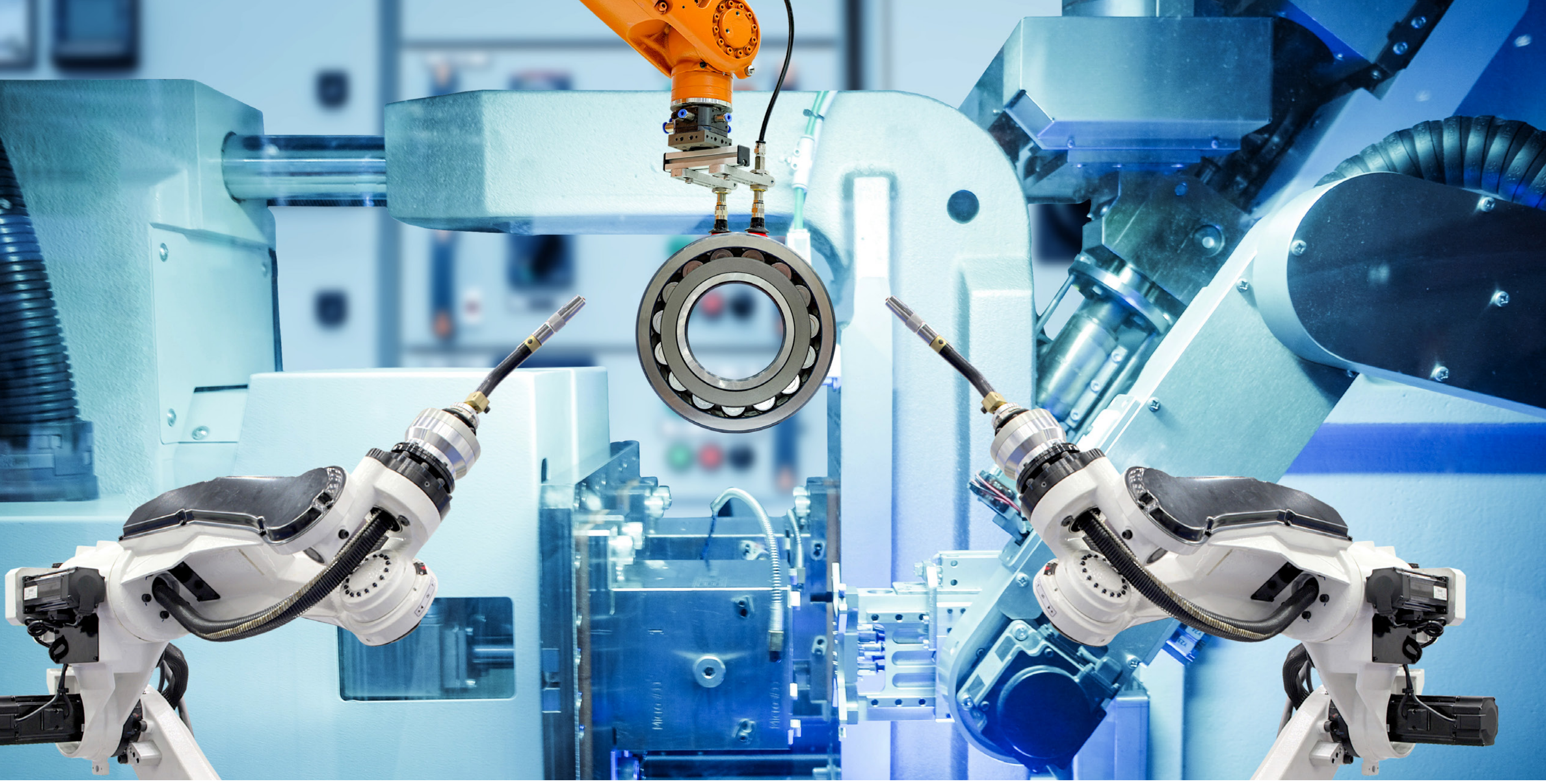

DIGITAL INDUSTRIES SOFTWARE

Intelligent manufacturing for industrial machines

Using artificial intelligence to increase flexibility, productivity and quality

Executive summary

Nowadays industry requires faster and more flexible, accurate and efficient production to drive the profit required to grow in an environment challenged by crises. The current changes to the landscape directly impact the product development of industrial machinery manufacturers and how they leverage artificial intelligence (AI). Just as the integration of AI technology into the healthcare environment almost a decade ago enabled automated and personalized services, the industrial shop floor of today is being reshaped via AI-based solutions, permitting flexible design and manufacturing, adaptable production machinery utilization, enhanced product quality assessment, optimized process parametrization, improved health status monitoring and more.

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Abstract

This white paper presents how AI can be exploited by industrial machinery companies that use manufacturing operations management (MOM) systems in a wide range of applications, from planning to post-production services. The presentation of specific use cases illustrates how AI technology can be profitable for industrial machinery producers.

Leveraging artificial intelligence to enhance manufacturing performance

Complexity is today's watchword for most of the manufacturing world, and the industrial machinery industry is no exception. Complexity in industrial machinery is growing exponentially. A multitude of new onboard electronics, sustainable and locally sourced materials, edge computing capabilities, hyper automation and many more changes result in components, subsystems and systems that are much more complicated than the ones built into industrial machinery just a decade ago. At the same time shortages of materials lead to redesigns and more frequent product variants that have to be resolved under time pressure.

Beyond the products, the industrial machinery production processes are also becoming more complex. Whether a manufacturer is using or building computer numerical control (CNC) machines, robots, automatic inspection systems, supervisory control and data acquisition (SCADA) or other machinery, that company's machine designers are creating a digital thread that is being extended and connected to manufacturing operations. Machine producers do this to handle the growing complexity and automate these processes to reduce risks and increase flexibility while working with a variety of commodity suppliers.

Machinery manufacturers also aim to adopt emerging technologies that will potentially provide new product features. These include the industrial internet of things (IIoT) and cloud computing, 3D printing and other additive manufacturing (AM) technologies, and the many emerging smart manufacturing systems that promise a great competitive advantage to the companies that can utilize them.

Within this context, AI has emerged as a promising technology since it enables machines not only to learn process steps, but also to improve performance so both productivity and quality are enhanced without additional human intervention.

Although manufacturing initiatives aim to address this growing complexity, they also must account for strong market trends in the industrial machinery space, including:

Global competition – As the vision for manufacturers to "design anywhere, build everywhere" gains traction, it is of paramount importance for machinery companies to reduce manufacturing costs and accelerate time-to-market. To keep up in a highly competitive global marketplace, machinery manufacturers must drive innovation and even address customers' core operational costs and risks.

Consumer-driven customization – Though the concept of mass customization has taken hold broadly in business-to-consumer (B2C) businesses, the business-to-business (B2B) firms that supply them – including industrial machinery makers – are experiencing a ripple effect that is driving up product variety and driving down lot sizes. Machinery companies have to accommodate ever shorter innovation cycles of more complex products. Many users of industrial machinery are changing their products more rapidly, and their product design dictates machine design. Industrial machinery must be more flexible than ever. A high level of customization reduces the opportunity to re-use past designs, and it can accelerate product obsolescence and even result in loss of business. Mass customization has also changed the competitive landscape for machinery companies: traditionally, the big competitor has beaten the small one, but now the fast one is beating the slow one.

Regulatory pressures – Throughout the industrial machinery supply chain, including machine builders, component suppliers and machinery customers, regulatory pressures are escalating. Environmental concerns related to climate change have compounded this challenge. So has globalization, which requires manufacturers to track, satisfy and verify compliance with evolving regulations from every location in which they do business. Under these conditions, machinery manufacturers need digital tools that provide the right information at the right time and in the manner needed while aligning with evolving major regulatory standards.

Paradoxically, in a rapidly evolving technological environment the machinery market disruptors will not be the companies that try to limit complexity, but the ones that embrace it, creating new business models and using innovation to defeat the competition.

What does it look like to embrace complexity? It demands a new perspective on the relationship between traditional digital manufacturing tools and AI technologies. Initially used in consumer and governmental efforts, AI is now being applied more widely to manufacturing. Like human intelligence, AI acquires experiences and self-trains as it analyzes data to recognize images and patterns. But in manufacturing a key difference between AI and human intelligence is AI's capability to analyze a vast amount of data and provide predictions and processes in significantly shorter times. As computing capacity has accelerated, AI now requires mere minutes to generate predictive models that might have taken weeks or months without it – if it could be generated at all.

What AI offers industrial machinery manufacturing teams is the capability to make smarter decisions using data analytics and machine learning (ML). Importantly in a post-pandemic world, AI also effectively shortens distances and widens the scope of manufacturing initiatives, enabling new location-independent technologies to be aligned despite physical distance.

The functionality and utility of AI

AI is designed to reproduce human capabilities of understanding, reasoning, learning and interaction. Specifically, AI systems can recognize text, images, video and voice in order to comprehend its relationships and context. AI also gives machines the capability to see, using optical tools and image-processing technology. It then processes and uses what it has visually captured to satisfy specific requests, such as unlocking a phone by recognizing the owner's face. In manufacturing, this capability may be used to identify a specific feature or attribute in a work-in-process (WIP), enabling automatic inspection that verifies correct assembly or sends an alert when a nonconformance is found.

Regarding reasoning capacity, AI is able to find logical relationships by connecting and contextualizing collected data by using mathematical algorithms. This capability may automate some logistics decisions, such as determining which supplier is able to meet the procurement schedule at the best price or lowest carbon footprint.

AI performs learning processes by using several methodologies to find input-output relationships. AI learning may uncover a hidden cost, such as machine operator idle time that can be minimized by modifying a production schedule.

Finally, AI addresses the interaction between people, machines and the environment by employing localization, mapping, navigation tools and systems such as natural language processing. Manufacturers might employ this capability to enable shop floor technicians to make oral inquiries regarding a particular work instruction.

Artificial intelligence is used to understand, reason, learn and interact via several learning models and techniques.

One of the most common automatic learning systems using AI is machine learning, which is comprised of algorithms that can learn from data without relying on rule-based programming. Machine learning systems collect inputs, use statistical methods and train algorithms so the machine effectively learns the tasks to be performed and is able to make classifications or predictions useful for the decision-making process.

Another AI learning model, called deep learning, is founded on machine learning training but also reproduces other functions of the human mind. It uses deep artificial neural networks and computational skills that support calculation and analysis layers. Specifically, it aims to speed process optimization while reducing model, memory size and computation power required per optimization step.

One application of these deep learning systems is the natural language processing technique. This technique allows computers to transform human language in the form of text or voice data. Its task is to comprehend the meaning and the context, including the human aim to respond with text or speech.

A new computer vision technique is also based on deep learning and it consists of comprehending image and video content. With this technique, computers acquire real-time images through video, photos or other technology; then process these images and interpret them, identifying and classifying objects including their position and orientation.

AI on the manufacturing floor

Although the growing complexity of industrial machinery products, processes and technologies create a formidable reality for manufacturers in this industry, thankfully, complexity is in AI's wheelhouse. Neural networks and other AI tools feed on the vast quantities of data produced by the sensors and inspection devices overseeing complicated processes and the production of complex products. They ferret out patterns and trends, and then they build algorithms to predict risks and help manufacturers reduce them – even before first articles are produced.

Today, for example, machine learning algorithms help systems that perform quality checks in production plants. Robots with vision systems can provide more flexibility as they react to unexpected situations and quality defects because they can respond automatically during runtime. They can operate much more efficiently because expert knowledge can be transferred to automation.

There are two types of AI systems that support various manufacturing operations: those based on software and services, such as facial recognition, virtual assistants and search engines; and those embedded in hardware, such as drones, robots and automated guided vehicles (AGVs).

As AI becomes an integral part of manufacturing operations, Siemens Digital Industries Software anticipates that its capacity to understand, reason, learn and interact will create significant benefits throughout product and production lifecycles. AI-supported production efforts can:

- Provide remote monitoring (dashboards to keep trends and runtime data under control)
- Use process data from previous production runs to predict and prevent reoccurrences of production deviations and failures
- Anticipate production changes required to accommodate product customization features and send alerts downstream
- Produce reliable and steady data
- Generate manufacturing insights based on aggregated, contextualized and analyzed data to support better decision-making by stakeholders throughout the product lifecycle
- Strongly support quality audits (automatic audit and help for operators)
- Identify unknown correlations that can have impact on the overall product quality or cycle time
- Accelerate and improve reporting by trend predictions and pattern recognition
- Build confidence and trust with customers
- Speed new product introductions
- Collect all data and generate the full history of each product

Leveraging AI for improvements in the manufacturing landscape depends upon the synergistic relationship between automated manufacturing equipment, MOM systems and AI applications. MOM systems enable the virtual and real worlds to converge on the manufacturing floor. They deliver a comprehensive digital twin, initially generated through the product lifecycle management (PLM) system, as well as production-relevant data from enterprise resource planning systems (ERP) to the plant's automated manufacturing equipment, enabling it to carry out virtual design and engineering directives as it makes the product. The workflow then moves from the real back to the virtual as quality systems generate data indicating how closely the real-world process and product match the digital twin. AI technologies enhance and accelerate the workflow by streamlining the movement of information between the manufacturing floor and the virtual realm of manufacturing software solutions.

AI is powered by data, and lots of it. It is fueled by information from data generated on the manufacturing floor, external data that is pertinent to manufacturing conditions (for example, ambient temperature and humidity), machine vision and other quality monitoring equipment, laboratory and research and development (R&D) data and field data.

Using this wealth of information, AI initially employs its neural networks for application development. For example, the neural networks use data to train classifiers that identify whether production and product attributes are in or out of tolerance. The algorithms on which the classifiers are built can be continually fine-tuned as additional production and product data is generated and evaluated by the neural networks.

With AI-based production monitoring algorithms in place to detect trends, deviations, nonconformances and drift, AI can be used to generate preventive information and actions. For example, traditional statistical process control (SPC) and root-cause analysis can be enhanced using AI-based algorithms. Closing a continuous improvement loop, AI-based manufacturing intelligence may be applied to support process and quality planning, risk assessments and risk reduction activities.

Manufacturing use cases

Use cases are presented here not to suggest a specific AI application for the industrial machine manufacturer, but to generate thoughtful consideration of the broad value that AI may offer manufacturers in this industry. To make the most of AI, each individual company must bring to light the particular goal it will pursue first; whether it is improved quality, greater throughput, a reduced carbon footprint or something else. AI may then be applied to uncover the parameters and key performance indicators (KPIs) that have the greatest effect on that goal, then clarify dependencies using data analytics and finally optimize processes in ways that lead to realizing the goal.

Although artificial intelligence can improve processes in nearly any domain of the industrial machinery manufacturing enterprise, perhaps AI's greatest value is it can be applied to manufacturing operations using a MOM system. When a company's newest model is ready to launch into production, manufacturing operations management communicates the information developed in product design and process engineering and orchestrates all production activities that comprise the manufacturing process.

The functionality of MOM can be categorized in five primary domains, each of which represents a pillar of MOM software:

The **manufacturing execution system (MES)** is used to manage production activities, equipment and processes in a proactive and systematic way, ensuring that quality and efficiency are built in and enforced in the manufacturing process.

A **quality management system (QMS)** enables manufacturers to monitor, manage and document their quality processes to help ensure products are manufactured within tolerance, comply with all applicable standards and do not contain defects.

Advanced planning and scheduling (APS) is used to develop and optimize both a long-term production plan and a short-term production schedule that accounts for demand (forecasts and orders), availability of supplies (raw materials and supplied components) and production capacity (machines and labor). APS also automatically recalculates the optimal schedule when changes occur.

Enterprise manufacturing intelligence (EMI) is used to integrate, connect and unify information from MOM and other systems into one accessible analytical data model, which can be used for shop floor visibility as well as closed-loop, continuous improvements.

Research, development and laboratory (RD&L) is used to streamline, optimize and align product data management. It is used to manage specifications, formulations and laboratory operations.

Siemens Digital Industries Software has tailored its MOM software solutions to meet industry-specific needs. For example, Opcenter™ Execution Discrete software, which is part of the Siemens Xcelerator portfolio, the comprehensive and integrated portfolio of software, hardware and services, is designed to optimize manufacturing efficiency, productivity and flexibility in the production of limited-volume, highly complex products. AI can be applied to MOM activities, and in general to the manufacturing process, to predict information about the supply chain, production, quality and more. Two AI applications that Siemens has experience implementing are production order management and parameter-setting.

1. Using AI to automatically split orders

APS is the MOM solution responsible for managing production orders. It is used to manage both long- and mid-term planning and day-to-day scheduling of the sequence of production operations. It also helps to make sure that resources and materials are available in the quantities and at the times needed to meet delivery dates.

One of the ways that production order management can improve quality, productivity and efficiency is by managing order splits – splitting a large sales order into several smaller production orders. Many issues may complicate this process. For example, a company may have several equivalent production lines or factories equipped to manufacture a machine but differ from each other in terms of material and resource availability, logistics and other important factors. Splitting orders is most challenging when they include different customized features for the same machine model.

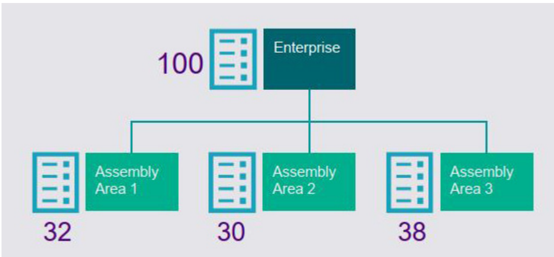

Figure 1. Production order split.

Artificial intelligence can be employed in the order-splitting process to ensure that orders are split not only according to known information, but also based on hidden knowledge that the AI system is able to uncover. Planners using this AI-enabled process are empowered to make better, more informed and faster order-splitting decisions.

The following are four order-splitting use cases identified according to algorithmic complexity and AI empowerment:

Centralized KPI optimization – Splitting an order while optimizing a certain KPI and respecting specific constraints. As an example, a manufacturer may wish to minimize cost per machine while keeping utilization of production capacity above a certain threshold. AI plays a limited but useful role in supporting this decision-making process.

Centralized KPI optimization and hidden knowledge discovery – Optimizing a given KPI while respecting constraints and taking into account the trend of other KPIs. In this case, AI brings an understanding of the behavior of the other KPIs, suggests clustering algorithms to indicate the correlations between the different indicators and generates forecasting algorithms, which predict likely outcomes by analyzing current and historical data.

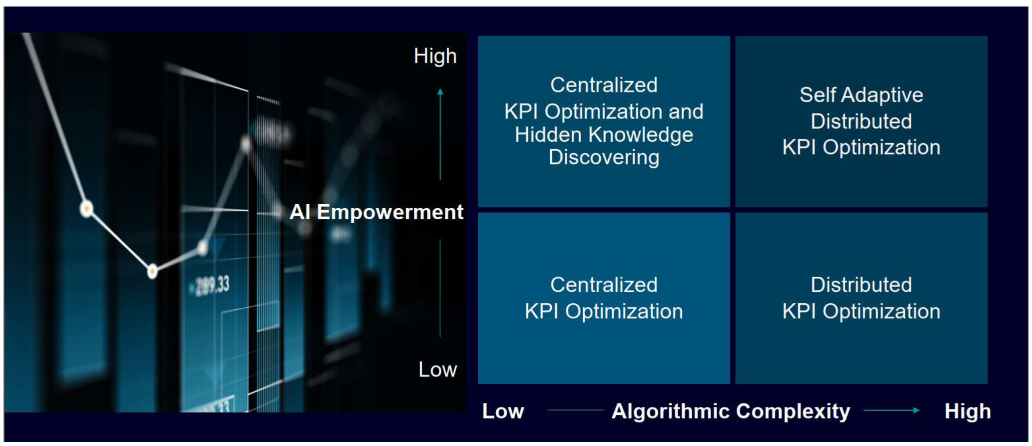

Figure 2. Use cases.

Distributed KPI optimization – Negotiating toward a compromise when there are actors who have differently weighted targets among the individual systems but have a common goal. The negotiating capability is found in autonomous AI systems, which are intelligent systems able to make decisions rather than simply informing the decision-making process of a planner.

Self-adaptive distributed KPI optimization – Using machine learning to arrive at a negotiated compromise. Applying machine learning to past data defines a reliability index for each system, and system reliability then drives the negotiation. This application may be extended with predictive modeling, a statistical technique using machine learning and data mining to predict and forecast likely future outcomes with the aid of historical and existing data.

These examples illustrate how applying artificial intelligence to production order management makes it possible to exploit both known information and hidden knowledge to accelerate and improve the results of the decision-making process for order splitting.

2. Using AI for parameter recommendations

A challenging phase of manufacturing execution is to optimize parameter settings, especially in complex, interactive and multi-stage processes. Typical objectives of parameter-setting are to improve output quality while reducing waste and energy consumption. Recent trends in the marketplace, however, have made the requirements and objectives for parameter-setting much more complex.

More frequent optimizing of parameter settings is often required, for example, as more and more machines are customized. Many industrial machinery manufacturers are not only responding to demands for customization but also proactively polling customers to better understand what they want and developing customized solutions to meet those needs. This trend toward product variation increases production complexity as different varieties may be part of the same (or a subsequent) order – one of the factors giving rise to more order splitting, as discussed in the first use cases. Product variations may require different raw materials or supplied components, process steps, sequences, quality checks and more, all of which may change the optimal settings for various parameters.

At the same they are meeting new customization demands, manufacturers also face increasing pressure for speeding time-to-market, which entails accelerated internal engineering and commissioning processes. Multi-level optimization or multi-target optimization may be required to maintain both throughput and quality despite producing fewer pieces of the same kind.

Quickly finding suitable process settings end-to-end is also needed when model variants involve new materials and components from new suppliers. For example, an engineer may be adding new printed circuit boards (PCBs) to support new digital capabilities in a machine model. What happens if existing machine noise interferes with new printed circuit board functionality? A switch from metals to composite materials may be required to damp the machine noise and changes to the computer-aided design (CAD) geometry may be applied so the new digital component operates effectively.

Siemens is evaluating an AI-enabled parameter recommendation system. The Siemens evaluation team initiated the project by listening to our customers and helping them to clearly define the problems they face during the parameter-setting process. The team's goal is to propose smart solutions that help line operators by recommending improvements to settings of machine and control parameters.

Following are two use cases in the food and beverage industry that illustrate how AI assists and accelerates parameter-setting and optimization operations:

Parameter-setting in beverage processing – Beverage quality, process costs, energy efficiency and reducing material waste are critical outcomes for many beverage producers. Furthermore, optimal utilization of installed equipment is a requirement across different industries.

Optimizing parameters is complicated by these multiple desired outcomes and also by process dependencies that begin with ordering raw materials. If the specified material is not available, then process parameters may need to be recalculated and adjusted.

AI is used to analyze laboratory and process data and to account for both as-planned parameters (for example, formulas) and real operating parameters (both experimental and in-process). In parameter-setting you must consider the raw materials used, the parameters of previous process steps and the history of previous batch quality as these factors exhibit complex interdependencies. Beverage quality is evaluated by an inspector's experience of taste and smell as well as by laboratory sample testing of numerous KPIs. These need to be included as labels in the learning dataset.

Results of the AI process provide beverage manufacturers with recommended adjustments to parameters. For example, AI may determine an optimal value for the dosing of beverage filtration aids. The AI system provides the operator with more real-time information of greater accuracy, and it also identifies important parameters and suggests adjustments, resulting in faster and better decision-making and taking into account all the previous batches and their filtration quality.

Parameter recommender with visualization for brewmasters – Breweries use a software module to support brewmasters in analyzing historic batches compared to current production, helping them to gain

new insights and make deep-seated decisions. In this project, Siemens is interviewing and holding discussions with internal and external brewmasters to determine how AI might support them in leveraging previously collected data on historic batches. The goal is to derive well-informed recommendations for best practices.

As an example, AI application could uncover and make visible the dependencies that led to the brewery's best batches. Another possibility is to detect deviations early in production process, incorporating lessons learned from previous batches, which could lead to suboptimal KPIs (production time, liters of water per liter beer, beer quality metrics).

In particular, AI can be applied to provide analysis of:

- Product quality
- Filtration parameter settings
- Parameters for cleaning in place (CIP) operations
- Laboratory data about raw materials and from sampling in the production process
- Effects of recipe changes
  - Caused by raw input material changes (from slight changes on datasheet up to using different combinations of suppliers)
  - Based on new customer demands for a new variant
- Analytics configuration
- Sensitivity of dependencies
  - Investigation of root causes of unmet process or product KPIs
- Lab and MES planning
- Maintenance and logs analytics

The AI-enabled parameter recommender reduces the likelihood of poor decisions by enhancing transparency during the decision-making process.

In the above use cases, AI facilitates global, secure knowledge exchange about multiple production runs and shifts. It also drives knowledge sharing among operators, motivating feedback that provides actionable information. AI supports better, faster and lower-risk parameter-tuning, ensuring that lessons learned help production floors to keep any problems from recurring.

In comparison to automated closed-loop optimization, a recommender enables the production lead with appropriate workflow-integrated tools to gain rapid clarity and confidence. It is a new data-driven tool that helps manufacturing team members do a better job. This AI project seeks to break down complexity, allowing operators to invest their time in applying the information available rather than in searching for it.

Conclusion

Reducing operational risk and increasing productivity are the perennial goals of manufacturing initiatives for any industrial machinery company, but the tools and methods for achieving these goals are constantly evolving. Manufacturers that wish to maintain or increase their competitive edge must keep up with new technologies that support their initiatives, artificial intelligence being one of the most recent and potentially the most powerful tools at their disposal. Siemens is ready to help machinery makers with both the open digital platform and the experience and know-how to leverage the latest generation of enabling technologies. Today this means partnering with companies to prepare for, and then implement AI in ways that keep them moving toward operational excellence. The recommended path of this journey is incremental. For example, AI may be applied to enhance KPI visibility, gain manufacturing insights with data analytics and execute specific operations like order splitting or parameter-setting optimization. This is done via decision support by recommending a course of action for shop floor staff, as described here, or closed-loop optimization. By applying AI to a specific area, reaping benefits from this application and then expanding to adjacent areas, manufacturers realize new benefits and higher returns at each step at relatively low risk.

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