

Achieving Cutting Edge Production

A Guide to Machine Learning
In Manufacturing

EBOOK

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Introduction

Machine learning is becoming even more prevalent as manufacturers continue their journey towards Industry 4.0 and digitally transform their factories. It has the capacity to make production more efficient by increasing output while maintaining quality standards.

Machine learning and industrial automation in manufacturing promises to overcome many of the industries most pressing challenges—including diminishing contribution margins and an expected skilled labor shortage. With continued advances in algorithms, computing power, and data availability, machine learning use cases in manufacturing are quickly emerging.

As industrial automation plays an ever larger role in manufacturing, the deep insights machine learning can offer are crucial for production optimization. But before manufacturers can introduce a machine learning platform, they must first understand how these solutions operate in a production environment, and how to choose the right one for their needs.

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In this eBook, we look at:



Manufacturing Before
Machine Learning



What is Machine Learning
in Manufacturing?



How Machine Learning is
Revolutionizing Manufacturing



How Machine Learning Works



Evaluating Machine
Learning Solutions

The History: Manufacturing Before Machine Learning



Precious time is wasted gathering data.

Data Then



Data Now



Data exists in many forms in manufacturing. There's data from machines and sensors on the factory floor, operator input data, and data from ERP, MES and quality systems. Traditionally, engineers have spent a significant amount of time gathering and transferring data from disparate sources in order to analyze outcomes, identify issues, and recommend process improvements.

Factory data is interconnected; products, runs, work orders, batches, process parameters and offline quality metrics all are related to each other. When data exists in isolation and there's a problem—a quality failure or a machine breakdown—precious time is wasted gathering data.

It can take days or even weeks to conduct root cause analysis or offer process recommendations, because teams have to manually compare data from siloed sources. Delays in obtaining accurate analysis and insights can lead to extended downtime, material waste, increased scrap rates, and ultimately lower contribution margins for manufacturers.

Advancements in cloud computing, however, have made it easier to stream, store and process tremendous amounts of data. The advent of machine learning technologies has made it easier to analyze data from various disparate sources and determine actionable insights.

What is Machine Learning in Manufacturing?

Innovations in machine learning are allowing manufacturers to make use of the diverse datasets they gather throughout the production process.

Machine learning applications in manufacturing leverage data gathered at different machines and sensors, and at different points in the manufacturing process along with real-time operator data, offline quality data, and data from historians and MES and ERP systems.

Machine learning for production optimization, quality control, and other applications allow manufacturers to identify and solve problems quicker. Predictive quality analytics help manufacturers predict and prevent problems while prescriptive analytics maximize quality and output by enabling quicker actions to insights.



How Machine Learning Is Revolutionizing the Manufacturing Industry

Before machine learning can optimize production, quality control, and other applications manufacturers must ensure that they have the requisite data. This is the first step in the smart factory journey that culminates in AI-driven automation.

01 CONNECTED

Centralize factory data generated by machines and sensors along with ERP, MES and quality systems to provide real-time operational visibility. Data can be displayed in interactive dashboards for teams to track and analyze.

02 PREDICTIVE ANALYTICS

Analyze production data to identify conditions that have previously led to failures on the floor then alert operators in real-time enabling them to take corrective action to prevent problems.

03 PRESCRIPTIVE ANALYTICS

Analyze process data to identify optimization opportunities, and recommend optimal process settings to replicate, or go beyond your most efficient runs.

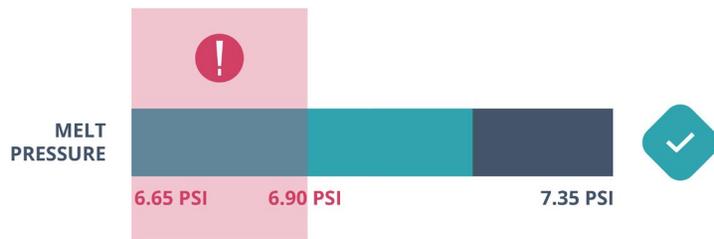
04 AI-DRIVEN AUTOMATION

Recommendations and optimized process settings are pushed directly to the factory floor so production can adjust based on current conditions and factories can consistently operate at peak performance.

The Four Analytic Capabilities



Predictive Quality



Manufacturers can prevent quality failures and reduce extensive scrap rates with machine learning based predictive quality applications. By combining live production data with offline quality and MES/ERP system data, machine learning in manufacturing can identify patterns and relationships between different variables. For instance, an algorithm can determine the impact of melt pressure on product density and diameter—if pressure is too low, it can negatively affect product quality and increase scrap rates. Furthermore, models can be leveraged to identify leading indicators for quality failures.

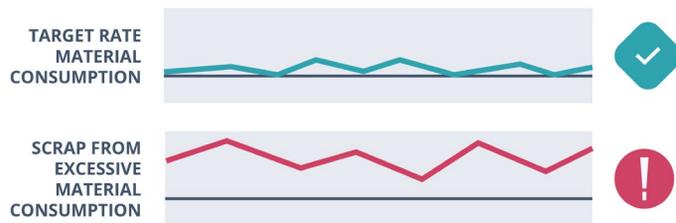
Predictive alerts can notify operators any time such leading indicators are identified, such as when melt pressure is trending towards below normal thresholds. Factory personnel are provided the lead time necessary to take corrective action, fixing the melt pressure problem and avoiding extensive production of defective products. Machine learning technologies can also provide recommendations for settings that will allow production increases while maintaining quality standards without increasing scrap.

Production Optimization

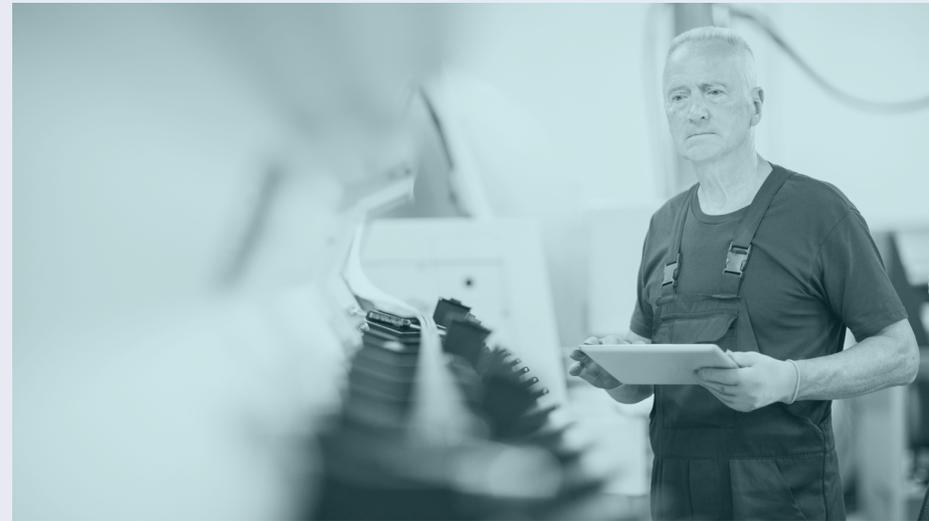
Machine learning for production optimization allows manufacturers to maximize throughput without sacrificing quality. Algorithms quickly analyze vast amounts of production data to identify best and worst performance, and perform a continuous search for improvements to the process. By recommending process settings, machine learning helps manufacturers replicate their most efficient, profitable runs more consistently.



Reduce Material Consumption



Machine learning in manufacturing helps reduce material consumption by predicting the optimal amount of material needed to produce a certain product batch, and continuously monitor and control the production settings to minimize wastage and material costs. Instead of over-ordering material to take into account defective output, machine learning can help manufacturers determine the ideal amount. Additionally, predictive performance can provide the optimal settings to reduce the amount of start-up and changeover scrap that typically occurs each time a new production batch begins.



Predictive Maintenance

Catch component problems before they occur. Condition-based monitoring can help you predict and prevent equipment failures. If a component, such as a fan, pump or motor, registers abnormal behavior—a too high temperature or a too low vibration level—a machine learning platform can identify the specific component likely to fail, and alert personnel to impending problems. Additionally, models can be used to identify operating conditions where the combined behavior of multiple such components is abnormal, even if each one is individually within its tolerances. Empowering maintenance and small adjustments to machine components reduces the likelihood of larger and costly problems or failures, avoiding extended downtime and more costs.

How Machine Learning Works



There Are Two Main Stages to Realizing the Value of Machine Learning

The first stage involves building the foundation for machine learning operations—this includes defining the use cases, data collection and cleaning, and data visualization for real-time production monitoring.

During the second stage, machine learning algorithms are used to build and deploy models, and provide predictive and prescriptive recommendations. This permits a continuous cycle of improvement.

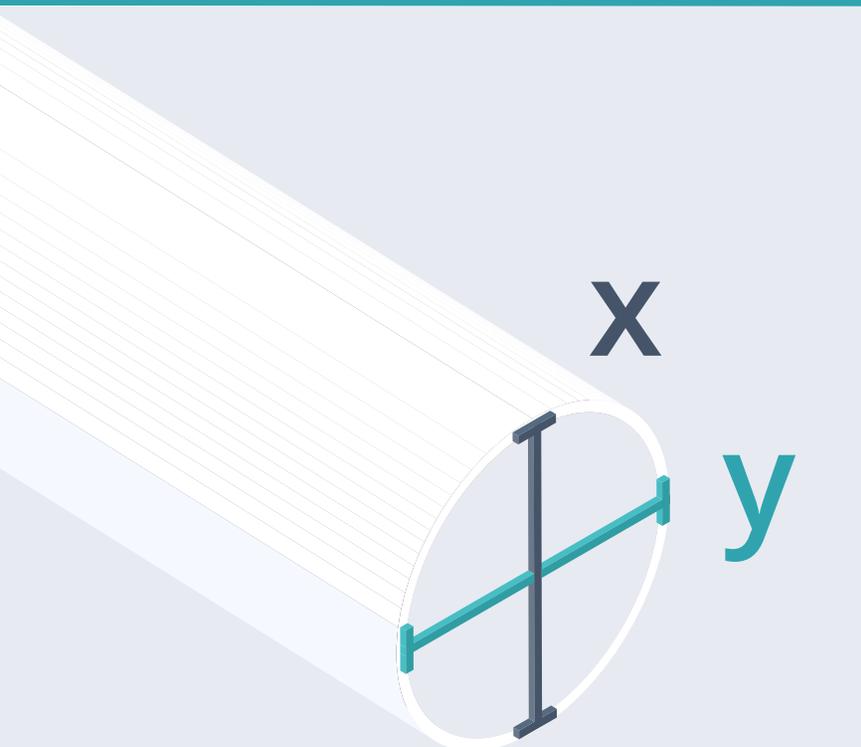
Define the Application and Gather Data

Begin an implementation by focusing on desired business impact to define the application. For example, if you have customer complaints about poor quality or high scrap rates, an initial application might be focused on quality optimization.

After you've determined the main application, identify what data needs to be collected and from which sources—including data from machines and sensors, real-time operator data, MES/ERP systems, and importantly inline and offline quality data. Also determine historical data availability and its location, such as in data historians or SQL databases.

Lastly, identify any gaps in data or infrastructure. Ensure that you have a data conduit, such as an OPC server, that enables interoperability by ensuring connectivity to any protocol or data type within your Operational Technology (OT) environment. Ideally, you'll also need a data historian to store your process data, as well as a SQL database to store transactional data.





$$\text{Average Diameter} = (x + y) / 2$$

Ingest, Clean, Correct and Structure Data

Consistency is key to maintaining a cohesive ecosystem that enables data-driven decision making. Historical data and live production floor data must be aligned. All data must be cleaned, formatted, contextualized, and organized into a taxonomy in order for machine learning technology to operate effectively.

A taxonomy—a hierarchy of labels and classifications derived from knowledge of the domain—provides context to the data. For example, while there might be separate metrics for machine temperature and material temperature; a taxonomy helps identify that these are both types of temperature metrics and also indicates which part of the process they control or affect.

It is also critical to align metrics with metadata such as the product, machine or quality state in order to make any analysis meaningful. For example, if a product tested offline is defective, but you don't know which line or shift that product was produced on, it's impossible to go back and find what other products might have been affected by the quality failure.

In this step, different types of algorithms are used to perform conversions, transformations and complex calculations to the contextualized data. These calculations might be simple like converting from Fahrenheit to Celsius or they can be more complex such as computing windowed temporal aggregations.

One scenario from cable manufacturing is measuring the diameter of a product. You might measure the diameter from top to bottom and then measure it from left to right. The algorithm will average these two measurements as well as calculate an acceptable standard deviation. For example, if the cable should be 10 centimeters but can go either up to 10.15 centimeters or down to 9.85 centimeters.

Data Visualization for Production Monitoring

To leverage machine learning in manufacturing, you also need accessible and immediate insights through easy-to-understand formats such as charts, graphs, and other visuals.

Software platforms that leverage machine learning technology offer data visualization that support the results via interactive dashboards. A comprehensive dashboard gives a snapshot of factory performance, including:

Output by product, line or shift

OEE including utilization and performance by line, shift or day

Products with the largest changeover

Evidence in support of machine learning recommendations

Model parameters and performance measurements

Data exploration capabilities allow performance comparisons across equipment, shifts, products, and interpreting results generated by the models. To help focus your efforts on where they'll have the most impact, Pareto analyses assess and prioritize competing problems so you'll know which to solve first.





Train & Deploy Machine Learning Models

Machine learning builds models that are trained to address several production scenarios. An algorithm will analyze live and historical production data to identify patterns in behavior that have previously led to issues on the factory floor (including quality failures or unplanned downtime). It will then establish relationships, ranging from strong correlations to cause-and-effect constraints, between different process parameters and outcomes. Several algorithms and types of models, along with their parameter settings, can be used during this process.

Then the trained models are validated against unseen data, specifically data that is known to exhibit the issues that the model was trained to capture. This allows tuning algorithm performance and generalizing the model, to ensure models can operate in a real production setting. Models are then deployed into a production operational environment, running against live data, either in the cloud or on the edge. Real-time process models look for specific patterns or a set of conditions that indicate a quality or machine failure may happen in the future.

Over time, models need to change—new processes, new products, new people, and even model recommendations all contribute to process evolution. Models become obsolete, their performance may falter over time, and updated data means that models must be constantly retrained, built, and deployed, within a continuous model lifecycle. Constantly monitoring and improving models keeps them up to date, and maintains their effectiveness.

Prevent Problems with Predictive Analytics

Once those models are trained, machine learning technologies will then identify patterns in key process parameters and their behavior that have previously led to problems on the factory floor, often as leading indicators.

When models are run against real-time production data, predictive analytics look for a specific set of conditions that indicate a quality or machine failure may happen. For example, machine learning models can predict that a quality failure will occur in 10 minutes because in the past when line speed has dropped, products have not met quality standards.

Models are validated—measured against historical and current performance data. They can be validated “live,” which is in real-time as production happens. Validation provides insights into how models are generalized. For example, past errors could have been avoided or outcomes improved, thereby informing current production.

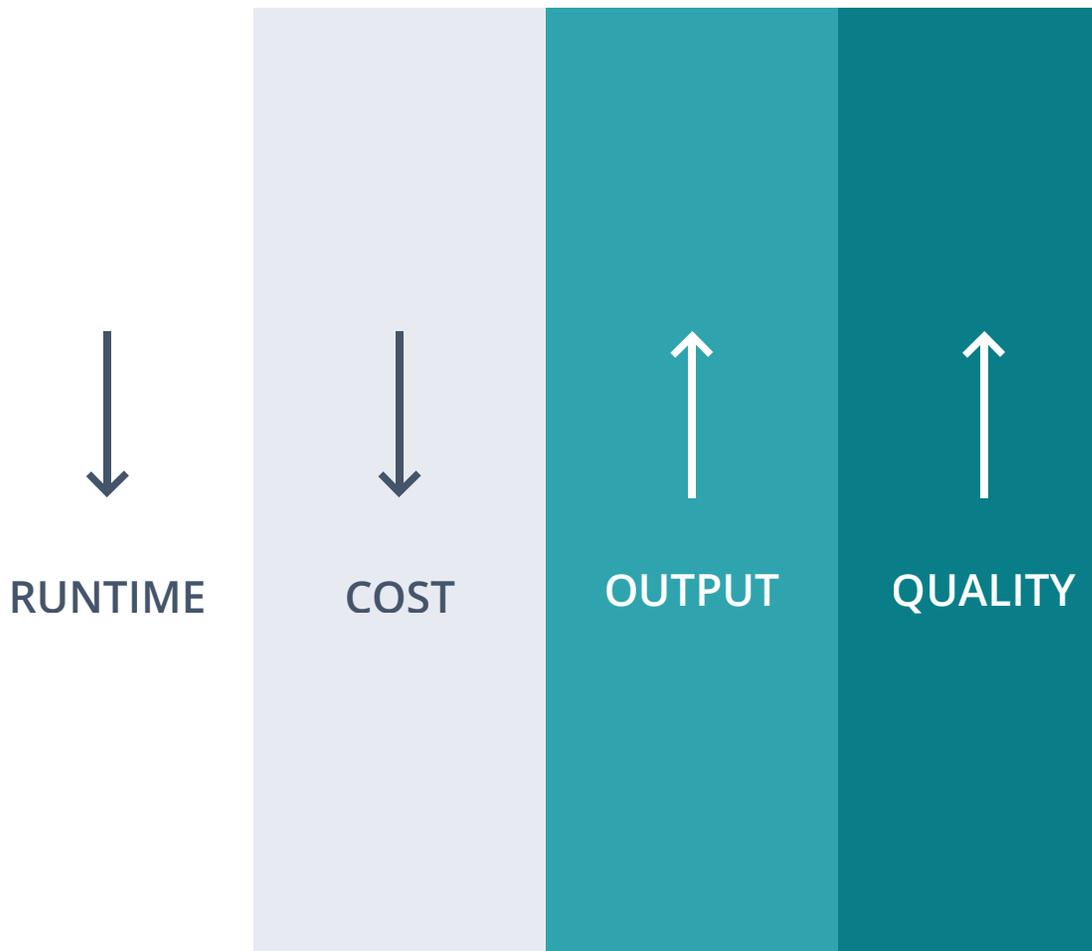
Predictive alerts are then deployed to help factory personnel proactively take action and avoid problems. Alerts are generated when the model identifies the patterns in the key parameters that indicate quality failures. For example, melt pressure needs to stay within a certain range for optimal quality. Any time it goes above or below those parameters an alert will be generated.

Alerts can be customized based on factory floor conditions or combinations of metrics and their temporal behavior. An alert can be triggered if line speed drops five times over ten minutes but not if it only drops once. This prevents redundant or irrelevant alerts that are ignored or cause operators to stop production unnecessarily.



BOTTOM LINE

Manufacturers get advance warning of problems, such as potential quality failures and/or unplanned downtime due to machine failure, and allow operators to take corrective action.



Maximize Quality and Output with Prescriptive Performance

Machine learning applications in manufacturing go beyond predictive to prescriptive to help optimize production. By analyzing available data, machine learning technology is able to identify the best and sub-optimal performing segments, as well as the key variables that impact quality, performance, and utilization. Prescriptive analytics recommends machine and component settings, enabling improvement of process parameters, such as performance targets to consistently replicate the most efficient runs, while maintaining high production quality.

Automated reports highlight key differences between good and bad runs, and key parameters to help ensure operators maintain better process control across lines to better enable control across factories.

Alerts are generated by coupling these prescriptive analytic recommended settings with live monitoring and predictive models. These live models can be used to provide alerts indicating early warnings of departure from optimized settings, allowing factory personnel to proactively address production issues.

For example, one manufacturer increased order efficiency by implementing machine learning recommended settings adjustments so that it could produce more in less time while maintaining quality—saving over 200 production hours. This allowed them to lower operating costs associated with individual orders as well as fill subsequent orders faster by reducing the opportunity cost of machine time.

Evaluating Machine Learning Solutions





Not every machine learning solution for manufacturing is appropriate for all factories and production needs.

Not every machine learning solution for manufacturing is appropriate for all factories and production needs.

The importance of assessing the various machine learning solutions available today before you make a commitment cannot be overstated.

To that end, here are the key elements to look for when choosing a machine learning application for your manufacturing environment.



Real-Time Data Processing and Computations

These have the ability to apply complex computations and machine learning models to metrics in real-time. These real-time computations can include rules or formulas combining multiple metrics and values into one measurement after applying an appropriate function. The ability to support real-time calculations supports both the requirements of machine learning, as well as provides manufacturers the ability to develop interpretable and contextual insights from the raw metrics that are being collected. This allows operators and engineers to understand why they are getting alerts.



Surface Insights as Reports & Recommendations

Insights can be pulled from analyses of historical data and surfaced in reports to inform current operations. Algorithms can detect patterns and develop predictions that can be run against live streamed data to identify trends and detect abnormal behavior. Alerts and alarms can be generated to notify teams, allowing them to proactively take action and prevent problems on the factory floor. Recommendations are also developed to quickly offer deep insights that factory personnel can leverage to optimize production as well as compare performance across lines, shifts, and factories.



Contextualization and Domain Knowledge

Contextualization and domain knowledge align with industry applications and can create flexible mappings of relationships between variables and processes and categories of metrics, such as control and performance metrics. Results from machine learning models are most valuable if they leverage and respect these domain knowledge based constraints, and provide acceptable production conditions.



Speed of Iteration

Machine learning for manufacturing environments needs continuous model adaptation, from concept through training, validation, testing to the final iteration. When this model lifecycle can be automated, it shortens the time-to-value significantly. You'll also want automated workflows that can set up, train, validate, deploy, monitor, and update models. Look for framework and processes that allow you to build any models you need and then update them as things change or problems occur.



Cloud-Edge Hybrid

The best of both worlds—a cloud-edge hybrid offers the advantages of cloud storage and elastic computation, along with local accessibility. This combination offers the utmost in flexibility along with the choice of deploying models where you need them.

Cloud offers better computing power and economies of scale for data storage and machine learning model training requiring large magnitude data analyses, building of sophisticated models, and hyper-parameter optimization.

Edge offers hyper-local storage, which reduces latency and removes dependency on external connectivity—meaning high reliability and quicker insights. This is important for situations where business continuity is crucial.



Costs & ROI

New machine learning platforms are flexible and can be integrated into existing infrastructures, which is great news for manufacturers who don't want to create an intelligent factory from scratch.

The optimal machine learning solution will have the flexibility to work with your current applications, and help you quickly realize value from new products and versions. It will also be cost-effective for your business use cases, and quickly provide return on your investment.

Also, remember that you'll need the right kind of data, and enough of it, to run and get the value of any machine learning platform.

TURN DATA INTO INTELLIGENT ACTIONS FASTER WITH **GOLDEN RUN™**



Golden Run™ is a proprietary recommendation engine specifically designed to address manufacturers' need for efficiency and to identify the most profitable way to make a product. It enables manufacturers to solve problems faster than ever before and unlock cost-saving efficiencies from data that could have remained hidden.

Using Machine Learning algorithms, Golden Run identifies where changes and improvements can be made and generates new settings so manufacturers can continually realize cost-saving improvements.

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MAKE MORE. WASTE LESS. INNOVATE FASTER.

Whether you're new to machine learning for manufacturing, or are looking for new implementations and improvements in your manufacturing environment, Oden can help guide your next steps to realizing the value of machine learning. Meeting the challenges of Industry 4.0 and the intelligent factory requires the right partners.

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