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S&P Global
Market Intelligence

Special Report

Achieving Manufacturing Excellence with AI at the Edge

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Executive Summary

In order to gain the most benefit from improving manufacturing KPIs with artificial intelligence (AI), organizations need to consider three main points that address various scaling requirements: the amount of data, the wide range of old and new machinery, and the workforce acceptance of AI.

Individual data points from IoT instrumentation help inform about machine and plant status, but the true benefit of instrumentation comes from aggregating this with many other data sources. AI techniques can be applied at this level to gain deeper insights into entire business processes. It is a technical challenge to orchestrate this at scale because it needs to operate across the continuum of edge and cloud.

Manufacturing plants are constantly evolving and, as such, generally comprise a complex mix of legacy and new equipment. Each plant, even within the same enterprise, presents a unique combination of engineering equipment, processes, electronics and software. Individual engineers may even apply their own routines and approaches to keeping the machinery running. Not everything is Industrial IoT-enabled or connected. Longtime organic growth generally includes technical advances that provide a different scale of challenge to overcome with regard to updating AI processes with the changes.

The final scaling challenge is to gain user acceptance – which includes social implications as well as operational factors and organizational change management – of the speed and ease with which AI models can be deployed with emerging 5G capability and increasing edge computing power. A manufacturing plant's workforce, from shop floor to control room, interacts directly with the machinery and processes, and their ongoing focus to keep the plant running relies on culture and morale. As such, employees are likely to bypass or circumvent complex tools that add overhead. This means that AI advances must scale across this landscape, be easier to use and provide a shorter time to value than existing tools.

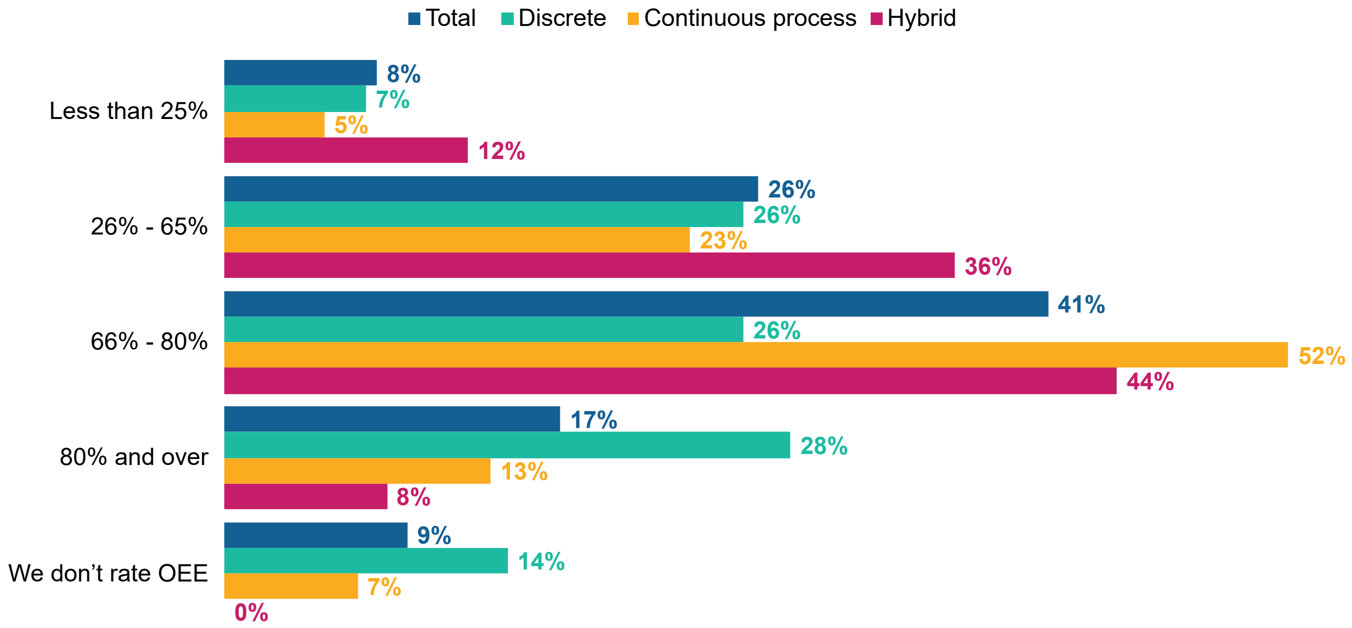
Technological Discussion

Many forms of technology have evolved to support manufacturing. Focusing only on the basic manufacturing process – raw materials in (that are transformed and combined) and a product out – hides the complexity and challenges that manufacturing plants face. Once a physical process is running, it is in a constant state of decay. Thus, an important KPI used in manufacturing industries is overall equipment effectiveness (OEE). This metric attempts to measure how well machines are operating, with end-to-end production time and quality as factors in the equation (Figure 1).

Incorporating AI into processes can significantly drive up OEE via predictive maintenance, for example – spotting problems in machinery before they become more serious and cause significant downtime. Our data shows that predictive maintenance is the top planned use case for AI/ML (Figure 2). Only about 17% of manufacturers regard themselves as having an OEE of 80% or greater. Many organizations could make significant improvements to become more operationally effective, and the application of AI techniques is significant. Not only does AI help improve the uptime of machinery, but it also can help manufacturing plants fine-tune processes to improve energy efficiency and reduce use of raw materials.

Figure 1: Overall equipment effectiveness KPI

Source: 451 Research's Voice of the Enterprise: IoT, the OT Perspective, Use Cases and Outcomes 2020
Q: Using your best estimate, what is your organization's overall equipment effectiveness today (OEE)? Note: by OEE, we mean 'a manufacturing industry standard for measuring manufacturing productivity and benchmarking improvements (i.e., the percentage of manufacturing time that is truly productive.'
Base: Manufacturing industry respondents (n=133)



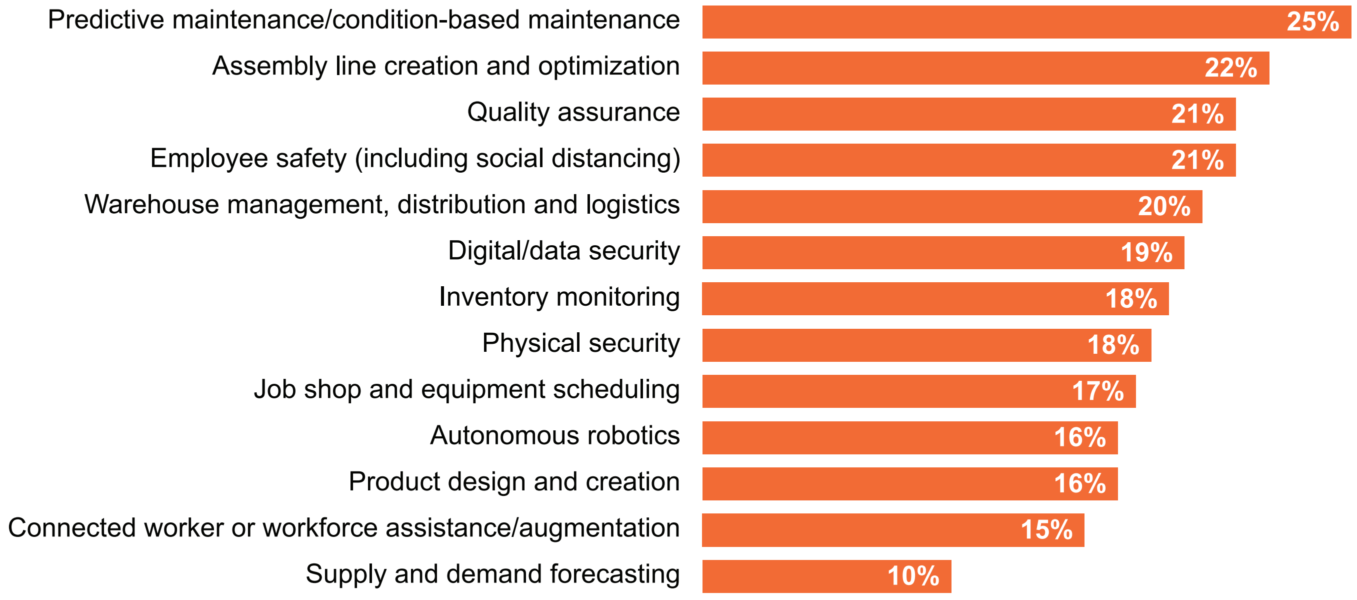
Similar to OEE, AI can also be applied to product output quality. Ensuring that the end product is consistently of the highest quality requires as much real-time data as possible. Traditional product inspections might look at a percentage of a batch and then flag a problem if one is found. With this process, it is already too late to fix the problem for the product currently in process. Using greater degrees of instrumentation and applying AI inspection in real time decreases potential wastage. Nearly a quarter (21%) of survey respondents cited quality assurance features as a key future use of AI/ML (Figure 2). This is an example of AI techniques being embedded in self-contained pre-trained devices, such as an inspection camera, that only send data about out-of-tolerance observations.

Figure 2: Manufacturing use case adoption in the next two years

Source: 451 Research's Voice of the Enterprise: AI & Machine Learning Use Cases 2021

Q: Looking ahead, which of the following machine learning use cases that your organization has not yet deployed do you plan to deploy in the next two years? Please select all that apply.

Base: Manufacturing industry respondents (n=154)



Legacy industrial instrumentation, before digitally connected systems, appeared on or near the machine itself out of physical necessity. It is, therefore, a cultural norm for OT engineers to expect any added computing capability to be at this physical edge. Safety and critical systems also sit on the device and on-site, so it is reasonable that engineers would find it more acceptable for new technology to be at this physical edge, under their control, than dealing with remote cloud systems – i.e., industry has always taken an edge-first approach.

451 Research's Voice of the Enterprise: AI & Machine Learning Use Cases 2021 found high adoption of AI/ML in manufacturing: a third of respondents are already implementing it, and 27% said they are at the proof-of-concept stage. This suggests a natural fit for the approach as the pace and volume of manufacturing increases with advances in automation. Monitoring and responding at speed is also done most effectively at the edge, reducing latency in data transmission. This in turn provides the resilience to be able to operate independently of external network connectivity. That is not to say that other layers of compute and storage in the continuum all the way to the cloud are irrelevant. Aggregation of wider data sources across multiple plants and business systems, such as the supply chain, and external influences, such as weather, has a place to inform the implementation and training of AI models, even if subsequently run at the edge.

One way to enable these AI models to run at the edge and yet be informed by multiple data sources (yet still not require the moving of large datasets around) is model fusion, a variation on what is known as federated learning. This enables models to be trained on local data at each site and then aggregated at a central site. This avoids the need to move the data from each remote site to the central one to do the training there. This fused model is then distributed to each site for the next round of training, which is a much lighter-weight exercise computationally than transferring the data back and forth.

Industrial use will continue to evolve from the basics of IIoT instrumentation combined with machine learning for predictive maintenance to greater infusion of AI into tools used on the shop floor. Industrial robots have, until now, been primarily 'computer numerically controller' devices, issued with a repetitive program to follow with little deviation. But already these legacy devices are seeing upgrades with attached edge computing and new sensors to make them more flexible in their operations. New branches of robotics are evolving around AI-powered autonomous systems using mobility and computer vision to perform more ad hoc tasks – a robot can be used as a sensor nest that can travel to a machine on the shop floor to gather more information or perform a basic operation on that machine, for example. Cameras with onboard processing power are using detection algorithms in situations such as determining COVID-19 safe distancing between people. Connected workforce tooling is also evolving due to embedded AI such as in the field of augmented reality (AR), which can be regarded as the user interface for IoT. Computer vision maps the user's view of the world to then create contextual digital data overlayed into that view, and natural language processing helps interpret hands-free instructions from an engineer. Other AI processes can evaluate documentation and previous work orders to provide contextually rich information to a worker.

Connectivity is key to gathering and understanding manufacturing data, and the emergence of 5G provides opportunities that industrial applications will benefit from. As a software-defined network approach, 5G allows different qualities of service to be maintained for different use cases. For example, safety control signals need high-priority low latency, but archived machine logs need bandwidth and less time criticality. The emerging Time-Sensitive Network standard in industrial use looks to address the sharing of traditional wired ethernet and is now also being combined with 5G approaches due to the similarity. Because of the complexity, managing these network slices in both protocols falls to machine learning and AI embedded in the network devices. The flexibility of the 5G approach also offers localized 5G, keeping signals and data to a single location, as well as wider connectivity to other venues, at a very granular level.

Use cases

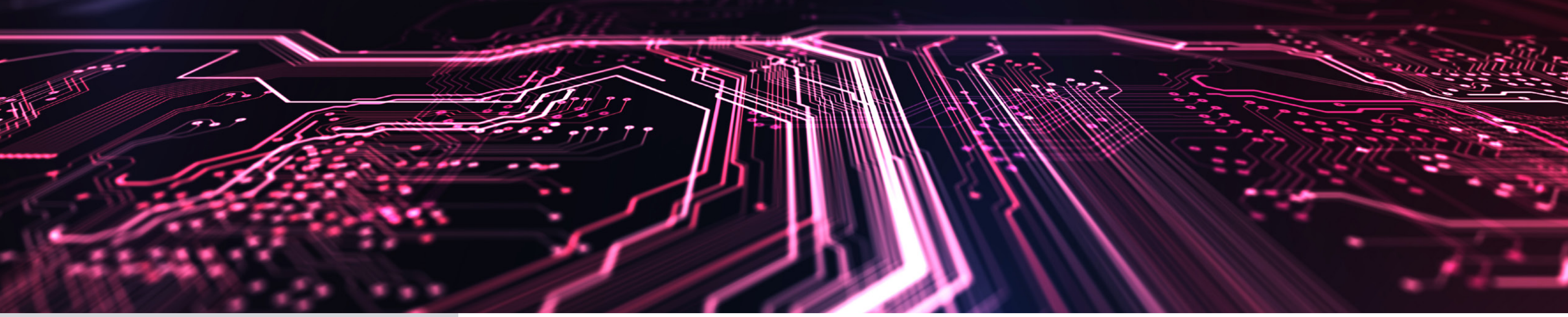
Quality inspection in traditional manufacturing often requires testing some products to destruction. A prime example is in welded products, where the weld is pulled apart to test its strength. Applying a higher degree of instrumentation, combining sensors such as acoustics, vision and temperature with AI techniques, can determine weld quality while it is happening. By flagging dry welds early on, corrections can be made with less product wastage.

In electronic component manufacture, machine vision at all stages of the line can be combined with other testing-generated parametric data. Embedded AI in these inspection systems not only can detect more obvious failures, but also slight degradation and quality shifts over time, which can be addressed before the end products start to fail quality control.

Augmented reality uses AI computer vision for the basics of creating a point cloud that can then be used to determine how to project digital artifacts in place. This same digital model can be used by other AI applications, such as providing object recognition to automatically find previous work orders or instructions for servicing a piece of machinery. AI is embedded in an AR toolset that is designed to help engineers complete their tasks more effectively.

Key Takeaways

- AI should be viewed as a people-centric tool to help subject matter experts perform their roles in an amplified way. This may be to enhance safety, speed up tasks or improve accuracy.
- The first wave of IIoT implementation involved connectivity to OT plant data, primarily needing only the OT side of the business. AI technology is an IT function that requires an IT/OT partnership: IT to deploy and run, with OT providing subject matter expertise for training.
- AI can make a significant difference to the core business processes of manufacturing across multiple use cases, and when targeted at those principal KPIs – such as OEE – the impact becomes clear.



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