictive quality goes beyond SPC

SPC is said to predict process issues and help stop the process before actual out-of-spec parts are produced. In practice, it is not predictive. SPC and control limits often become just another set of specification limits that are tighter than the engineering specifications. Parts that do not meet SPC control limits can be signed-off by the quality department and shipped... as long as they still meet the engineering specifications.

Typically, when manufacturing operations discover a process has exceeded control limits, the quality team is notified. In theory, the process is stopped until the root cause of the out-of-control conditions is found and corrected. In practice, the risk of the exceedance is unclear. The process is allowed to continue running without thoroughly understanding the impact on quality.

Often, lineside SPC results in downtime and reduced line rates with no real improvement in quality or reduction in costs. The temptation for quality managers to "okay" out-of-control processes to continue is understandable. Conducting a thorough root cause analysis is a lengthy, complicated process that often does not reach a definitive conclusion.

AI-powered vision inspection is what most people think of when hearing "artificial intelligence" and "quality" together.

Vision inspection detects defects, it doesn't predict them. It cannot verify the performance of the part or trace the defect back to the point in the process where it was introduced on its own. It can, however, be used in conjunction with predictive quality to provide a quantitative measure of quality.

CHAPTER 4

The shift left

From defect detection to defect prediction

Many manufacturers still rely on detecting defects as their sole focus to control quality. Quality gates are set up throughout the process to ensure defective products don't make it to the customer. Costly and time-consuming testing machinery is used to ensure the performance of complex parts. Some manufacturers are doubling down on defect detection by investing in AI-powered vision inspection tools.

Detecting defects can help prevent shipping of bad parts, but it does not fix scrap or eliminate the other costs of poor quality. To address this, the focus on quality must move from the end of the process towards the beginning. We must shift toward defect prediction and rely less on defect detection. Quality management is shifting away from a single post-production inspection point to a multi-faceted approach that is interwoven within the operational process.

By shifting left, quality is assessed long before final quality gate inspections. In-process verification is a step in the right direction. These tests act as quality gates within the process to catch problems before the end of a cycle. Adding more quality gates isn't a perfect solution. They are expensive to implement as additional equipment investments are required, not to mention the engineering labor required to define, implement, and maintain the additional testing steps. Manufacturers continue to face similar quality challenges by still limiting themselves to detecting issues that can only create more rework or scrap.

By adopting a systematic approach throughout the entire lifecycle of the manufactured product, quality control becomes part of the process itself. Predictive quality can be used to anticipate problems and can do this without heavy investment into more quality gates.

So exactly how can our "Industry 4.0 hat-trick" of big data, artificial intelligence, and cloud computing be applied to create this shift?

First let's start with the data. The manufacturing environment is rich in information that can enable predictive quality, spanning multiple data sources:

- Process parameters and measurements (including direct machine readings)
- Product dimensions and attributes (serial numbers, part number, BOM, material, etc.)
- Test data (quantitative measure or indication of quality, including failure modes) as well as high fidelity test performance data
- Audit inspection and warranty information

Basically, anything associated with the part or product produced can be aggregated in a part-centric way—creating a digital thread of data for every part produced.

A typical manufacturing line with quality gates

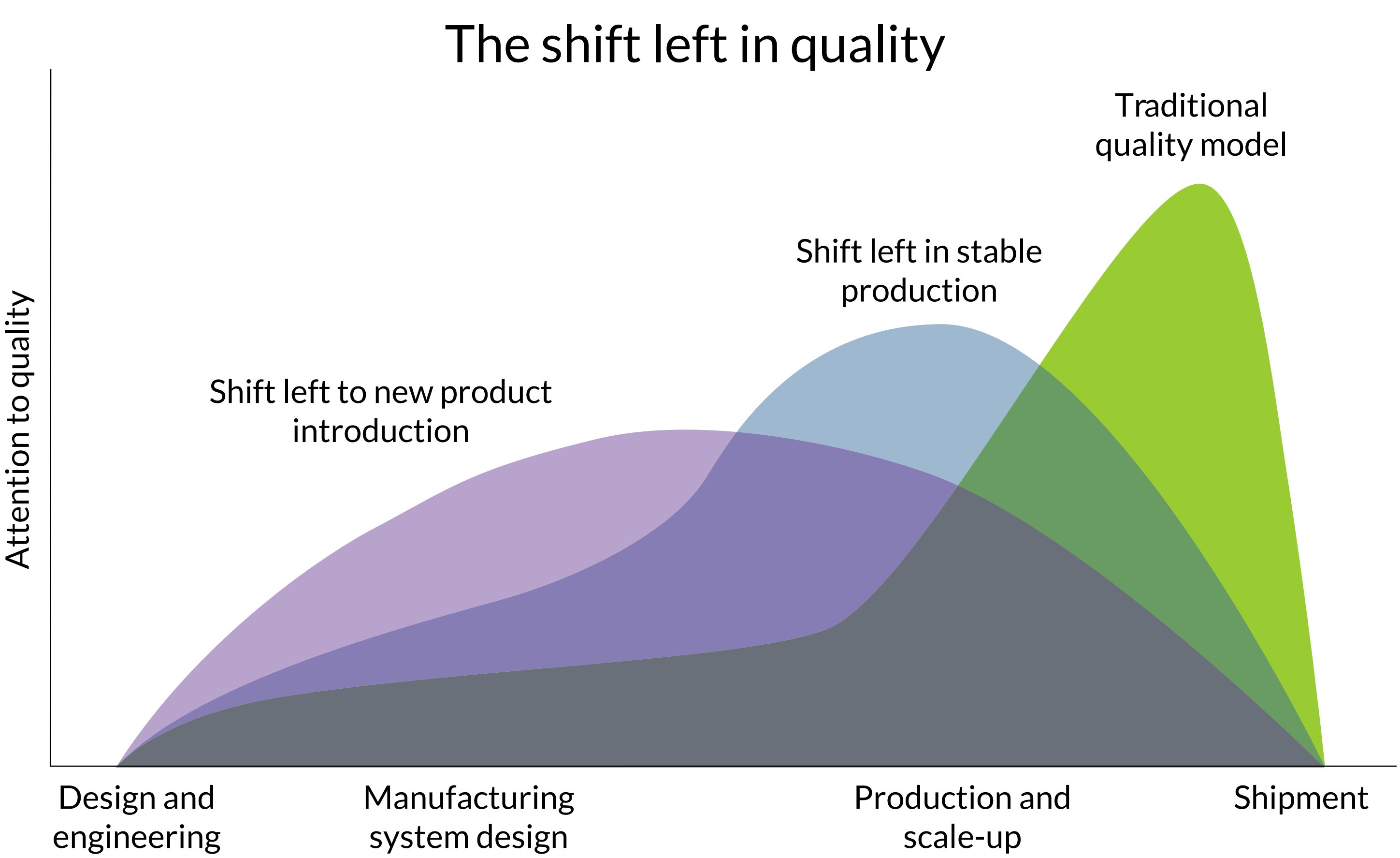
By monitoring process and product parameters together with test (or “quality gate”) data, relationships between process (or even material) variation and part quality can be determined. Throughout production, detailed manufacturing and test data can be scored against AI models that have been trained for the specific purpose of predicting quality issues.

The more process variation can be used to anticipate end-of-line and in-process issues, the more it is possible to divest from expensive quality gates over time. When the process is more volatile or less trusted, more testing is necessary. When there is more insight into the relationships between variables in the process, less reliance is needed on inspection and testing.

Applying this approach to a machine or a production line can result in major improvements. But we can even take it one step further. Data can be traced not just within a single facility, but through the supply chain, with visibility upstream before value-add processes lead to higher costs. Identifying an issue in the $3 component at a Tier-2 supplier, rather than the $200 sub-assembly at Tier-1, or $1000 repair/rework at OEM final assembly—this is where the data, and predictive quality, become not just cost effective, but invaluable.

Where can we start to realize the shift-left approach in practice? Every manufacturer has a diversity of facilities, where some have been around for decades, while others are green field sites or lines with newest equipment and ramping production of new products. This creates an opportunity to realize it in two phases:

- Shift-Left in stable production
- Shift-Left in New Product Introduction (NPI)



Shift left in stable production

The goal of this stage is to optimize production. It is characterized by lines or processes that have been in operation for at least a year. Scrap is at most 10% on worst days, but <5% on average. Rework is 20% on worst days, but less than 10% on average. FTT (first time through) may also fluctuate at 80% or above. The impact of digitalizing and applying predictive quality is to optimize these KPIs and improve profit margin. Production processes that have reached stability and have history are also a great place to start to evaluate solutions—and a great place to prove out and build trust in AI capabilities within the organization.

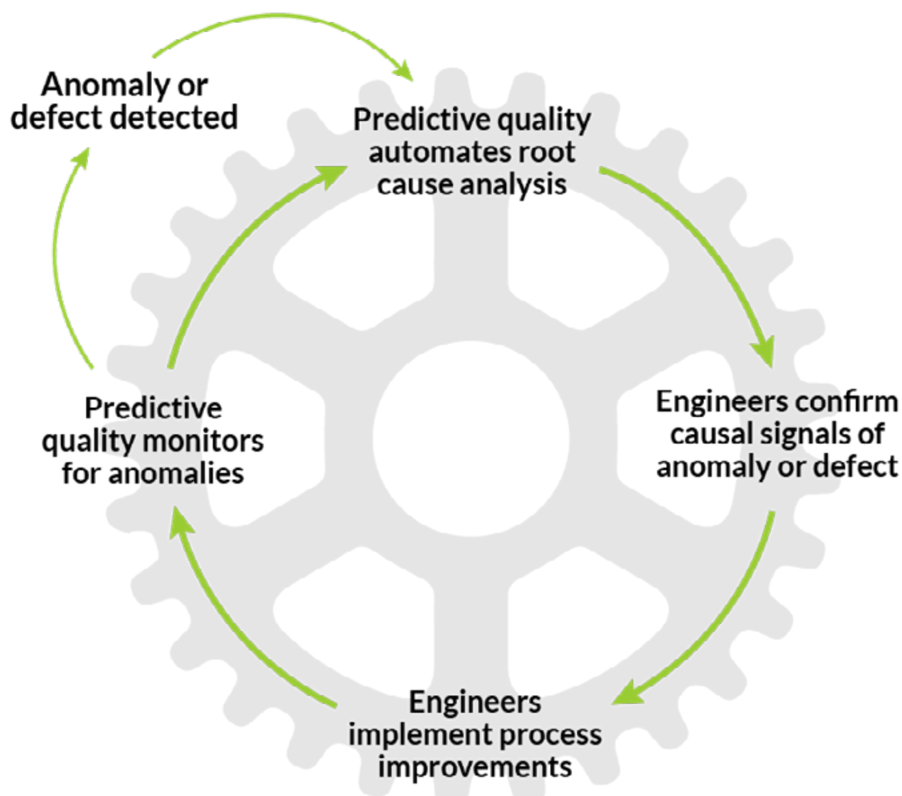
A manufacturing process that has obtained stable production already has a wealth of historical data, which can be used to train predictive quality models to create insights. It has an abundance of historical failures—the relationships between historical process and outcome data can be learned and used to identify critical process parameters or measurements to be monitored.

For example, in welding processes, destructive tests must be performed to ensure quality. Of course, only a small number of units can be tested this way. By connecting data from these tests with data from the welding process, predictive quality tools can predict which units will have defects by detecting anomalies in the process data that match the conditions that led to failed tests in the past. This can ultimately inform destructive test sampling, focusing the attention on high-suspect parts.

In processes with 100% sampling, the learning and understanding of relationships between in-process data and outcomes is even more reliable. Predictions can continuously be validated and improved, and a feedback loop can be established between process variation and trends, and final part quality.

This feedback loop is the conceptual backbone of predictive quality. Anomaly detection and root cause analysis are the main axis on which this loop turns.

The predictive quality feedback loop



Anomaly monitoring

As the production process runs, the process and product data are collected and ingested in real-time. A combination of machine learning models can be trained on the data to learn the "normal" or expected conditions. The predictive quality tool leverages these models to monitor significant and critical signals in production in real-time and alerts engineers of an anomaly that can lead to defects.

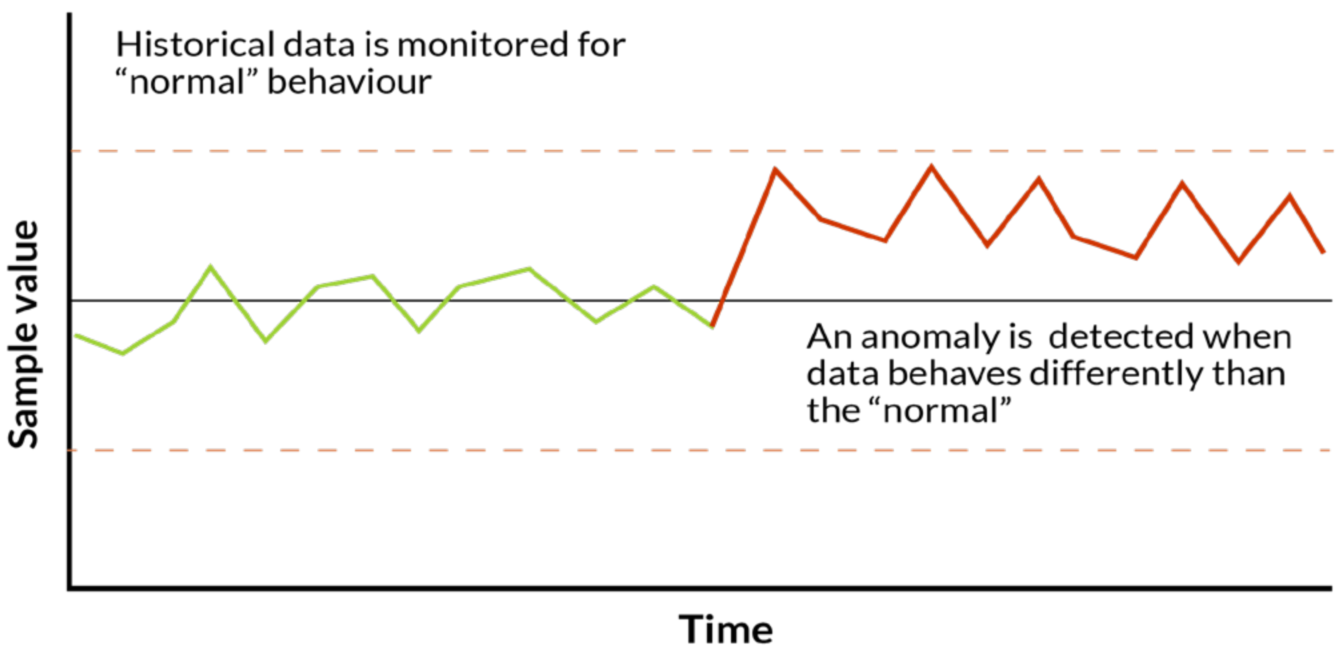
This way, whether the process is becoming less controlled, tolerances are stacking, or measurements are starting to trend or spike, anomaly detection can call attention to suspicious patterns automatically and early.

Suspect signals can be monitored in isolation, or a group of signals can be isolated together to better keep a close eye on them, all accessible within the same platform. Traditional SPC charts can be viewed and capability reports generated with a few clicks, since all relevant data is always available.

Anomaly detection can work in tandem with SPC. SPC relies on fixed, pre-determined control limits. Anomaly detection is adaptable, even if the process center changes. It can be used to monitor multi-variate relationships, which greatly expands its scope across multiple production stages.

Both SPC and anomaly detection have their place in the new quality paradigm. Anomaly detection can be used to inform new fixed control limits. It can also detect issues that SPC overlooks. As algorithms improve their accuracy over time, engineers may find they rely on SPC less and less.

Basic anomaly detection



Automating root cause analysis

Whenever defects slip through and are discovered during testing or audits, automated root cause analysis accelerates the troubleshooting process. The underlying ML and AI models link the defect with any anomalies in the upstream data from the affected part's production cycle.

It generates a list of possible contributors to the defect, arranged by the likelihood of their contribution. This enables an automated and data driven investigation where the root cause can be identified in a fraction of the time it would take to conduct a traditional manual analysis.

Next, the causal variables found can be isolated and monitored through the anomaly detection process described above. Engineers are alerted when the conditions that caused the previous defect occur again, so they can intervene immediately to prevent another quality gate failure.

Automating root cause analysis is in itself revolutionary for manufacturers. No longer do quality teams need to struggle with the decision to "sign off" on out-of-control processes, since performing the investigations and solving the problems poses less risk to production.

Operationalizing the predictive quality feedback loop

The predictive quality feedback loop enables manufacturers to continuously improve quality outcomes. Any predicted or detected defect can be verified in a timely manner through the root cause analysis process. Continuous confirmation of a defect and its cause fuel the learning process of anomaly monitoring, improving the impact of predictions and identified insights.

Data from products produced globally is aggregated in a single cloud-based platform, which scales this learning across the entire organization, and not just in the isolated silos of a production line or facility.

The predictive quality feedback loop presents an Industry 4.0 version of continuous improvement. It empowers engineers with data and AI to support their domain knowledge, and offloads laborious number-crunching. Quality and engineering teams can focus on what they do best, with unparalleled speed and accuracy.

Shift left to the new product introduction (NPI) phase

The shift-left in stable production is still revolutionary for some manufacturers. But the technology is already advancing to shift left even further in the process. Predictive quality can help accelerate the ramp-up of new product lines.

Line construction

When a system integrator initially builds a production line, acceptance tests ensure its capability to produce high-quality parts and meet specified requirements. However, the process of dismantling, shipping, and setting up the system at its final location can introduce variations that challenge the replication of the initial production conditions. This can lead to the risk of unexpected operational issues and the production of defective parts.

To mitigate these challenges, a predictive quality tool can monitor manufacturing data from both the initial setup and the onsite operation. Feeding data from these two locations is made simple through the cloud. The tool efficiently identifies any process variations or inconsistencies between the two setups. This approach facilitates a smoother transition from design to onsite setup, overcoming the limits of traditional on-premises systems and aiding both integrators and manufacturers in resolving any discrepancies more collaboratively.

Process control

Compared to stable production, line ramp-up is plagued with inefficiencies. Typical ramp up times can last up to a year. In the first 3 to 6 months, a manufacturer is very likely to see high rework rates of 40-60%, and >10% scrap rates. For lines where the manufacturer is introducing a product they don't have experience producing, figuring out how to control the process is especially difficult, as there are no existing control plans they can fall back on.

By leveraging manufacturing data, a predictive quality solution can allow manufacturers to experiment with potential controls and predict their impact on quality KPIs. It could also similarly recommend changes to the fixed control plans by learning from the process data for good parts.

Over time, predictions from the platform become more accurate. These early insights are invaluable for manufacturers. Engineers and algorithms learn together what makes their new process work. Testing time can be kept as short as possible, and the impact of process improvements is transparent.

Design for manufacturing

Ramping up the process to stable production typically involves iterations in the original design and specs to account for unexpected oversights in design for manufacturing. New part numbers are introduced at the design stage. With the ease of isolating these part numbers through the predictive quality tool and tracking where exactly in the process they may be causing defects, feedback can be quickly relayed to design teams.

An automotive seat manufacturer reveals an example of this use case. To move to a just-in-time (JIT) approach, the manufacturer recently invested in an advanced flex line that changes between seat frame models automatically. The manufacturer starts to notice sporadic defects in the end stops of the seat adjustment motor, causing the seat to stall at end range during a functional test. The process data showed that the installation location of the motor varied with each model change, causing some motors to be misaligned. Before the new flex line was installed, the line operator would make this adjustment during model changeover. This detail was unknown to the product and line designers.

By applying predictive analysis, the data showed that the pickup points for the frame allowed more variation than required. They also varied from batch to batch. With this information, the design team was then able to adapt by adding a reference point to the seat frame design so that the motor mounting station no longer needed calibration with each changeover as the reference came from the part itself.

Predictive quality fills gaps in domain knowledge

Today's conversion to EV manufacturing means that net-new manufacturing lines are being created everywhere, often for parts that were recently designed. Manufacturers lack the decades of knowledge put towards streamlining these processes that exists for ICE parts.

In these cases, it is necessary to rely on the insights from manufacturing data. Predictive quality accelerates the understanding of newly created products and helps then ramp up quickly from the NPI phase into mass production.

Predictive quality compared to existing tools and methods

It is important to understand how the shift-left in predictive quality is a departure from the tools used to manage quality today. Predictive quality is a new category of its own.

Here's a comparison of the main attributes of a predictive quality solution and other quality tools:

	Contains SPC functions	Audit-ready capability reporting	Real-time anomaly detection	Assists root cause analysis	Scalable solution	Does not require a data scientist	Uses machine learning and AI
Lineside SPC	✓				✓		
QMS					✓		
Minitab or Q-DAS	✓			✓		✓	
One-off ML models				✓			
Excel or Power BI						✓	
AI vision inspection					✓	✓	✓
Predictive maintenance			✓		✓		✓
Predictive quality	✓	✓	✓	✓	✓	✓	✓

Predictive maintenance

Predictive maintenance, established in the late 50s, uses vibration analysis and FFT (Fast Fourier Transform) analysis to predict equipment failures and reduce downtime, but it does not guarantee the production of quality parts. These tools monitor machine condition, not part quality. They do not ingest test or other data outside of machine performance.

Predictive quality can uncover problems with machine functioning through anomaly detection. An anomaly could represent a blade wearing down, or a torque tool spinning incorrectly, which could necessitate machine maintenance. However, predictive quality is a complementary solution to predictive maintenance, not a replacement.

CHAPTER 5

Putting predictive quality to work

These case studies demonstrate how predictive quality can be used in real-world scenarios to help manufacturers achieve their quality goals and solve production problems.

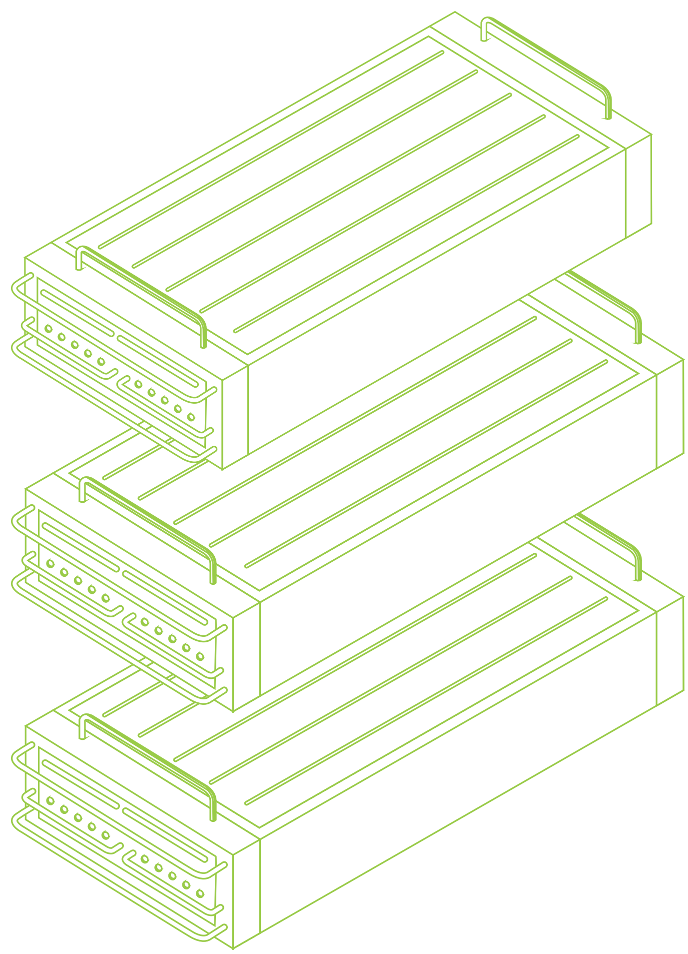
Shortening end-of-line test time for fuel cells

The transportation industry is transitioning very quickly away from internal combustion engine (ICE) powered vehicles and moving to battery and fuel cell electric vehicles. For hydrogen fuel cell stacks to become a scalable alternative to battery, the manufacturing of these stacks must mature quickly to rival battery module production facilities (e.g. Tesla's Giga factories).

For Ballard, as a leading manufacturer of fuel cell stacks and Fuel Cell Engines, a major bottleneck for the large-scale manufacturing of fuel cell stack assemblies is long factory acceptance tests (FATs) which are executed for every stack assembly to ensure consistent high quality. These tests are hours long and require expesive resources like hydrogen and other supporting fluids. The test stations cost over $1M a piece. While this testing procedure generates large time-series datasets, current acceptance criteria are based on averaging techniques at the end of the FAT, when the performance checks are executed.

To scale the volume of production, Ballard would need to increase the amount of test stations to avoid creating bottlenecks at the end of the line. Adding more test stations would be a very large capital expense, and the physical space within the factory footprint would limit the amount of testing stations that could be installed.

Instead, Ballard chose to apply a predictive quality solution to leverage the test datasets and take advantage of the power of machine learning and AI to infer testing outcomes from large amounts of data with unknown noise factors. Predictive quality allowed Ballard to develop next-generation test stations to enable accelerated FAT for stacks without compromising product quality. The newly deployed testing capability, with predictive quality, allows Ballard to shorten the testing time to 30 minutes. Production volume can be scaled efficiently, without enormous extra capital investments.



Solving backlash and NVH problems in axle assemblies

Dana Incorporated is at the forefront of the automotive industry in implementing and benefiting from predictive quality . Dana is a leading Tier-1 automotive manufacturer of axle and driveline systems, among other products, for traditional and electrified vehicles. Across the organization, digitalization and data collection have been a priority, leading to vast amounts of data being collected. But as with many other organizations, they were not satisfied – the collected data grew in volume, but they were not seeing a return on investment. There was little improvement in their day-to-day operations or KPIs.

Dana decided to deploy a predictive quality solution to improve First Time Through (FTT) and rework rates. Backlash and noise are common quality challenges in axle assembly, thus requiring dedicated backlash and noise, vibration, and harshness (NVH) testing stations at final stages of assembly.

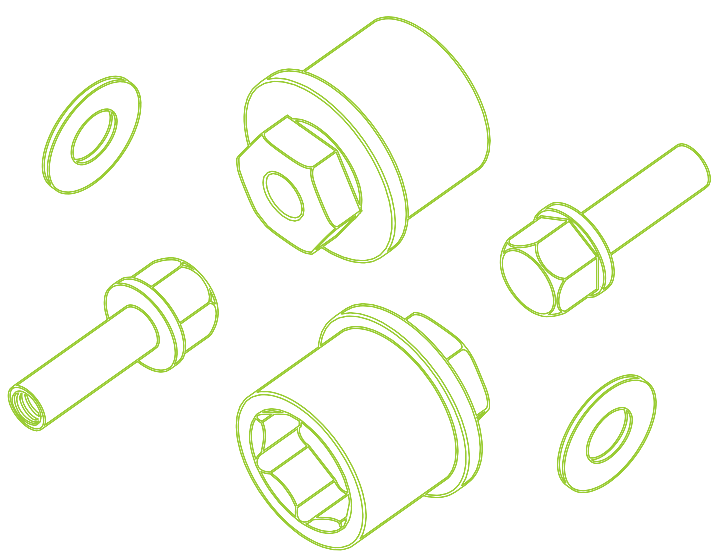
Dana began by leveraging the predictive quality solution on the lines with the lowest FTT rates, where at times over 10% of newly produced parts had to be reworked. The focus was first on leveraging the data to determine the upstream processes that contributed to the backlash failures. The in-platform root cause analysis tool helped narrow down hundreds of signals to a small number that were indicative of the stations and operations resulting in the failed parts. With this information, line engineers can target their investigations to a select group of signals in the process and quicky apply corrective actions to those operations. Since automated root cause capabilities can be targeted against any recurring failure condition of interest in production, other issues can be targeted and explained quickly, saving line engineers hundreds of hours in troubleshooting efforts.

After determining the operations that were contributing to failed backlash tests, Dana configured the predictive quality tool to isolate the problematic signals and monitor them continuously in real-time. They set up custom alerting criteria for when the signals were running out of control, or trending towards it. Line engineers were alerted whenever the state of the process was bound to impact quality at the end of the line.

By using a predictive quality solution to solve for backlash problems, the line had the infrastructure in place that could be used to quickly root-cause or prevent other future defects as well. Over subsequent months and years of use, the breadth of use and ROI only increased, resulting in greater efficiency and cost savings.

As a result of deploying a predictive quality solution in their facilities, Dana saw a significant improvement in FTT and rework rates. The capabilities are helping lines run consistently at <4% rework. The solution is running reliably even in high volume facilities with production of over 1 million parts per year.

Predictive quality is being scaled across over 40 facilities globally, covering a diverse set of processes, subcomponents, and assemblies. Their return on investment was finally making itself known.



CHAPTER 6

The future of predictive quality

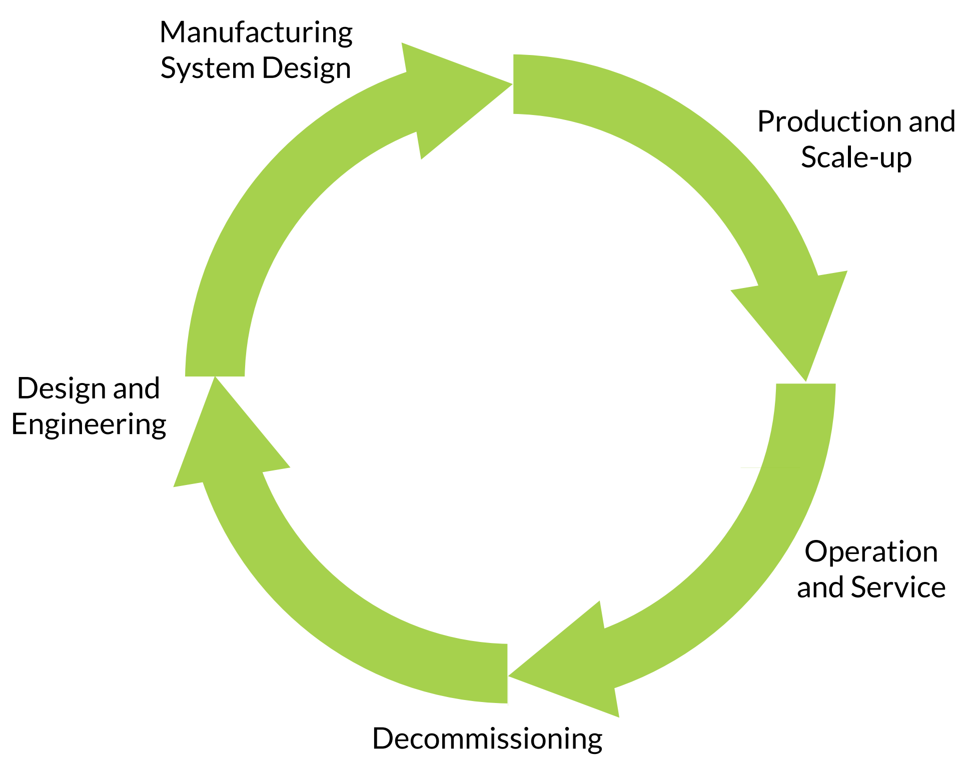
If we zoom out from the shop floor and consider all stages of a product's lifecycle, we discover numerous opportunities to predict the quality experience for customers. A simplified view of the full lifecycle of a product is:

- **Design and Engineering:** Conceptualizing and designing products that meet market needs.
- **Manufacturing System Design:** Translating the engineering design into a manufacturable design achievable with available tooling and processes.
- **Production and Scale-up:** Manufacturing the product at scale with repeatable and consistent processes.
- **Operation and Service:** The majority of a product's life is spent in useful service to the customer, requiring maintenance and services throughout this stage.
- **Decommissioning:** Phasing out older models and introducing new generations or entirely different products to replace them.

At each stage of this lifecycle, relevant product data is produced that can inform the quality experience of another stage. The lack of availability of a component may necessitate a redesign to accommodate alternatives, creating a ripple effect through the entire lifecycle that can alter carefully tuned production parameters. A material choice may affect durability or serviceability in ways that are difficult to anticipate when creating a CAD model or structuring a bill of materials (BOM).

In short, quality doesn't begin and end at a manufacturing line. Modern product designs are digital. The manufacturing process is described in digital work instructions. Industrial automation and IoT systems collect data about each step of the manufacturing process. Products are increasingly connected, sharing useful telemetry throughout their useful life. These trends over the last decade or more present an exciting opportunity to tap into these data treasures to predict holistic quality. As these trends evolve, buoyed by the aforementioned advancements in cloud computing and artificial intelligence, we can lean on the ubiquity of the cloud and the deep insights that AI is already demonstrating.

Shift left in the product lifecycle



Quality maturation over time

The stages of quality maturity have generally progressed over time and in-step with broader industrial advances. In the early days of mass production, defects were detected and measured. The development of continuous improvement, SPC, and six sigma in the 20th century allowed diagnostic quality to take shape. Today, predictive quality is becoming possible.

Predictive quality will progress into "prescriptive quality", which uses the same model as explained in this paper, with additional context provided about why upstream factors influence outcomes. Suggestions will be provided on how to implement necessary process changes.

Autonomous quality will occur in the future when full integration between all aspects of production is possible. The manufacturing process will be self-adjusting, eliminating the need for root cause analysis and most human intervention.

Stages of quality maturation