



eBook

Reducing End-of-Line Testing with Predictive Quality



Executive summary

End-of-line (EOL) testing is commonplace in automotive manufacturing as an effective method of ensuring quality conformance. However, EOL testing presents some significant limitations including cost, increased cycle time, and a lack of ability to prevent quality issues and defects from occurring in the first place.

This eBook offers an alternative quality control methodology for automotive manufacturers and suppliers to enable predictive and proactive quality improvements in production. By performing advanced analytics on production data in real time, automotive manufacturers can avoid subjecting every unit to end-of-line testing. This will improve first time through (FTT) and operational efficiency, while lowering production costs, reducing downstream quality spills and even preventing warranty claims.

A photograph of industrial machinery, featuring a prominent blue electric motor with a circular cooling fan. The motor is part of a larger assembly with various pipes and structural components. The image is partially obscured by a large, curved green graphic element that sweeps across the top and right side of the page.

End-of-line testing in automotive manufacturing

The primary goal of end-of-line testing for automotive manufacturers is to identify quality issues before they leave the facility. This will minimize or eliminate future warranty claims or recalls, prevent costly non-conformance penalties, and preserve important contracts with end-customers.

Due to the high costs of quality spills, automotive manufacturers allocate considerable monetary and human resources towards prevention of non-conforming goods leaving their facility. These end-of-line tests are effective in reducing the number of bad parts being shipped, and help to avoid costly repercussions further down the supply chain.

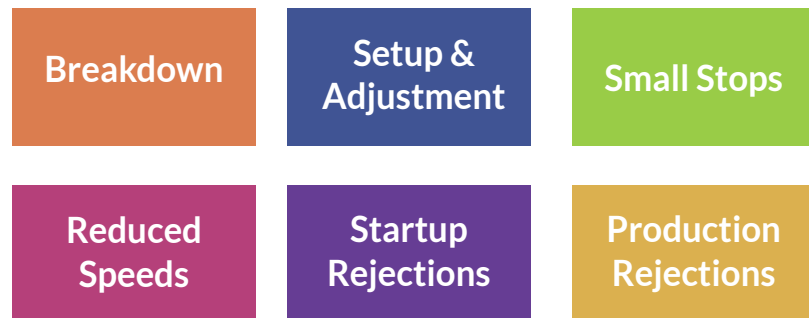
However, traditional end-of-line testing does not address the challenges created when a quality issue occurs early in a production process. Adding value to bad parts, tear-down costs, rework, and scrap all increase the further down an assembly process non-conformance testing occurs.

Real-time analytics and ongoing quality testing help to improve metrics such as first time through, reduce costs associated with scrap and rework, and help to improve throughput.

First Time Through

First time through (FTT), also known as “right first time” or “first time yield”, is the concept of moving parts through the production process without any defects, and represents one of the six big losses in OEE, production rejections.

Six big losses in OEE



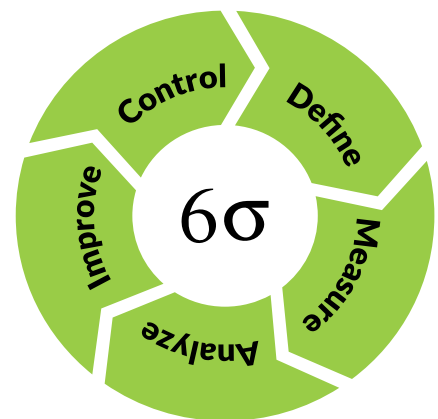
At 100% FTT, a facility is producing parts that meet specification every time which also means that their parts do not require rework and they are not producing any scrap. Unfortunately, this level of perfection has traditionally been next to impossible to achieve in automotive manufacturing.

$$\text{First time through (FTT)} = \frac{\left(\overset{\text{gear}}{\text{units produced}} \right) - \left(\overset{\text{gear}}{\text{defective units}} \right)}{\left(\underset{\text{gear}}{\text{units produced}} \right)}$$

Six Sigma and Kaizen

Six Sigma is a common process control practice used to improve FTT. This methodology strives to continuously improve the manufacturing process to the point that a defective unit statistically cannot be improved. Japanese automakers who practice Kaizen, a business philosophy based on continuous improvement, have managed to achieve some of the highest FTT in automotive manufacturing.

Six Sigma: A process using statistics and data analysis to reduce defects



The majority of automotive manufacturers attempt to obtain FTT between 90-100%, claiming that is the highest they are able to achieve with their manufacturing systems. However, examples from medical equipment manufacturing, where eliminating defects could mean the difference between life and death for a patient, prove that a manufacturing process can indeed be perfect. In such industries, perfection is a requirement, not an aspiration.



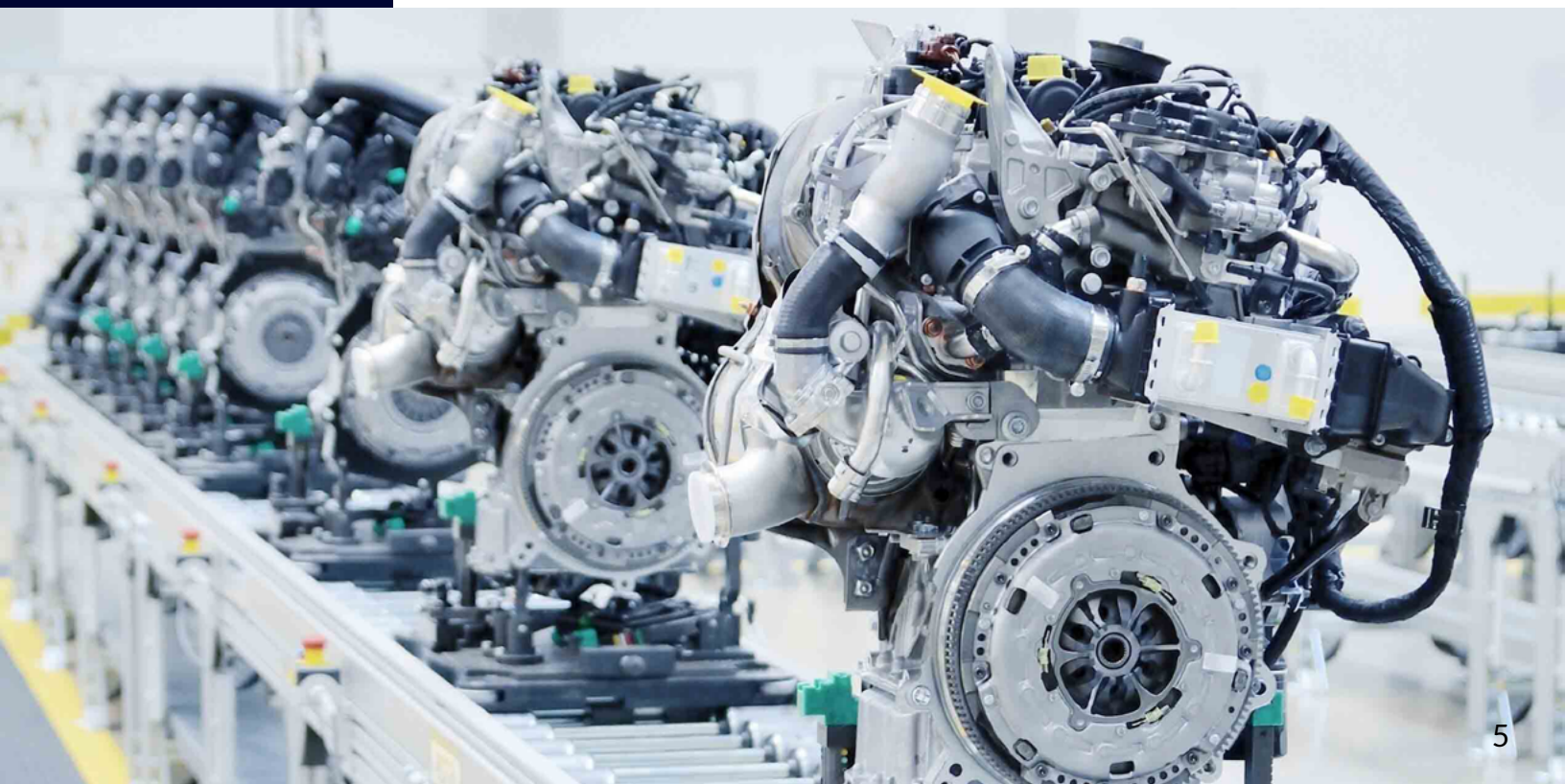
Right: Medical devices being manufactured in a tightly-controlled facility

Still, much focus is placed on improving the manufacturing process in modern automotive manufacturing facilities. Checklists, protocols, regularly scheduled equipment maintenance, machine monitoring through SCADA, SPC, and MES are all used in varying capacities to keep the assembly line running smoothly by its “perfect” design.

In theory, the principle of aiming for 100% FTT driven by highly monitored processes makes sense. In practice, it does not stand up to the physical realities of automotive manufacturing.

Machines wear over time and break down in countless ways. They need downtime to be maintained. Humans introduce error. Power supply issues, weather, employee turnover, and global pandemics can all interfere with well-designed processes.

End-of-line testing acts as a fail-safe, to ensure that despite every best effort to adhere to perfect processes, there is still a means to validate a part before it leaves the facility in case something failed along the way.





The downsides to end-of-line testing

The downsides to end-of-line testing are that it is inefficient, costly, and occurs at the *end* of the production line. For example, consider hot testing, in which a completed engine is run on a test bench with the aim of checking all the engine's operating parameters.

The tests mimic engine function in a vehicle. Conducting them requires dedicated and specialized equipment. Between rigging, de-rigging and running the test, the process can take up to 45 minutes.

Eliminating the need to run even a fraction of these tests would significantly impact the company's bottom line.

And, if an engine were to fail the hot test? The costly and complex part must be retested, disassembled and re-worked, or scrapped entirely. Relying only on insights at the end of the line instead of checkpoints throughout the process can be costly and wasteful.

Time lost producing bad parts is revenue lost. Wasted materials that end up in a scrap pile mean increased costs. Time and money are obviously valuable resources to an automotive manufacturer in terms of the viability of their operation. There are also hidden costs.

Right: an engine during a hot test



The hidden costs of EOL testing

When a high percentage of parts are being built and scrapped, energy, time, and materials are being used to test failed components. By catching quality issues as they occur, energy and natural resource consumption is reduced and environmental impact is lessened. By using only end-of-line testing, sustainability goals move further away, costs increase, and public perception can turn negative.

And, what if a defective part somehow gets shipped to a customer? Contracts often contain harsh financial penalties for failing to deliver high-quality parts. These penalties are punitive and damage the relationship between supplier and customer.

When there are frequent quality issues, contracts may also require more human labour to be employed to hand-sort parts or manually validate them at various stages on the line to ensure that no defects are shipped. This additional labour adds weight to budgets as well.

In a recent AIAG & Deloitte Quality Report, automotive OEMs and suppliers both ranked Problem Solving as one of the most critical issues impacting quality. Both also cited Lack of Root Cause Analysis as one of the main reasons for this issue. While end-of-line testing can point to the existence of a problem, it cannot explain why the problem occurred or how to fix it. To put it another way, end-of-line testing may catch defective parts, but it cannot improve first-time through on its own.

“Reworking a single gear pulled off the production line is not too costly, pulling a gear out of an assembled transmission is expensive, but pulling a transmission from a completed vehicle to fix that gear is prohibitively expensive and unacceptable – that vehicle actually reaching a customer, worse yet.”

— Brüel & Kjær

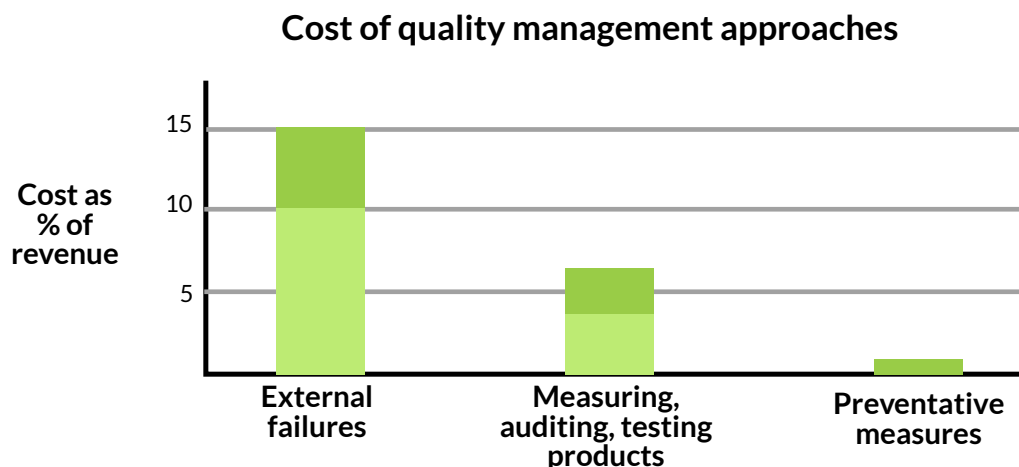
End-of-line testing – All geared up and ready to go



Reducing the dependency on EOL testing

Although there are limitations to end-of-line testing, it would be presumptuous to eliminate the process entirely. Fixing problems at EOL is costly, but it's worthwhile compared to the costs of dealing with problems that reach the end customer.

In fact, a review of the costs of quality for the automotive industry found that external failures can cost a company 10-15% of sales revenue, versus 4-6% of revenue for measuring, evaluating, or auditing products, including end-of-line testing.



However, the same review also found that preventative approaches only cost 1% of sales revenue. So, if end-of-line testing can be even partially eliminated in favour of a more proactive, preventative approach, there are efficiencies to be gained and costs to be saved.

SPC's role in part quality

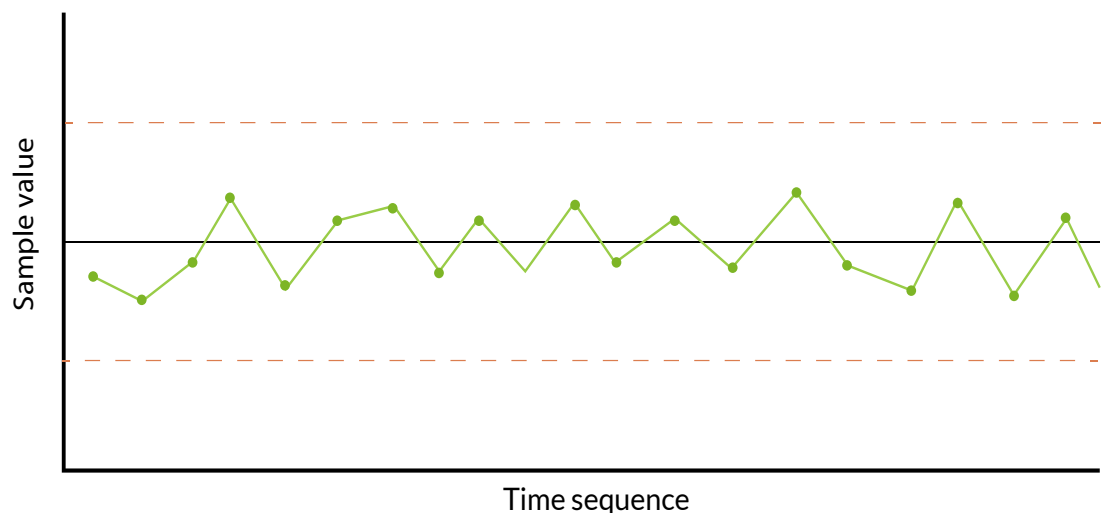
On manufacturing lines, the capabilities of traditional solutions have already been thoroughly exhausted when it comes to improving part quality. Statistical process control, or SPC, promised to be the early intervention that would track manufacturing data in order to keep the process within specified limits.

SPC is great at monitoring processes. In this way it can indirectly affect part quality, since machines that are not running optimally are likely to create suboptimal parts. But optimizing processes does not guarantee that perfect parts will be created. It is possible for defects to happen even when all processes are running within their control limits.

SPC is designed to look at one signal at a time. As we will explore more deeply later, this is limiting compared to new technologies that can identify relationships between multiple signals on the line, expanding our ability for complex analysis.

SPC does not tell the whole story of quality. It is also not a preventative approach. Another solution is needed to reduce reliance on EOL testing.

Right: a basic SPC control chart looks at one signal in isolation



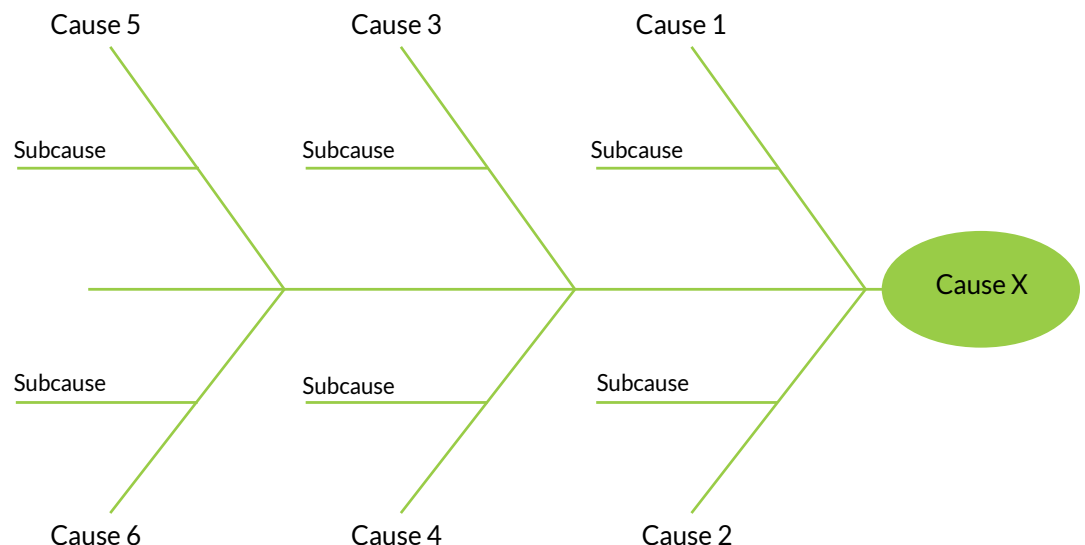
Other ways to monitor quality

Since it has been identified that preventative approaches to quality are less costly than relying on EOL testing alone, let's explore some techniques that are currently being used by manufacturers to reduce the reliance on end-of-line testing.

Manufacturers have found ways to detect defects earlier in the process such as In-Process Verification (IPV). They can reduce the amount of rework or scrap. However, implementing these in-process tests are costly, and in some cases not thorough enough to reduce reliance on end-of-line testing. They also don't offer deeper information about the cause of defects.

Efforts to increase first time through via manual root cause analysis using manufacturing data are often completed manually, but these one-off processes are lengthy, complex, and need to be performed again when new issues arise. They often identify the source of issues long after there has been an impact on production, and only provide a snapshot view of that single component at that one point in time. This type of manual analysis cannot be scaled to other problems in the facility.

Right: a classic Fishbone diagram often used for manual root cause analysis



A better solution to augment EOL testing

Today's Industry 4.0 technological advances have prompted us to reconsider the traditional methods of manufacturing, and to take a closer look at end-of-line testing.

Ask any quality professional for their advice on reducing scrap and rework, and the first suggestion is almost always to collect more data to analyze.

By collecting data from every stage of production, any defects encountered during end-of-line testing can be traced back to specific parts or processes. That way, these parts of the process can be identified and fixed. But no amount of data collected will improve the overall process if the analysis of the data is too time-consuming and too difficult to scale. This is why we created LinePulse.

Acerta's LinePulse is a predictive quality solution that allows manufacturers to identify potential quality issues in real time. It is powered by machine learning, which makes data analysis lightning-fast and easy to scale.

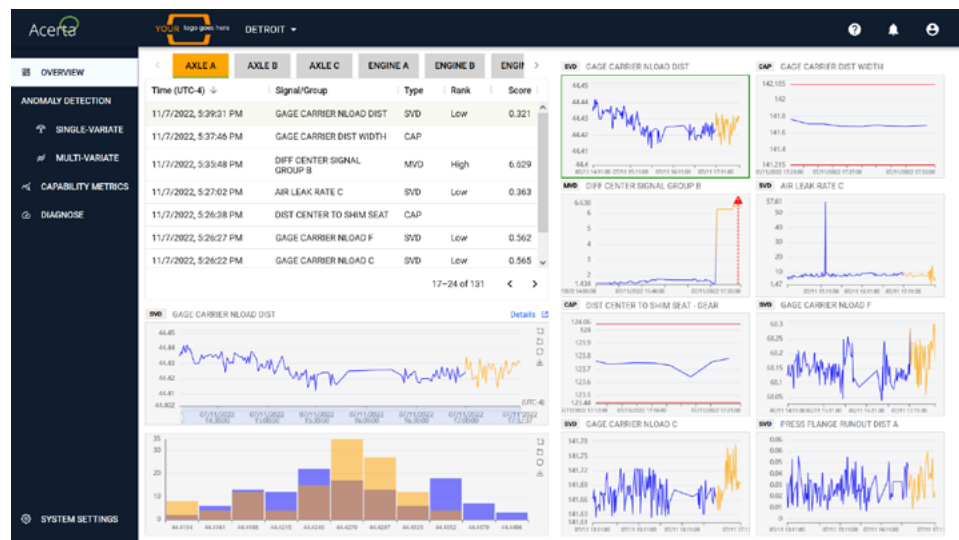
Right: collecting manufacturing data



Right: A screenshot of the LinePulse predictive quality software solution

Machine learning for predictive quality management

By using a predictive quality tool like LinePulse, reliance on end-of-line testing can be reduced. This helps to improve throughput at these critical bottleneck operations. Fewer defective parts will reach test stations. Scrap and rework rates will decrease.



Machine learning, a type of artificial intelligence and the backbone of these new software solutions, offers us unparalleled computing power. It has the ability to process, analyze, and compare massive amounts of data in fractions of a second, compared to what would take a human many hours or even days. And with LinePulse, this analysis occurs in a platform that can send alerts in real time and scale across multiple lines.

“Effective identification of root causes was consistently cited by OEMs and suppliers. Leverage advanced predictive analytics capabilities to sift through big data and improve root cause analysis capabilities.”

— Key Takeaways
AIAG & Deloitte Quality 2020 Report

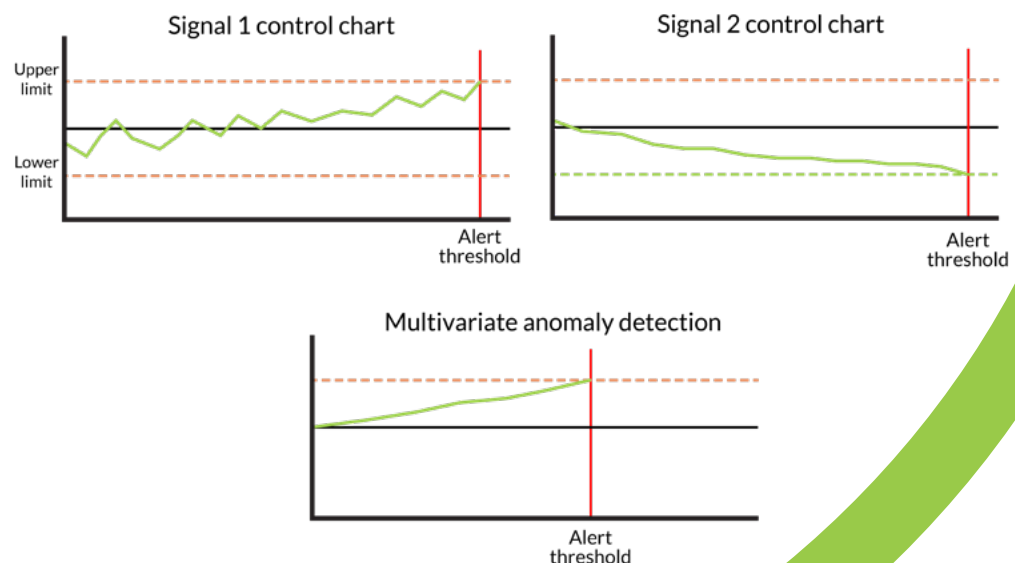
Multivariate anomaly detection

A benefit that machine learning has over traditional methods like SPC is that it analyzes multiple data points to show complex correlations using **multivariate anomaly detection**.

LinePulse can monitor multiple groups of signals over time, comparing present results with historical data to detect which combinations of signals are shifting in the wrong direction.

It does this through multivariate anomaly detection (MVA). MVA is a relative measurement of how much a group of signals deviate or “drift” from their normal patterns over time. By identifying a relationship between the two (or more) signals, MVA can help identify where issues may be occurring.

With knowledge of these relationships, it is possible to detect potential issues sooner, and also to identify different types of anomalies that previously were challenging to understand.



Right: An example of how MVA can detect anomalies sooner by looking at two signals together

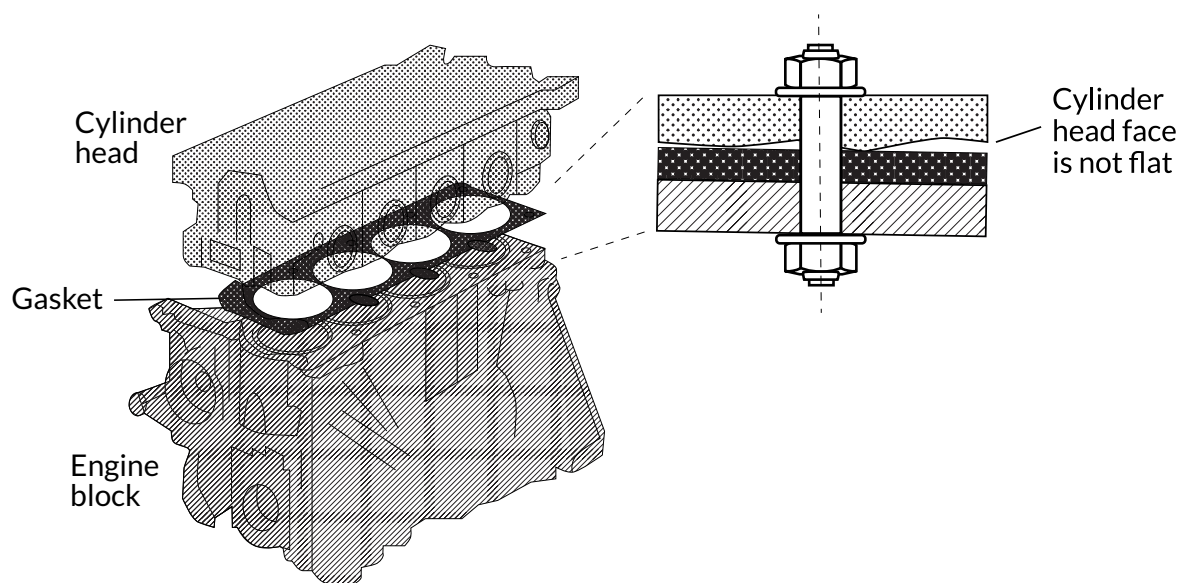
An example of MVA from the manufacturing floor

To understand the concept of MVA in practical terms, here is an example. In the engine assembly process, a block and cylinder head are bolted together on the long block portion of the assembly line. This is a process most customers see as “Critical to Quality” and so lots of data is collected and analyzed.

On the cylinder head machining line, the spindle that is responsible for making the deck face flat has a cutting tool that is worn and is causing chatter. The chatter is within acceptable limits but ends up producing slight variations in the flatness of the surface. If the tool were to vibrate too much, the machine that monitors the process would stop and issue an alarm. Currently, it appears to be running normally.

Later, when the cylinder head is assembled, torque tools are running down fasteners to bolt the cylinder head to the block. Because the head has arrived at the station less flat than expected, the torque tool is working at a skewed angle, and must apply more force than necessary to complete its task. In the worst case, the torque tools could make a good joint, leaving a space (non-visible) between the parts that could leak when the engine is in service.

Right: A crooked cylinder head face can create an opportunity for leaks in the seal between cylinder head and engine block



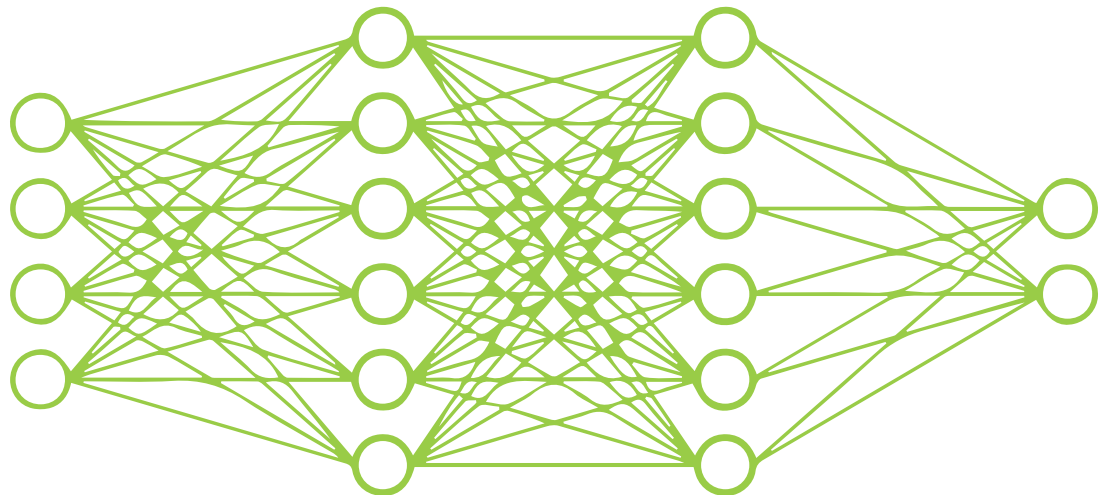
The signals at this station measuring speed, angle and torque from the torque tool could be shifting within specification limits, making it very challenging to identify that a problem has occurred by looking at SPC data.

By tracking the vibration of the machining tool along with signals from the torque tool using multivariate anomaly detection, a pattern would emerge. Increased chatter from the cutting spindle has a relationship with either increased torque or reduced speed from the torque tool, or both.

Machine learning that scales

LinePulse measures drift and learns what “normal” is based on initial data from the signals on the line (or lines) it’s monitoring, meaning that LinePulse is completely customized to the unique manufacturing ecosystem of each particular facility in which it’s installed.

It can easily adapt to changes in the manufacturing ecosystem, and can learn to accept new signals or groups of signals on an existing line into the total picture of quality for that process.



Right: A visual of a typical machine learning neural network that allows it to adapt over time

Not all machine learning is created equal

LinePulse is a scalable solution that should be differentiated from one-off analytics solutions that use machine learning models to address problems. These custom models are time-consuming to build and usually do not scale to be helpful to the organization after their initial purpose is served.

Also, not every organization is in an ideal place to execute these types of analytical deep-dives. Here are some common situations that prevent organizations from properly analyzing their data:



No one **has the skills** to analyze data



The facility **has no tools** to analyze data



No one **has time** to analyze data



The data is siloed and hard to analyze.

LinePulse can be applied in all of these situations. As long as a facility has data, LinePulse can provide beneficial analysis to improve part quality in a flexible, scalable way.

The impact of a scalable machine learning platform

Each manufacturing plant faces a unique set of challenges when it comes to improving quality. Consider an example of a major Tier 1 supplier who wanted to reduce the rate of product fallout and associated work for axle assemblies. To make their problem more challenging, each of their production lines consists of more than 20 different operations which collectively generate over 200 measurements per assembled unit.

Through some initial data analysis performed by Acerta, and by applying LinePulse across their facilities globally, the supplier was able to achieve a 65% reduction in failure and rework rates, which also led to an improvement in FTT and significant cost reductions. The LinePulse platform has more than paid for itself in the cost reductions it has achieved for these facilities.

 **65%** Reduction in failure rates and rework

As the digitalization of manufacturing continues, these examples will become more common. Processes will increasingly be improved by data-based solutions and software instead of relying only on manual labour. Companies that are driven by increasing competition in the marketplace will adapt to these new ways of operating and will see increased efficiency, quality, time-to-market, and profits.

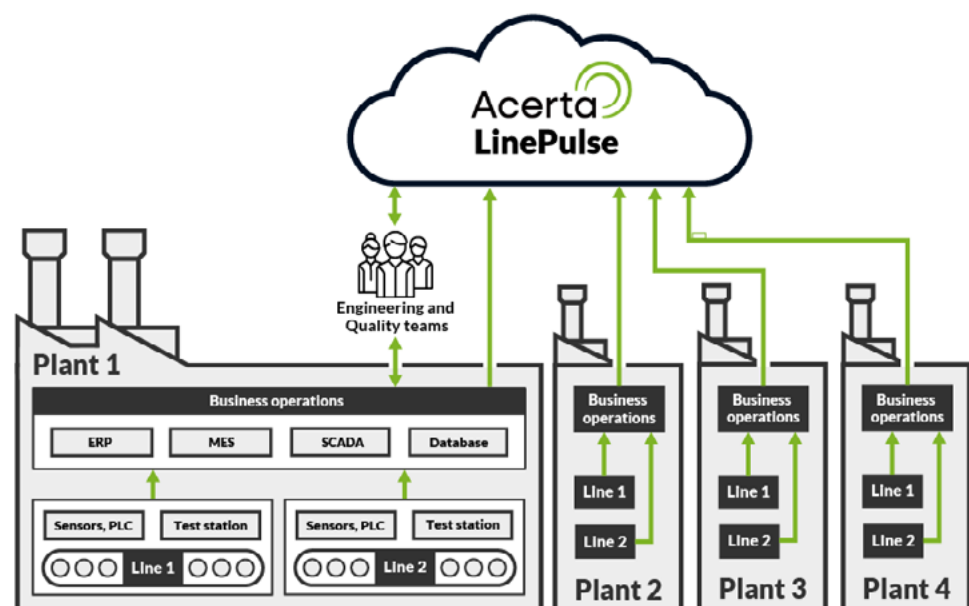
Other advantages of LinePulse

With LinePulse ingesting data continuously during production, the odds of a defective unit escaping the factory drop considerably. The idea is not to replace end-of-line testing with machine learning, but rather to use machine learning to supplement traditional quality tests.

As scrap and rework is reduced, costs can decrease. Reducing the weight on EOL testing stations can also reduce the staffing requirements for these stations, which can also reduce labour costs.

Flexible applications for any facility

Many investments in a manufacturing facility can cost not only capital, but time and risk to install and ensure cooperation with existing systems. LinePulse, since it is a cloud-based SaaS solution, does not have a lengthy setup process.



Right: How Acerta's LinePulse connects to manufacturing data

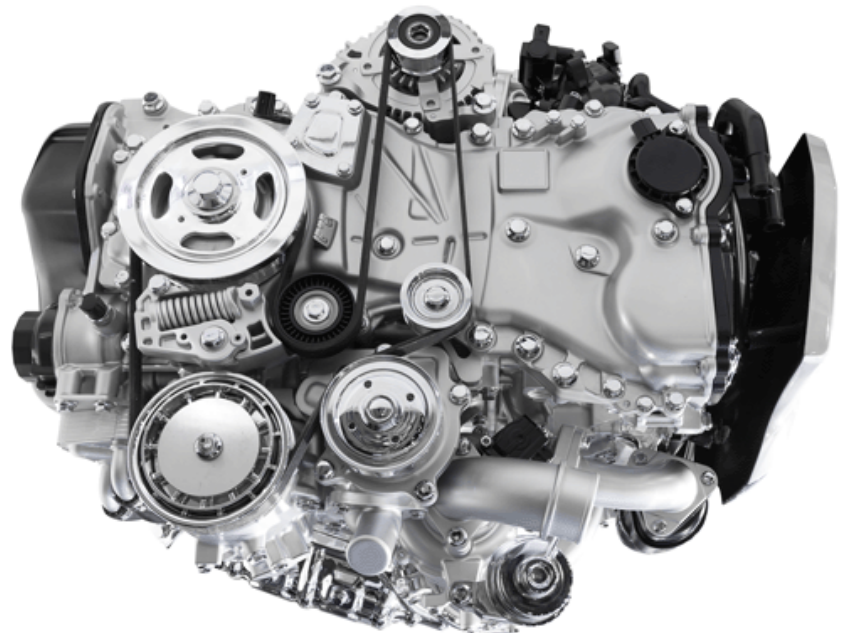
LinePulse can handle data from any source on the manufacturing floor down to PLCs, sensors, and other third party verification systems. It can be set up quickly to connect all manufacturing lines in a plant.

Control limits and specifications can be customized completely. Alerts can be sent to other team members, ensuring that any warning signs or anomalies are addressed immediately.

Your predictive part quality solution

LinePulse has the ability to transform operational quality processes for automotive manufacturers and suppliers. It can monitor production data in real time, and perform advanced analytics far more quickly and with much higher degrees of accuracy than humans could ever achieve.

When AI and machine learning are leveraged to their fullest potential in automotive manufacturing, a new paradigm of quality control emerges: one that is proactive instead of reactive when it comes to improving quality, and one that is focused not on perfecting the process to produce a perfect part, but on producing the highest quality part the first time, every time.



Glossary

End-of-line (EOL) testing

The practice of testing parts at the end of a production line to ensure overall functionality or performance of parts before they leave the facility. Specialized equipment is often used.

First time through (FTT)

A measure of the percentage of units that complete a manufacturing process and meet quality guidelines the first time, without being reworked, scrapped, or repaired. Also known as **First time yield, first pass yield, first time right, do it right first time, or through first time.**

Multi-variate analysis (MVA)

A means of monitoring and performing advanced analysis on a group of signals to detect relationships. (see page 13)

Overall equipment effectiveness (OEE)

A metric for measuring manufacturing productivity. OEE is calculated with the following formula: $OEE = \text{Availability} \times \text{Performance} \times \text{Quality}$

Statistical Process Control (SPC)

The use of statistical techniques to control a process or production method. The signals generated by the process are designed to fall between a lower and upper control limit, and are often visualized on a control chart.

References

“Cost of Quality for Automobile Industry: A Review” Equinox 2018
– 4th International Conference on Engineering Confluence. S.N. Teli
& Amar Murumkar, September 2018 https://www.researchgate.net/publication/327077180_Cost_of_Quality_for_Automobile_Industry_A_Review

“Metric of the Month: Reduce Scrap and Rework Costs” Supply and Demand
Chain Executive, July 2, 2018 <https://www.sdcexec.com/warehousing/blog/21004027/apqc-reduce-scrap-and-rework-costs>

“Hadoop is Data’s Darling for a Reason” Forrester Blog, Mike Gaultieri,
January 21, 2016 <https://go.forrester.com/blogs/hadoop-is-datas-darling-for-a-reason/>

“Productivity Improvement in Engine Assembly Line at GM India Ltd. Pune,
India” International Journal of Latest Trends in Engineering and Technology.
C.K. Deotare, U.A. Dabade. September 2015
<https://www.ijltet.org/wp-content/uploads/2015/09/2.pdf>

AIAG & Deloitte Quality 2020 Report <https://www2.deloitte.com/us/en/pages/manufacturing/articles/automotive-quality-2020-report-aiag.html>

“End-of-Line Testing” in Assembly Line Theory and Practice Wolfgang Klippel,
August 17, 2011 <https://www.intechopen.com/books/299>

“Scrap and Rework: How You Can Reduce Errors and Cut Costs” Arena Best
Practices <https://www.arenasolutions.com/resources/articles/scrap-rework/>

“End-of-Line Testing - All Geared Up and Ready to Go” Brüel & Kjær <https://www.bksv.com/en/knowledge/blog/perspectives/automotive-line>