AI Business
eBook Series

AI in the **electroindustry and medical imaging sectors**

Tactics and strategies for deploying AI by electrical equipment and medical imaging manufacturers

In association with:

OMDIA

In partnership with:

NEMA
National Electrical Manufacturers Association

Scope of this white paper

Based on interviews with National Electrical Manufacturers Association (NEMA) members, other Fortune 1000 manufacturers, and AI platform and software vendors, as well as extensive research within the AI and manufacturing community, this white paper provides a comprehensive overview of AI technology. Omdia presents market drivers, use cases, and strategies for deploying AI and provides case examples of manufacturers that have successfully completed proof-of-concept (POC) demonstrations or commercial deployments. Potential challenges to AI deployments, including technology hurdles, operational issues, human capital concerns, and regulatory impacts, are also discussed, along with specific recommendations for deploying AI within a manufacturing environment.

Manufacturers seeking to deploy AI should consider this Omdia paper as a starting point for internal and external discussions, focusing on identifying the key considerations, tactics for deployment, and potential pitfalls that could negatively affect a POC demonstration or enterprise-wide rollouts of AI technology. By considering all the benefits, challenges, and examples contained within this paper, leaders can devise both a short- and long-term strategy for AI deployment.

eBook in partnership with:

National Electrical Manufacturers Association

In association with:

Executive summary

Artificial intelligence (AI), which can be defined as a collection of technologies and approaches that allow a machine to perceive its environment and take actions toward a specific goal, has become a near ubiquitous presence in today's world. It is most prevalent in the consumer world, where it drives apps and services in smartphones, set-top boxes, and home security cameras. But AI is also helping and will continue to help B2B companies innovate, improve efficiencies, and better serve their customers and partners for years to come.

Within the manufacturing industry, AI is being used in a variety of environments. These range from the factory floor, where it improves the production and distribution of manufactured goods and enhances safety, to the back office, where it streamlines administrative tasks and bolsters customer service efforts. AI is also being incorporated into manufactured goods to allow others along the value chain, including distributor, retail, and service partners, to leverage the intelligence provided by the technology to provide better customer service. In addition, these partners can use AI to improve aspects of product design and lifecycle management.

The list of potential use cases for AI is both broad and deep, covering horizontal use cases, which can be applied in any manufacturing organization, as well as vertical market-specific use cases. Key commonalities between each of these use cases include the following:

- *Strong reliance on multitudes of clean data*
- *Need for a strong infrastructure to allow the collection, distribution, and analysis of the data*
- *Demand for a team of professionals, both internal and external, that can properly monitor, manage, and act upon the insights generated by the AI*

Manufacturers that have successfully incorporated AI technology generally have a strong grounding and knowledge in how analytics and AI can complement each other and which tasks or use cases are best suited to being handled separately. In addition, developing AI projects requires setting realistic goals and benchmarks for success for each use case, as well as establishing processes to confirm or override outputs that do not deliver expected or useful results. To establish useful goals and metrics, AI development teams must identify and understand the problem to be solved, how an AI algorithm can deliver results, and methods for verifying or modifying the algorithm quickly.

Perhaps most importantly, manufacturers that have successfully launched AI into their organization's processes and products have been and continue to be champions of AI. They have instilled a corporate culture that encourages trust in and use of AI from the C-suite on down. That does not portend blind faith in AI—or any technology, for that matter. Regular oversight over the use of AI is critical to ensure that algorithms are delivering the benefits they should while also remaining in compliance with applicable regulations.

Developing and incorporating AI is a challenging proposition for even the most technically astute and forward-thinking organization. That is why it is important to establish or leverage industry working groups to identify and vet new AI use cases, technology approaches, and integration strategies that can mitigate much of the initial risk involved with AI development. Education is key, and vendor partners can be an extremely valuable source of technical and domain-specific knowledge, particularly those that have worked with other manufacturers.

AI will continue to power the manufacturing industry for years to come. Partnering with research institutions with strong AI/data science programs can help construct a bridge between future AI and data science talent and the manufacturing industry. The industry often finds itself fighting an uphill battle against technology companies for individuals that, as part of a larger operations, analytics, and management team, can help ensure manufacturers remain on the cutting edge of AI implementation.

Background

AI can be used across a variety of use cases within the manufacturing process itself, as well as in use cases that focus on sales, customer service, and support functions, many of which tie back into overall manufacturing operations.

AI in manufacturing

AI is an umbrella term that covers several different technologies inspired by the human biological system. These technologies give computers human-like abilities of perception (hearing, seeing), reasoning, planning, and decision-making—even if they do not work in the same way. Most of the AI systems today are machine learning (ML)-based systems. Computers can learn data patterns in a supervised or unsupervised manner, and then apply these learnings to make predictions, classify data, recognize objects or images, and understand speech or text.

Deep learning (DL), which is a branch of ML that uses multilayered neural networks (NNs), has been especially good at understanding multidimensional data such as language (voice, speech, and text) and vision (images and video). DL has helped computers become good at perception tasks, allowing them to see, hear, and speak. In contrast, traditional ML, or statistical ML, is good at processing relatively low dimensional data (such as text) compared with images or speech and making predictions.

Within manufacturing, most of the activity can be categorized as prediction machines run by statistical ML techniques. In specific cases, some manufacturers will deploy perception machines run by DL, generally to identify new patterns or ways of looking at data via an unsupervised approach.

Further, techniques such as DL have been used in combination with reinforcement learning (RL) to improve the performance of AI systems, as they complement each other to provide increases in speed, accuracy, or both. Increasingly, AI systems are using a combination of these methods to solve of subset of intelligence tasks. They are ultimately building toward a grander vision of generalized intelligence, which was the goal of the original AI pioneers from the 1950s.

AI can be used across a variety of use cases within the manufacturing process itself, as well as in use cases that focus on sales, customer service, and support functions, many of which tie back into overall manufacturing operations. While individual manufacturers have different priorities for deploying AI, there are a few common elements required. These include copious amounts of clean, structured data; a robust data infrastructure; and a strategic plan for handling data integration and interactions with partners, distributors, and customers.

The manufacturing market exhibits some contradictions when it comes to automation and technology. On one hand, manufacturing has been among the first industries to integrate any type of technology, going back more than a century when factories incorporated tools to aid in the production process. In the latter half of the 20th century, automation at manufacturing plants became widespread, particularly in assembly line operations. Repetitive activity could be done more quickly, more accurately, and more efficiently using automated robots in addition to, or instead of, using human workers. An enduring image of technological progress is the image of an automobile factory floor, replete with a plethora of automated robots.

That said, manufacturing companies are also considered to be more risk averse when it comes to implementing new technology quickly. This is mainly due to the large amount of capital and time at stake should the new technology fail to perform as designed, given that even a few minutes of downtime on a production line can result in thousands of dollars lost. It is rare to see manufacturers incorporate new technology unless it has been tested extensively and has shown that it can operate reliably and generate real ROI above the currently used production technology or methods.

The use of AI technology that includes ML and DL, often in conjunction with other enabling technologies such as computer vision (CV), natural language processing (NLP), and machine reasoning (MR), is projected to be incorporated within manufacturing environments at a modest, yet steady, pace. Although well-capitalized and larger manufacturers are increasingly incorporating AI across a variety of use cases, the market is still in its infancy, with significant future potential.

AI market factors

There are specific enabling market factors that are driving the implementation of AI, from the development of Internet of Things (IoT) networks to improvements in ML algorithms themselves. In the following sections, both internal and external market issues affecting the utilization of AI and ML within the manufacturing sector are discussed.

The manufacturing industry is somewhat unique. A relatively small number of enabling technologies will enable a wider range of use cases, which can be categorized as encompassing the following:

- *Enhanced operational visibility*
- *Pattern analysis enhancement*
- *Command and control applications*
- *Sensor data fusion in machinery*

Within each category, specific use case adoption is likely going to take time. Each manufacturer has its own set of processes, current level of technological adoption, risk tolerance, available capital, and expertise to devote to developing specific algorithms to support new use cases.

AI is a dynamic, ever changing technology, with new use cases, vendors, and strategies emerging constantly. Manufacturers need to become educated about the benefits, risks, and implementation strategies of AI to best determine how it can be incorporated into their processes, products, and service offerings.

Defining AI and the components required for a successful deployment

Since the dawn of AI in the 1950s, the capabilities of the technology have been prone to hyperbole and outsized expectations. A key reason for this delta between the expectations and reality of AI lies in the way early system designers tried to approach AI. They tried to develop technology that attempts to solve problems by mimicking the way humans approached and solved problems.

But features of so-called "intelligence" must be mathematically modeled and simulated in a machine. Even at their most complex, these features are not yet capable of matching a human brain's breadth and depth of knowledge and reasoning. However, within limited fields of interest, ML, DL, and other technologies can be configured in such a way to provide greater speed, accuracy, and efficiency compared with humans on specific tasks.

This is particularly true within the manufacturing field. As companies seek to improve quality, operational efficiency, and profitability, AI is increasingly being used as a catalyst to help harness and leverage the vast amount of data being generated by production assets. It is also being used to leverage a host of external, nontraditional data that can further refine and improve analyses and predictions.

AI can encompass one or more technology approaches, depending upon the use case, data available, and end goal of the user. The following technology approaches are the most commonly used to deliver machine-based AI.

Machine learning

ML is a type of AI that involves using computerized mathematical algorithms that can learn from data and can depart from strictly following rule-based, preprogrammed logic. ML algorithms build a probabilistic model and use it to make assumptions and predictions about similar sets of data.

Deep learning

DL is a form of ML that uses the model of human neural nets to make predictions about new datasets. Within the manufacturing field, the use of DL is most often found in situations when a company is seeking to find a novel solution to a problem and is not constrained by specific parameters or processes. By allowing an algorithm to search for a solution that may deviate from established procedures, there is a significant opportunity to uncover more efficient ways of accomplishing a task or completing a process. However, the use of DL may not be appropriate in all situations, given that many manufacturing processes have stringent safety requirements or other constraining factors that must be considered.

In the following example of an AI system that is designed to recognize an image as a car, an ML approach will handle feature extraction via a supervised approach. That is, the system will be provided with specific details or attributes that can be learned to represent a car, and then the algorithm will then classify the elements of the image and decide whether the elements taken together are that of a car. In a DL approach, feature extraction and classification tasks are handled by the algorithm itself, with the system determining which elements of an image likely fit together to return a decision on whether the image is a car.

Natural language processing

NLP enables computers to understand human language as it is spoken and written and to produce human-like speech and writing. Natural language generation, where human speech and text is generated from raw data, is also considered part of NLP. NLP has a number of subcategories of steps that are undertaken, including topic modeling, text categorization, text clustering, information extraction, named entity recognition, relationship extraction, and sentiment analysis. All of these can be used to understand the meaning and context of spoken or written words.

One of the ways NLP can be used within a manufacturing environment is to augment an information retrieval system. Using NLP, systems can extract relevant information from different text sources such as scientific papers, documents, and feeds. It can also extract information from various production or supply chain systems containing order information, delivery schedules, or production documentation.

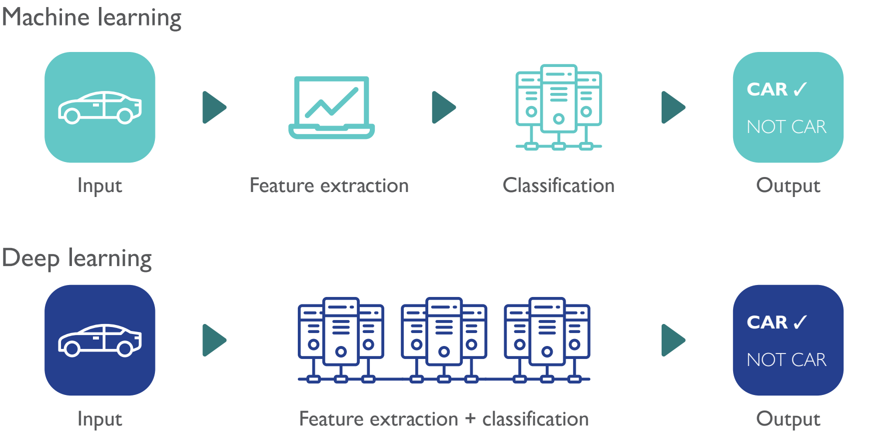
Computer vision

CV techniques include image acquisition, noise reduction, motion detection, feature extraction, and more, with the end goal in manufacturing to allow machines to identify and react to visual feedback from cameras. By using ML, systems can be trained to recognize specific parameters, including features, appearance, size, color, shape, and other markers, allowing a number of specific tasks to be handled automatically.

Some of the key tasks that use CV and can be augmented by ML include the following:

- ***Predictive maintenance:*** *Software that is powered by machine vision and ML can be deployed within the factory environment to monitor manufacturing robots. For example, robot maker FANUC has developed its ZDT (Zero Down Time) application, which collects images from cameras attached to robots. The images of the robots working are augmented with metadata, which is then pushed to the cloud for processing. When a failure occurs, there is usually some sort of data anomaly or signal, which can then be used to identify future problems prior to them occurring. During an 18-month trial, ZDT was deployed to 7,000 robots in nearly 40 production lines around the world, and it detected and prevented more than 70 failures.*

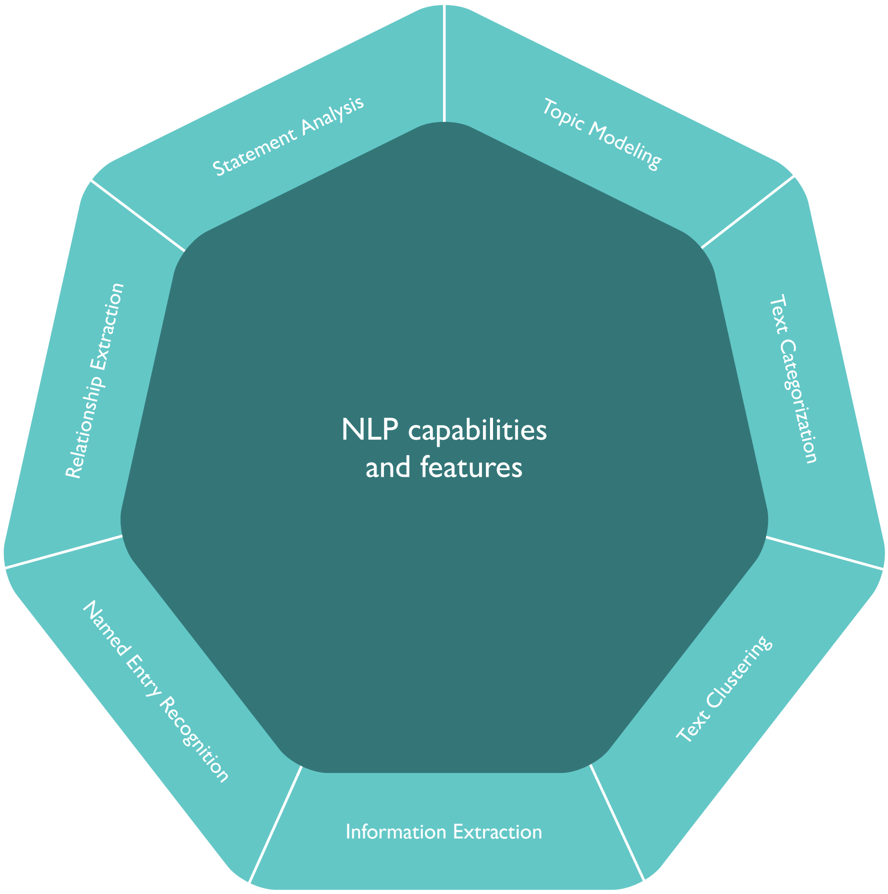
Figure 1: Machine learning vs. deep learning



Source: Omdia

- ***Goods inspection:*** *Machine vision and ML can be used to inspect goods to ensure they meet manufacturing standards and are not broken or otherwise compromised. Cameras can feed inspection data through an algorithm that will compare the attributes of the product being inspected to known examples of items that are within spec. By using ML, the system can train itself to become more accurate over time.*
- ***Health and safety improvements:*** *Machine vision and AI can also be used to help improve the health and safety of humans by tracking human and equipment movement within a work environment. Using a combination of real-time cameras and video analytics, a company can track human movement and, powered by DL, predict the movement of equipment to help avoid dangerous situations.*

Figure 2: NLP functions and capabilities



Source: Omdia

Machine reasoning

MR is a technologically driven way to simulate human thought processes by using a computerized model of language to acquire knowledge, and then make decisions like expert systems or knowledge-based inference engines. Rather than being programmable in the traditional sense, expert systems are designed to build the model's own understanding of the world based on the relationships between words and concepts and come up with inferences.

Within manufacturing, the goal is to develop systems that can understand how to accomplish a task or set of tasks without explicitly programming each step. The aim is to create a knowledge-based inference engine that understands the end goal of the task at hand, along with any constraints that may be required, and then identifies ways to solve a problem using that combined knowledge, skill sets, and constraints. However, deriving ROI from this type of approach within a production environment is likely several years away, given the need for an extremely high degree of accuracy and repeatability.

Strong AI

When AI is able to solve problems in wider domains (language, vision), rather than narrow domains (games, image recognition, English speech), and it is flexible and adaptive in learning with no human supervision or handcrafting of features, "strong AI" has been achieved. These strong AI systems learn to learn and are self-adaptive.

Within a manufacturing context, strong AI systems likely will not be deployed within the decade. Because manufacturers tend to seek out investments where there is a meaningful financial return in a relatively short timeframe (months, instead of years), finding use cases that utilize strong AI and can meet these requirements are unlikely to be high on the priority list.

AI in manufacturing: Market factors

The use of AI within the manufacturing sector is being driven by specific enabling market factors that include the digitization of data, the development of IoT networks, and the steady improvements in ML and DL algorithms. AI technology introduces scale and efficiency and is best applied to two types of problems:

- ***Data analysis and subsequent predictive recommendations and actions:*** *ML and DL technologies excel at analyzing massive datasets very quickly. They can complete data analysis computations much more quickly than manual human analysis or hardcoded computer analysis.*
- ***Routine, redundant tasks:*** *AI technologies are successfully handling redundant, linear thought-focused tasks (clerical work, order taking, food service), freeing up human resources to focus on higher value, human-exclusive skills (creative thinking, problem solving, interpersonal skills, emotional intelligence, reasoning, negotiation, and decision-making).*

Many AI systems also draw from other adjacent technologies, such as computer and machine vision, natural language processing and understanding, and various information classification and clustering techniques. The goal in manufacturing is to harness the power of existing systems and combine the data output with ML or DL to generate insights. These insights can then be interpreted and shaped via automated algorithms, instead of requiring humans to do the analysis of the myriad data points.

Key elements for AI deployment

To properly harness the benefits of AI, manufacturing organizations require the elements discussed in the following sections.

A focused AI strategy

Despite the hype, AI is not dissimilar from other technology initiatives. The best chance of deploying and generating ROI is by developing a comprehensive strategy covering short-, medium-, and long-term goals, key performance indicators (KPIs), and milestones.

AI likely will replace many job functions that are often deemed repetitive, lower value, or in some cases, simply more efficiently handled by a machine than a human. There is often significant opposition to incorporating new technology within an organization from those who might be replaced by that technology or those who may be forced to learn new skills or take different types of positions within the organization.

AI is also likely to shift the way manufacturers and others in the value chain interact. For example, utilizing a cloud-based consumable monitoring system, combined with an ML algorithm to predict when a customer might need to purchase refills, likely will introduce additional complexity into the value chain.

Data

A significant barrier to adoption is that most AI systems require statistically valid, clean, and accurate data. As with any information system, bad data will result in bad assumptions and predictions. But with AI technologies, such as ML and DL, clean data will be even more critical.

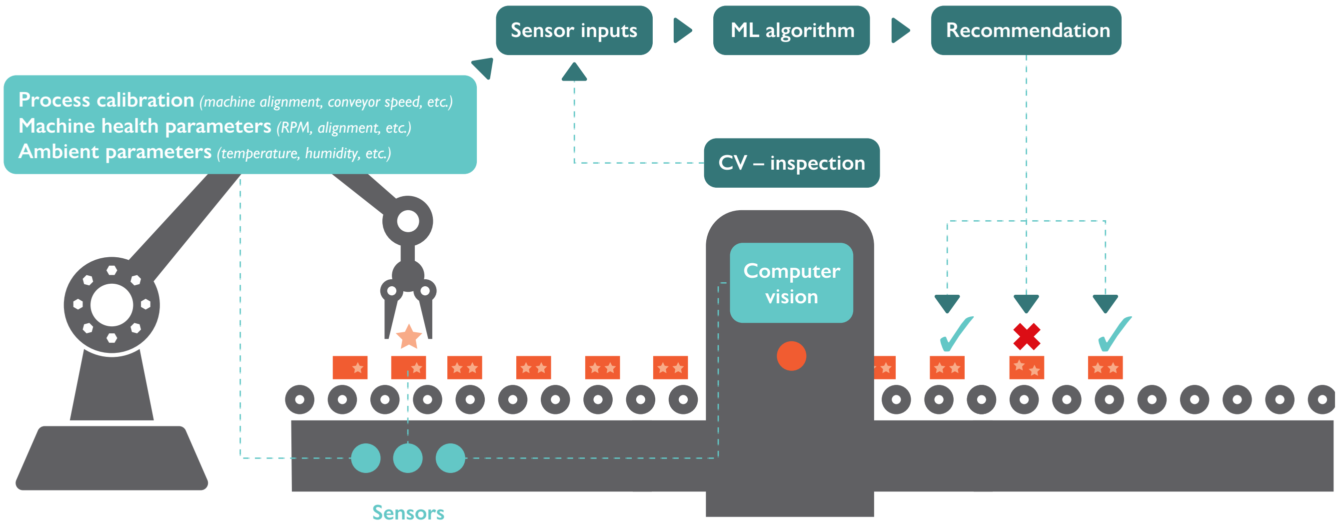
Many vendors are now offering data cleaning and formatting services, either on a standalone basis or as part of their AI offering. These services may use ML to help classify and clean unstructured data, such as images or unlabeled data, which can then be properly processed by the ML or DL algorithm.

Infrastructure

One of the key catalysts that allowed manufacturers to improve both quality and yield was the introduction of robots to handle a variety of specific assembly tasks on the manufacturing line. These robots, which could have their movements programmed to fall within exacting tolerances, provided manufacturers with a cost-effective, accurate, and repeatable way to increase the speed of production of a wide range of products.

By the dawn of the 21st century, manufacturers realized that by attaching sensors to these machines, it would be far easier to pinpoint where anomalies or failures in a specific line or process were occurring. Sensors that measure ambient environmental factors, such as temperature, humidity, dust content, and other factors, further help manufacturers identify issues. Within this connected environment, a number of benefits can be derived, including transmitting operational data, enabling condition-based maintenance, providing real-time visibility and control over the production process and material supply, enhancing inventory management, and improving worker safety and security.

Figure 3: Example of factory infrastructure



Source: Omdia

Processing power
The most notable advancement in computation at scale is significant improvements in hardware speed, thanks to the advanced use of parallel processing and graphics processing units (GPUs). Parallel processing (dividing the work among multiple processors) and the increasing use of GPUs (designed to support simultaneous processing) allow more complex and powerful algorithms to be developed and run, thereby increasing the breadth and depth of potential AI use cases.

ML/DL algorithms
Increases in algorithm power and efficiency are also driving the adoption of AI within manufacturers. In a DL paradigm, new learning occurs in the succession of approximations, each set of which is built based on the previous layer, enabling a far greater degree of abstraction, nuance, and accuracy. Furthermore, NNs are designed to run probabilistic calculations to approximate the answer with a percentage degree of certainty.

Today's NNs are able to leverage training methods that pretrain individual layers of the network to recognize features at different layers, which makes it easier and more efficient to train networks with several layers. The minimization of the number of machine instructions used to iterate a layered solution is directly related to the growth of DL in the last few years. Hardware speed and data volumes are now available to support NNs at far greater scale and speed.

Human capital issues

ML's blend of data science and software engineering demands a very specific skill set that few people, particularly existing employees within manufacturing companies, possess. Furthermore, finding talent that understands ML, as well as the distinct operational challenges associated with manufacturing a particular product or line of products, can be an expensive and difficult problem for the market.

As such, manufacturing organizations must consider the talent pool for AI beyond traditional computer science degrees, given the intense competition for those with strict computer science backgrounds. Few manufacturers will be able to position themselves as direct competitors to the Googles of the world, either in terms of the ability to provide competitive compensation packages or the cachet of being a Silicon Valley stalwart. A strategy being utilized by many manufacturers is to seek out employees with a strong manufacturing background or affinity, but who also possess a natural curiosity about ML.

Roles and responsibilities
Within a manufacturing company, there are several stakeholders that must be brought into alignment to ensure a structured and strategic incorporation of ML. Each has their own particular goals, needs, and concerns that must be addressed within their own group, as well as within the larger organization.

Ultimately, the key challenge, which often falls to outside consultants and vendors, is to align the needs and goals of each of these stakeholders. One way to do so is to ensure that any algorithms being developed can be fully explainable, so that all parties understand which data is being used for analysis and how the various data points are being weighted. They must also understand how the algorithm can be recreated or modified, particularly if the manufacturer switches vendors or loses a key person involved with the algorithm's development.

AI success criteria and KPIs

The list of factors affecting a successful AI deployment is both long and varied. Some KPIs used in AI deployments are simply direct analogs to the KPIs used to measure production. Therefore, they are easy to quantify and calculate; the goal is to leverage the power, speed, efficiency, and accuracy of AI to further improve on those benchmarks. Examples of manufacturing-specific KPIs that can be improved upon by AI include the following:

- ***Availability:*** *Availability is a measure of machine uptime and downtime. The goal for all manufacturers is to maximize uptime and minimize downtime, whether planned or unplanned, in order to maximize productivity and efficiency. AI can be used to analyze the factors that are influencing uptime and downtime and allow the manufacturer to make adjustments to the machine, operator, or other elements of the production and maintenance schedule.*

- ***Capacity utilization:*** *This KPI refers to the ability of a machine to produce goods at an ideal cycle time, which refers to the time it takes to complete a product, from order to delivery. If a machine is producing goods at an ideal cycle time, it can be referred to as running at 100% capacity. AI can be used to identify available capacity and slack in the system, based on other production factors, and then implement more agile job scheduling that mates machine availability to exact production timelines.*

- ***Changeover time:*** *Changeover time refers to the amount of time required to unload/load, retool, calibrate, and program a new job. By using ML to track changeover time, manufacturers can identify total cycle times by part, fine-tune their estimates, and optimize planning schedules or introduce better operator training to reduce the time it takes to change over machines or entire production lines.*

- ***Customer return rate:*** *Increasing customer returns might indicate a flaw in the production process or quality control issues. Using ML to assess customer return data can be useful in identifying the most common defects, thereby helping the company identify the weak points in the sourcing, production, or shipping process that is affecting product quality.*

- ***On-time deliveries:*** *A measure that assesses the percentage of orders delivered on time. Delivery times can be improved through ML, which can assess each portion of the supply chain to determine where bottlenecks or delays are occurring.*

- ***Planned maintenance percentage:*** *This KPI is used to assess the level of planned maintenance compared with unscheduled maintenance. Planned maintenance is far less expensive compared with emergency maintenance (with some estimates of 3x to 9x the cost). AI can be used to assess machine operating performance to better predict when a particular machine will fail so that maintenance can be scheduled at an optimal time.*

- ***Profit per hour:*** *Profit per hour is based on an analysis of everything that happens within an end-to-end production process to work out exactly how much profit is created. It is used to review thousands of parameters to establish how best to optimize each part of the manufacturing process. Using data captured from sensors, along with advanced analytics tools, industrial companies can deploy self-learning models that simulate the expected value and cost of individual processes and even entire factories on a continuous basis. This type of micro-analysis is being conducted by both discrete and process manufacturers, allowing them to create business and production efficiencies through better understanding of the data that they are creating.*

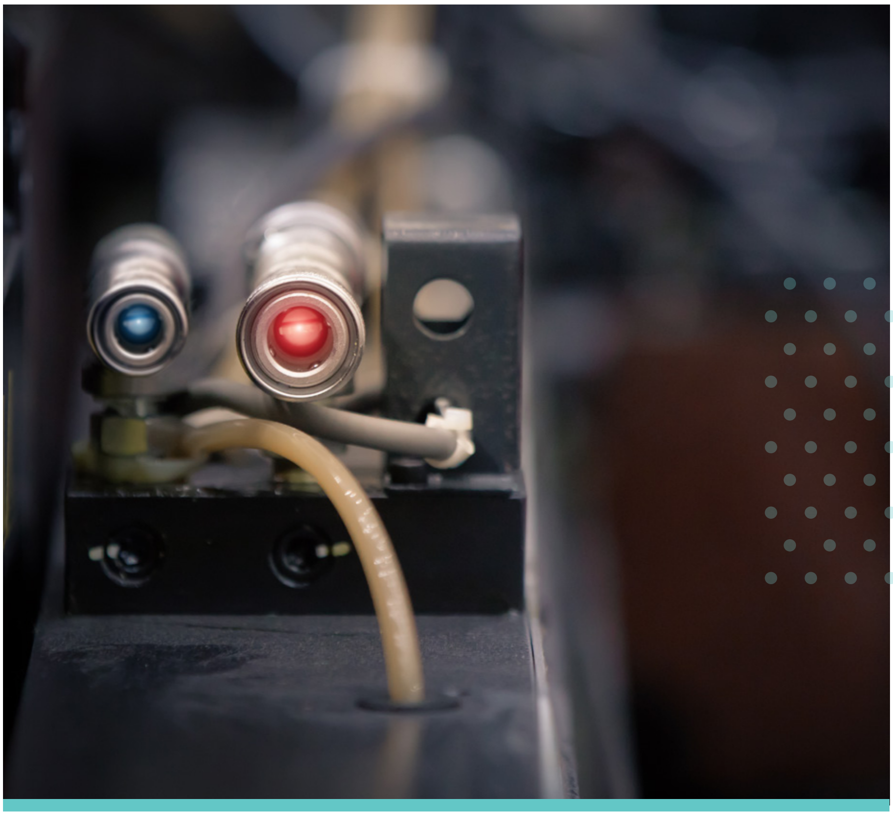
- ***Scrap/waste:*** *Scrap or waste is the discarded, excess, or rejected material from the manufacturing process. While some organizations track defective items as scrap or waste, others may focus on the leftover raw material from a subtractive manufacturing process. AI can be used to closely analyze the production process to determine whether greater efficiency can be gained by instituting tighter manufacturing processes, which result in reduced scrap.*

- ***Yield:*** *Yield is a measure of quality and performance and is at the heart of production efficiency and profitability. By assessing the sourcing and production process via ML, anomalies can be identified that could indicate problems with machines or processes that may affect production levels.*

The power of data, IoT networks, and AI-driven analytics

Manufacturers have realized that the IoT, which involves attaching sensors to equipment, can be useful within a factory environment. These sensors, along with sensors that measure ambient environmental factors, such as temperature, humidity, dust content, and other factors, can be used to pinpoint where anomalies or failures in a specific line or process occur. Within this connected environment, there are a number of benefits that can be derived:

- *IoT-enabled machinery can transmit operational data to OEMs and field engineers, thereby enabling remote management and allow process automation and optimization.*
- *IoT sensors in manufacturing equipment enable condition-based maintenance alerts, thanks to sensors that are mounted directly on the machines themselves.*
- *IoT in manufacturing can enable the monitoring of production lines from the introduction of raw materials to the finished product, permitting real-time visibility and control over the process.*
- *Inventory management can be managed more efficiently using IoT applications, tracking and tracing inventory on a line item. This provides cross-channel visibility into inventories, and managers are provided with realistic estimates of the available material, work in progress, and the arrival time of new materials.*
- *IoT data that is analyzed can enhance worker safety and security by monitoring the KPIs of health and safety, like the number of injuries and illness rates, near misses, short- and long-term absences, vehicle incidents, and property damage or loss during daily operations.*



Data governance, data quality, and cybersecurity issues

Using process, ambient, and product usage data, algorithms can identify specific patterns or anomalies in the data that can be used to improve efficiency, reduce waste or cost, or improve quality. The key to the successful use of ML is ensuring that the source data being used is both plentiful and of sufficient quality.

There are several benefits to establishing good data governance (where the data has been properly cleaned, segmented, and labeled), particularly when planning a comprehensive AI strategy.

Good data governance

- *Can track and safeguard usage of the right data, but also recognizes data errors and promptly raises red flags and helps eliminate those errors.*
- *Can permit an organization to spend less time unearthing the accurate data source or sources needed to feed the ML algorithms, instead focusing on creating, testing, and refining AI models.*
- *Certifies data is reliable and consistent, as the reliability, consistency, and accuracy of AI models are directly tied to the data that feed into them. This is imperative since operational efficiency, safety, and compliance issues are increasingly relying on AI and predictive analytics, which are driven by data.*
- *Can reduce the amount of time it takes to cleanse, prepare, and backfill holes in data.*
- *Allows organizations to treat data as a strategic asset, which allows for better and more specific goal planning and measurement.*
- *Permits the use of higher quality and more precise ML algorithms.*
- *Enables faster and more efficient online inference.*

AI environments and architecture

Within the context of AI, an environment can be thought of as the combination of infrastructure, software, storage, and services that are required to capture, analyze, and process data, resulting in data-driven decision-making, predictions, and automation. Manufacturers must evaluate the type of data they intend to use to support AI initiatives. They must also assess where the data is to be stored, processed, and utilized and what level of expertise, resources, and experience they have with data science, data integration, and security prior to building out their environment.

There is no single template; instead, manufacturers should assess their needs, and if necessary, consult with integrators or consultants to ensure their desired approach is feasible.

The environments depicted in Figure 4 and discussed below are among the most commonly used by manufacturers and other large enterprises.

On-premises environments

Not all enterprises are comfortable with training models in the cloud, largely because it involves significant expense in terms of sending data offsite to be trained and paying for cloud-based data storage. Others are simply not comfortable having proprietary data handled by third parties.

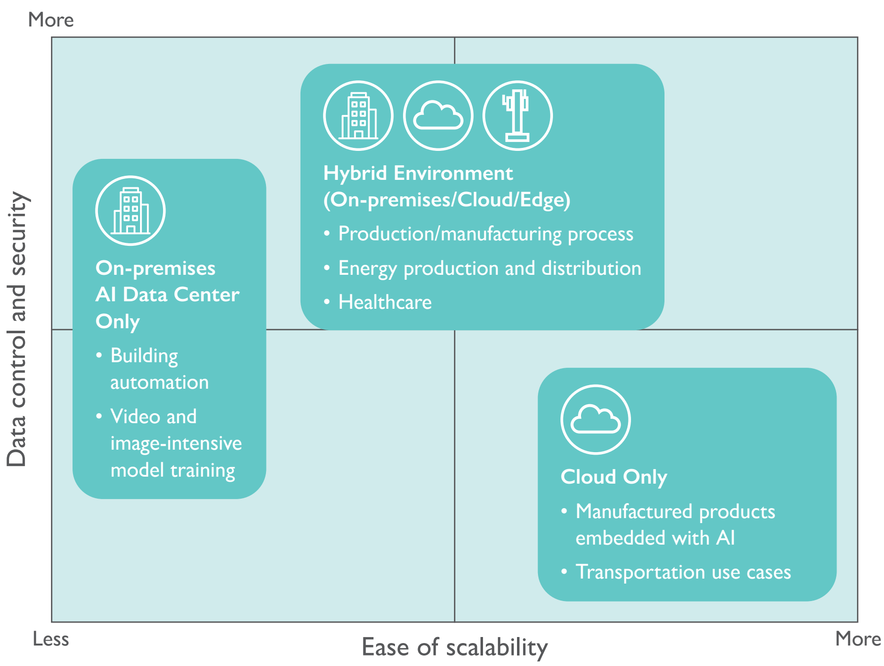
This on-premises approach provides several benefits for manufacturers with the capital and expertise required to acquire, manage, and monitor the hardware and software required to train and run AI models. By owning the hardware and software, they retain complete control over the data, which can be a concern for manufacturers that are worried about trade secrets or intellectual property leaking out. For some companies that rely solely on machine and internal company data, it is often less expensive to keep the data behind the firewall, rather than pay to have it uploaded and/or downloaded from cloud-based servers.

Cloud environments

AI technology would not be affordable for many enterprises if not for cloud providers such as Google, Amazon Web Services (AWS), and Microsoft. These public cloud providers are exposing APIs and services that can be accessed without the need to create custom ML models, helping to drive adoption of cloud-based AI services. To enable customers to enjoy the benefits of cognitive computing based on custom datasets, cloud vendors are moving toward custom cognitive computing. In this model, customers bring their own data to train cognitive services to deliver niche, specialized services. This cloud approach allows manufacturers that may not have the technical expertise or the capital required to set up their own ML infrastructure to take advantage of the benefits of ML. It also removes the burden of choosing the right algorithms and training custom models.

Generally speaking, large platform and tool companies allow enterprises to pay for model training by the hour while developing and refining the model. Enterprises then pay for deployment based on a rate for a number of compute cycles, jobs, or other predefined metrics. Pricing schedules are split into separate training and inference pricing. Training hours are multiplied by units of capacity, reflecting the various levels of compute power. As such, pricing can vary based on the complexity of the model and how much the model is being used for inference (e.g., an NLP model deployed as part of a virtual digital assistant is likely to see far greater utilization than one deployed a small, single-function production machine).

Figure 4: AI environments



Source: Omdia

Because manufacturing processes and manufactured goods can generate a significant amount of real-time data, there is a desire to reduce the amount of information that must be sent back to a centralized processor, thereby driving the use of edge-based AI.

Hybrid environments

Hybrid environment solutions can be deployed by a single vendor or a combination of vendors. These solutions generally include hardware and software infrastructure deployed behind the firewall, as well as additional processing power deployed in the cloud or at the edge. This arrangement provides significant flexibility to the enterprise. The training and inference tasks can be conducted behind the firewall (providing more data security and potentially reduced data handling costs) or in the cloud or at the edge—particularly if data is being generated at disparate points around the world.

Hybrid environments allow manufacturers to manage their AI data according to the organization's operational, security, and financial needs, which may be multifaceted and may change over time. Additionally, by deploying some infrastructure and data behind the firewall, data privacy and security controls can be deployed robustly without needing to provide access to other parties. The use of cloud or edge services in tandem with on-premises infrastructure can also allow the enterprise to scale its AI efforts when needed without incurring additional hardware costs.

Edge computing implications

The manufacturing industry is one of the earlier adopters of edge computing, with many potential use cases for deploying AI outside of the data center. Because manufacturing processes and manufactured goods can generate a significant amount of real-time data, there is a desire to reduce the amount of information that must be sent back to a centralized processor, thereby driving the use of edge-based AI.

At present, a number of tasks can utilize AI at the edge for inference-based tasks. For example, manufacturers can implement condition-based monitoring using AI at the edge to link disparate machines, processes, and systems, many of which do not utilize common data standards. By incorporating edge-based processors to filter and process data from these proprietary systems, manufacturers can monitor the condition of their assets remotely and generate additional revenue streams. Instead of selling machines on a one-off basis to end customers, they can provide ongoing maintenance services based on the current, actual condition of the asset or charge customers a managed service fee for ensuring uptime.

Similarly, predictive maintenance can be enhanced via AI edge data processing. Predictive maintenance uses AI to detect changes in data that allow operators to preemptively detect when a machine will fail through data analytics and then conduct maintenance in advance of potential breakdown. Edge computing can allow the processing of data closer to the end device, removing the cost of transporting data to a remote cloud as well as ensuring data is accessed reliably.

Infrastructure selection criteria

Regardless of the environment utilized, the infrastructure selected should be reviewed to ensure it meets certain operational parameters, including the following:

- ***Support of current frameworks:*** *Infrastructure must be able to support AI applications based on AI frameworks like TensorFlow, Caffe, Theano, and Torch in the same way as web applications and backend processes. Thus, an infrastructure should not exclusively focus on AI frameworks but design the portfolio in the interests of a developer.*

- ***GPU-optimized environment:*** *An infrastructure has to make sure that every AI process can be processed. The most notable advancement in computation at scale is significant improvements in hardware speed, thanks to advanced use of parallel processing and GPUs. CPUs process instructions one at a time (though some multicore processor chips are used in complex environments). However, the advent of parallel processing (dividing the work among multiple processors) and the increasing use of GPUs (designed to support simultaneous processing) allow more complex and powerful algorithms to be developed and run. Thus, an infrastructure must support GPU environments in order to provide fast computational power. Microsoft was the front-runner in this area by offering its N-series GPU instances.*

- ***Support for parallel processing:*** *Parallel processing is a more robust form of processing in which instructions are divided among multiple processors to accelerate the time it takes to run a program because there are more processing units working on the same code. As a result, this parallel design permits significantly faster processing of applications that need to process large blocks of data simultaneously, which is usually the case with ML algorithms. Researchers have found that 12 GPUs in a 3-machine cluster can rival the performance of the 1,000-node CPU cluster.*

- ***Management environment and tools:*** *One of the biggest challenges of current infrastructure environments is the drawback of management tools for running AI frameworks. Here, in particular, direct interaction between AI frameworks and the infrastructure is necessary to ensure the best balance and thus deliver the best performance.*

- ***AI-integrated infrastructure services:*** *The infrastructure provider must not and will not only support AI functionalities; rather, it will integrate AI as a central part of its infrastructure and service stacks. This type of AI-defined infrastructure will increase the intelligence of cloud services and applications while also simplifying setup and operations by the customer.*

Current and future AI trends

Within the manufacturing sector, several pronounced trends are likely to shape the development of the market for AI-based tools over the next several years:

- *There has been a shift toward cloud-based analytics and ML (both in the public and private cloud), as well as to the use of hybrid environments, particularly when data security, privacy, and confidentiality are an issue.*
- *Vendors are overcoming resistance to their solutions from internal teams by demonstrating the effectiveness of their solution and showing how it can free up data science personnel to do more interesting work. For operations professionals, demonstrating strong ROI immediately without changing the daily operations workflow is key to gaining acceptance.*
- *Vendors are pushing self-service to allow all types of users (power users, analysts, operations professionals, etc.) to take advantage of ML. They are essentially positioning their service as a way to enhance and get more out of the data that is already being captured by existing IoT networks.*
- *Much of the activity in the manufacturing market is concentrated at the top tier of each manufacturing vertical. These market leaders are looking to what other vertical markets are doing with ML and are seeking ways to similarly leverage the manufacturing/operations data they are already collecting.*
- *Other market trends are likely to affect the use and growth of AI within the manufacturing environment. The AI market continues to mature, and companies within and outside of the manufacturing sector are increasingly viewing AI and intelligent tools as must haves to ensure their businesses remain efficient and profitable:*
  - *Manufacturers of all types are investigating or actively using manufacturing execution system (MES) solutions that are infused with ML algorithms.*
  - *Vendors are highlighting solutions that capture, clean, and prepare data for analysis. These solutions enable data science professionals to work on more interesting data analysis problems.*
  - *Vendors are focusing on making the tools as self-service as possible, thereby allowing non-data scientists to interact more closely with the algorithms without needing to be experts in data science or programming.*

Manufacturers that have successfully deployed AI generally have one or more of the following elements:

Process maturity: AI leaders will have processes in place for confirming or overriding questionable results, as well as strategic and tactical plans in place to significantly improve business processes using AI.

Connecting analytics to AI: Many use cases do not require AI in order to derive benefits, but a core understanding of how to connect analytics to ML algorithms is a key enabler of success.

Trust in AI: Operations and development teams and, perhaps most importantly, upper management must trust that AI will deliver tangible benefits.

Healthy levels of AI oversight: Organizations with consistent and rigorous oversight processes in place tend to have better success with AI because they are reviewing outputs and making adjustments to the algorithm frequently.

Increase in the use of private clouds: AI technology would be unaffordable for many enterprises if not for cloud providers such as Google, AWS, and Microsoft. These public cloud providers are exposing APIs and services that can be accessed without the need to create custom ML models, helping to drive the adoption of cloud-based AI services. To enable customers to enjoy the benefits of cognitive computing based on custom datasets, cloud vendors are moving toward custom cognitive computing.

Increase in the use of automated ML: Developing ML models requires a time-consuming and expert-driven workflow, which includes data preparation, feature selection, model or technique selection, training, and tuning. The complicated nature of developing ML models has led to the development of more automated tools to speed up the creation of algorithms.

Vendors such as Google (AutoML) and Microsoft (Neural Network Intelligence) aim to automate this workflow using a number of different statistical and DL techniques. These tools are part of what is seen as a democratization of AI tools, enabling business users to develop ML models without a deep programming background. AutoML aims to automate the following tasks in the field of ML: model selection, parameter tuning, meta learning, and ensemble construction. It uses a range of algorithms and approaches:

- Bayesian optimization, which involves modeling the uncertainty of parameter performance so that different variations of the model can be explored and then provides an optimal solution.

- Meta learning and ensemble construction, through which meta learning techniques are used to increase accuracy by finding and picking optimal hyperparameter settings.

- Genetic programming makes use of a tree-based pipeline optimization to automatically design and optimize ML.

- Neural network intelligence is a toolkit that permits data scientists and ML developers to perform tasks such as neural architecture search and hyperparameter tuning, as well as customize AutoML models across various training environments. The tool is marketed as a competitor to Auto-Keras, another open source AutoML library for DL. Auto-Keras has quickly generated traction with more than 3,000 stars on GitHub, suggesting significant growth in the popularity of automated ML.

Recent hardware investments from Amazon, Google, Microsoft, and Facebook have made ML infrastructure cheaper and efficient. Some cloud providers are now offering custom hardware that is highly optimized for running ML workloads in the cloud.

Increasing demand for explainable AI: One of the big barriers to the adoption of AI, particularly in regulated industries, is the difficulty in showing exactly how AI reached a decision. Explainable AI is a movement to develop ML techniques that produce transparent models with audit trails while maintaining prediction accuracy. While regulatory concerns are fewer within the manufacturing industry, operational teams and decision makers still want to understand how algorithms are arriving at their conclusions. If the initial data science teams leave, there should be a way to deconstruct how the algorithms work and ascertain how the data that feeds them is assessed and analyze.

That is why manufacturers are requiring that AI vendors provide explainable AI. As models become more complex, the task of producing an interpretable version of the model becomes more difficult. Any lack of transparency is a problem for the data scientist or operations worker who wants to understand the way the model works to help them improve their service or product. AI that is explainable, provable, and transparent will be critical to establishing trust in the technology and will encourage the wider adoption of ML techniques.

Horizontal AI use cases/applications

The manufacturing sector is increasing its use of AI (primarily ML) technology to manage the massive amount of data being collected during both discrete and process manufacturing operations. By utilizing ML, organizations are able to identify patterns in operational data that can allow better efficiency and bolster production yields, predict when equipment may be on the verge of failure, and even improve the quality of their product.

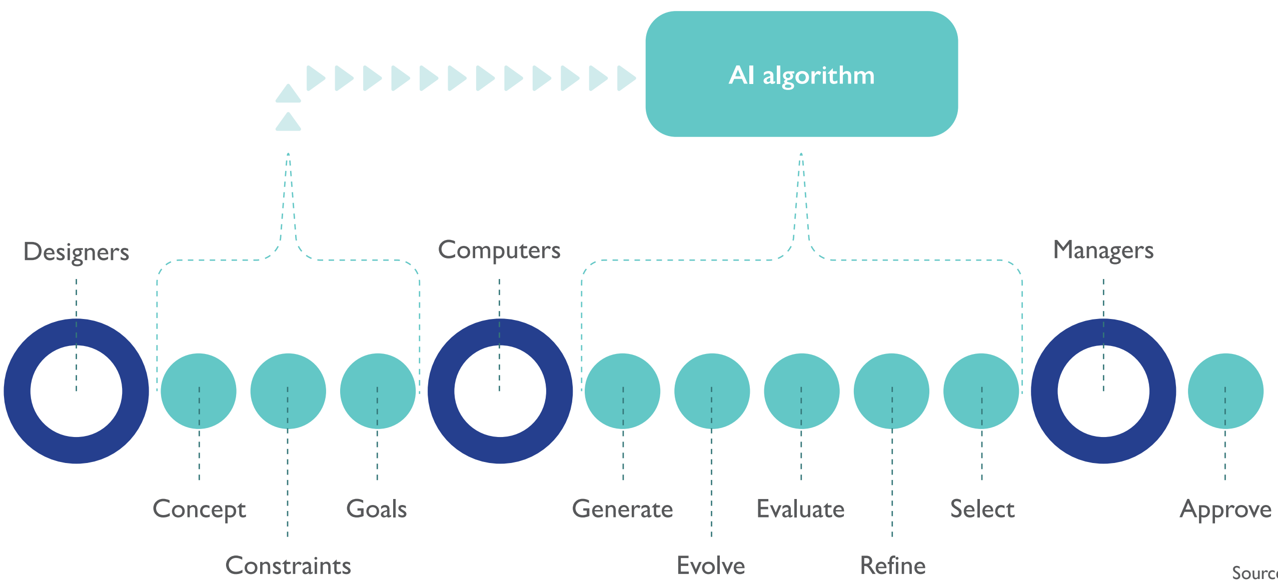
The manufacturing industry is somewhat unique, in that a relatively small number of enabling technologies will enable a wider range of use cases. As such, use cases can be segmented into several categories that encompass a common underlying ML or DL technique. While some use cases incorporate multiple ML or DL techniques, use cases can be classified by the dominant technique utilized:

- ***Enhanced operational visibility:*** *Incorporates IoT, ambient or external environmental data, and ML to provide a more granular view of manufacturing operations.*
- ***Pattern analysis enhancement:*** *Utilizes ML to uncover hidden patterns in large datasets to enable production improvements.*
- ***Command and control applications:*** *Incorporates ML to provide more granular control over manufacturing processes and equipment.*
- ***Sensor data fusion in machinery:*** *Integrates ML to analyze multiple data sources to allow for greater control over entire manufacturing ecosystems.*
- ***Natural language understanding:*** *Uses NLP to ingest human data input (text and speech), and then uses ML to understand what is being said, allowing more automation between customers, partners, and other stakeholders via virtual digital assistants.*

Within each category, specific use case adoption is likely going to take time. Each manufacturer has its own set of processes, current level of technological adoption, risk tolerance, available capital, and expertise to devote to developing specific algorithms to support new use cases.

The following manufacturing use cases can be applied to nearly any type of manufacturing company, regardless of the industry vertical or product,

Figure 5: AI for generative design



Source: Omdia

Figure 6: Tasks that can be handled by ML

Intelligent decision-making

Tools that are infused with AI and predictive analytics techniques can

- Gauge future risks and take appropriate decisions.
- Rely solely on the data to drive decisions.

Intelligent data processing

PLM tools can benefit from advanced data validation and cleaning, a process that is required when data is prepared for processing by and algorithm.

This process will eliminate or reduce existing invalid data that may be negatively affecting the PLM system.

NLP and text mining

A significant portion of useful data that feeds into PLM tools is unstructured, and there is a need to leverage this unstructured data for better product digitization.

Intelligence and flexible integration

Most integrations with PLM systems are hardwired.

Incorporating AI integration via an API will allow more flexibility in how two systems talk to each other.

Source: Omdia

given that they are relatively general applications of AI. While there is a degree of customization required in order to ensure the use case meets a company's specific needs, the approach and strategy for each use case are applicable for nearly any company.

Generative design

The use of ML or DL can drastically affect the product development and design process, increasing process efficiency and workflow and allowing for a greater diversity of design elements to be considered. One of the key bottlenecks in traditional design is being able to allow a designer or decision maker to make intuitive design choices due to the myriad number of options or choices.

ML can be used to bring together a wide range of disparate data sources and then identify patterns within the data, thereby speeding the design or development process. In addition, it can open up new avenues for design by allowing a strictly data-driven approach to design, reducing or eliminating human biases that often creep in inadvertently.

An AI algorithm is completely objective, and it does not default to what a human designer would regard as a logical starting point. Furthermore, everything is tested according to actual performance against a wide range of manufacturing scenarios and conditions.

One example of how generative design is being used today comes from Airbus, which used generative design to reimagine an interior partition for its A320 aircraft. Through the use of generative design, the manufacturer unveiled a new design that reduced the weight of the part by 45%, resulting in a massive reduction of jet fuel consumed and a cumulative reduction of hundreds of thousands of tons of CO2 emitted when applied across its fleet of planes.

Because the partition needed to meet strict guidelines for weight, stress tolerance, and physical displacement in the event of crash, Airbus' design team chose to program the generative design software with algorithms based on two growth patterns found in nature: slime mold and mammal bones. Then, the team digitally mapped the thousands of options created in the generative design process against weight, stress, and strength parameters to decide which to prototype. The end design was a latticed structure that looks random but is designed to be strong and light and to use the least amount of material to build, thereby meeting all of the initial design requirements.

Product lifecycle management

Within the manufacturing industry, product lifecycle management (PLM) is defined as the process of managing the entire lifecycle of a product through several phases, including inception, engineering design and manufacture, service, and disposal of manufactured products. PLM requires integrating workers, data, processes, and business systems and is designed to provide a product information backbone for companies and its stakeholders.

AI technology, such as ML, combined with enabling technologies like NLP can empower the development of smarter and more responsive PLM systems. These types of systems include both structured and unstructured data sources that are considered with change management decisions, service optimization, customer quality programs, and other key decision areas. By incorporating ML into or on top of a PLM system, many of the tasks can be completed faster. Data-driven decisions can be handled by an algorithm, which solely focuses on the data, rather than human biases.

Predictive analytics

Predictive analytics is the process of using data mining, statistics and modeling to make predictions about future outcomes. In other words, historical data defines a set of parameters, which computers can then apply ML to in order to determine what user behavior/ responses might be in the future.

The key factors driving the predictive analytics market include increasing business interests toward advanced analytics for future estimations. Prior to ML giving computers the ability to adapt in real time, predictive analytics struggled with scale.

Because AI systems can operate without human intervention, they can process more information. Asset maintenance is a key area that can drive major cost savings and production value for industrial businesses around the world. It is generally thought of as a component of Industry 4.0. With industrial AI and ML, the global industry now has the ability to process massive amounts of sensor data at an unprecedented rate.

> *The key factors driving the predictive analytics market include increasing business interests toward advanced analytics for future estimations. Prior to ML giving computers the ability to adapt in real time, predictive analytics struggled with scale.*

Vertical AI use cases/applications

Within specific vertical markets, there are several use cases that leverage the power of AI to deliver ROI while employing ML, DL, NLP, and CV approaches that are commonly used across vertical segments. Choosing which use cases to deploy is an organization-specific decision, driven by the availability and usability of data, the specific goals of the organization, the ability of an organization to hire or outsource software and algorithm development, and the level of support provided by the company.

Electrical equipment manufacturing

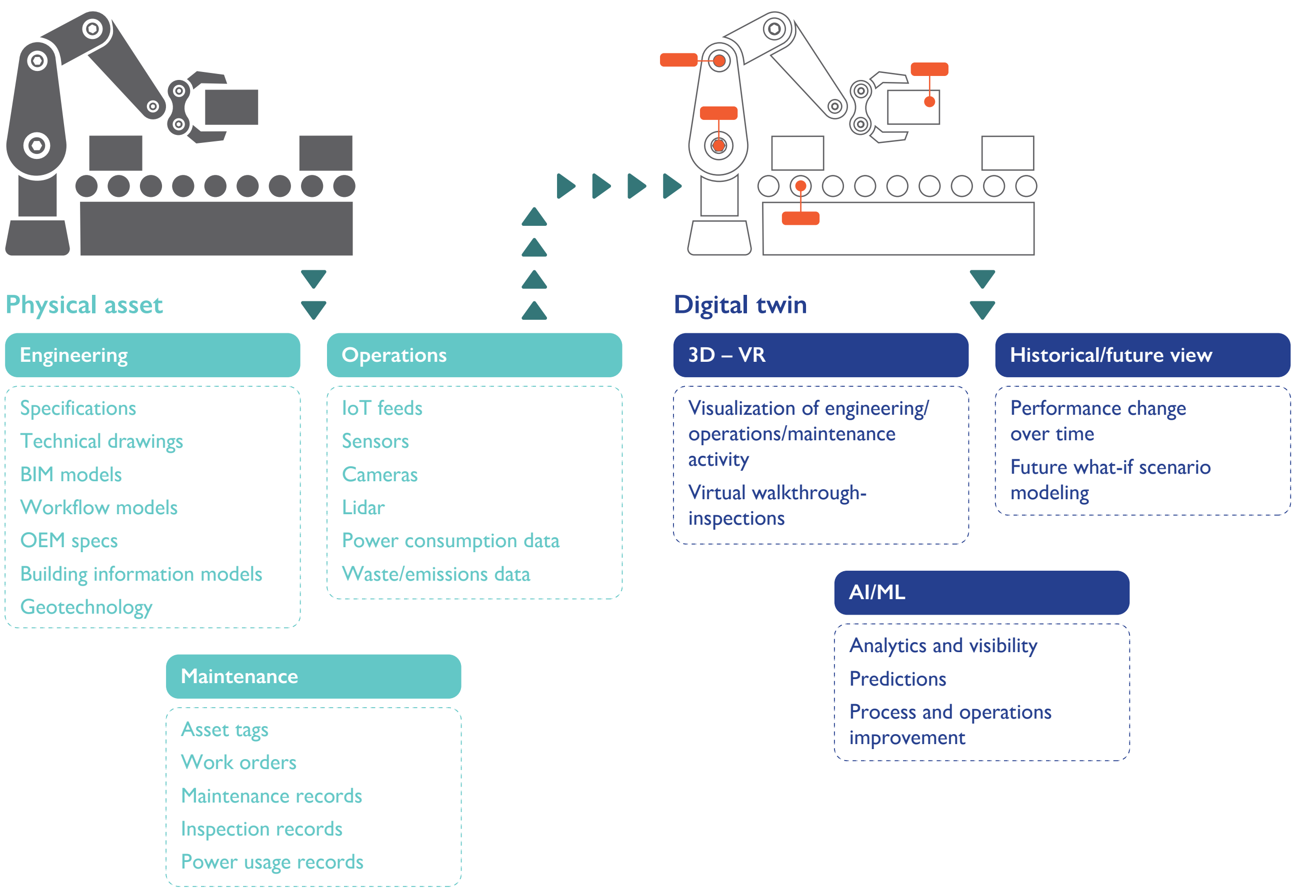
Electrical equipment manufacturing is rife with opportunities to deploy AI to improve the design and production process, as well as the manufactured goods themselves. Below are several use cases that demonstrate the power of AI to deliver significant benefits to electrical equipment manufacturers and relevant stakeholders along the value chain.

Digital twins

A digital twin is a digital representation providing the elements and the dynamics of how a device or ecosystem operates and lives throughout its lifecycle. Digital twins combine sensor data with ML and software analytics, which are then used to create spatial graphs that provide a digital simulation model that is updated and changes in real time in tandem with their physical counterparts.

In manufacturing, machines, systems, and even entire plants can be modeled via a digital twin. A digital twin continuously learns and updates itself from multiple sources to represent its near real-time status, working condition, or position. It also integrates historical data from past machine usage to factor into its digital model.

Figure 7: Digital twin example



Source: Omdia

Digital twins are useful for simulating machine tools' capabilities in a safe and cost-effective way, as well as identifying root causes of problems occurring in the physical tools or infrastructure. If a physical machine tool breaks down or malfunctions, engineers can evaluate the digital traces of the digital twins' VMs for diagnosis and prognosis.

Some of the notable vendors offering digital twin services include GE, IBM, Microsoft, Siemens, Bosch Rexroth, and Sight Machine, among others.

Supply chain optimization
AI, which can identify and optimize workflows, can be extended throughout the supply chain, bringing greater levels of intelligence, visibility, and control. By using ML, new insights into a wide range of supply chain activities, including logistics and warehouse management, collaboration, materials management, and on-demand production management, can be found, therefore increasing productivity and efficiency.

Traditional analytics, even bolstered by a strong processing infrastructure, is no match for the power of DL or ML. The latter technologies can take massive amounts of data from a plethora of sources, analyze and optimize the data, and then learn from those results, which can allow a much greater degree of control and optimization. This is because an algorithm can optimize based on a number of factors at once, as well as figure out which factors to prioritize, to a much greater degree than a human can while simultaneously eliminating any biases.

Digital twins are useful for simulating machine tools' capabilities in a safe and cost-effective way, as well as identifying root causes of problems occurring in the physical tools or infrastructure. If a physical machine tool breaks down or malfunctions, engineers can evaluate the digital traces of the digital twins' VMs for diagnosis and prognosis.

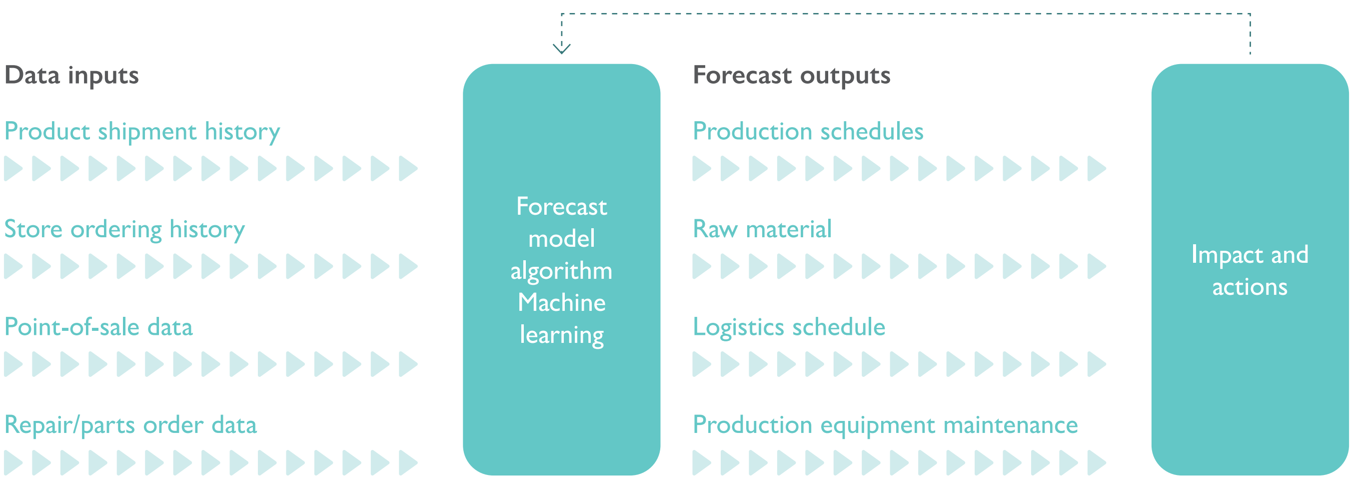
Some of the notable vendors offering digital twin services include GE, IBM, Microsoft, Siemens, Bosch Rexroth, and Sight Machine, among others.

Supply chain optimization
AI, which can identify and optimize workflows, can be extended throughout the supply chain, bringing greater levels of intelligence, visibility, and control. By using ML, new insights into a wide range of supply chain activities, including logistics and warehouse management, collaboration, materials management, and on-demand production management, can be found, therefore increasing productivity and efficiency.

Traditional analytics, even bolstered by a strong processing infrastructure, is no match for the power of DL or ML. The latter technologies can take massive amounts of data from a plethora of sources, analyze and optimize the data, and then learn from those results, which can allow a much greater degree of control and optimization. This is because an algorithm can optimize based on a number of factors at once, as well as figure out which factors to prioritize, to a much greater degree than a human can while simultaneously eliminating any biases.

ML can be applied to a variety of tasks that are reliant on a large number of disparate, yet interrelated, data sources in order to help optimize the process. Historical data can be analyzed quickly, with thousands of possible iterations checked for efficiency, speed, and accuracy. Some of the examples in supply chain management include the following:

Figure 8: Supply chain/production optimization



Source: Omdia

- ***Intelligent robotic sorting***
- ***AI-powered visual inspection***
- ***Improved demand forecasting accuracy***
- ***Supplier data management***
- ***Enhanced customer experience***
- ***Improved production planning and factory scheduling***

The result is more accurate and controllable production activity, allowing build-to-order capabilities that incorporate AI to predict demand and optimize the flow of critical parts to keep production moving smoothly.

Healthcare and medical image equipment manufacturing

The healthcare industry is increasingly utilizing AI to provide more efficient and better care for patients, as well as improve the speed, accuracy, and efficiency of administrative processes. Manufacturers of medical equipment, in particular, should be aware of the various use cases for AI so that they can appropriately design in the necessary hardware, software, and communications functionality to facilitate ML, DL, and other enabling technologies.

Healthcare virtual digital assistants

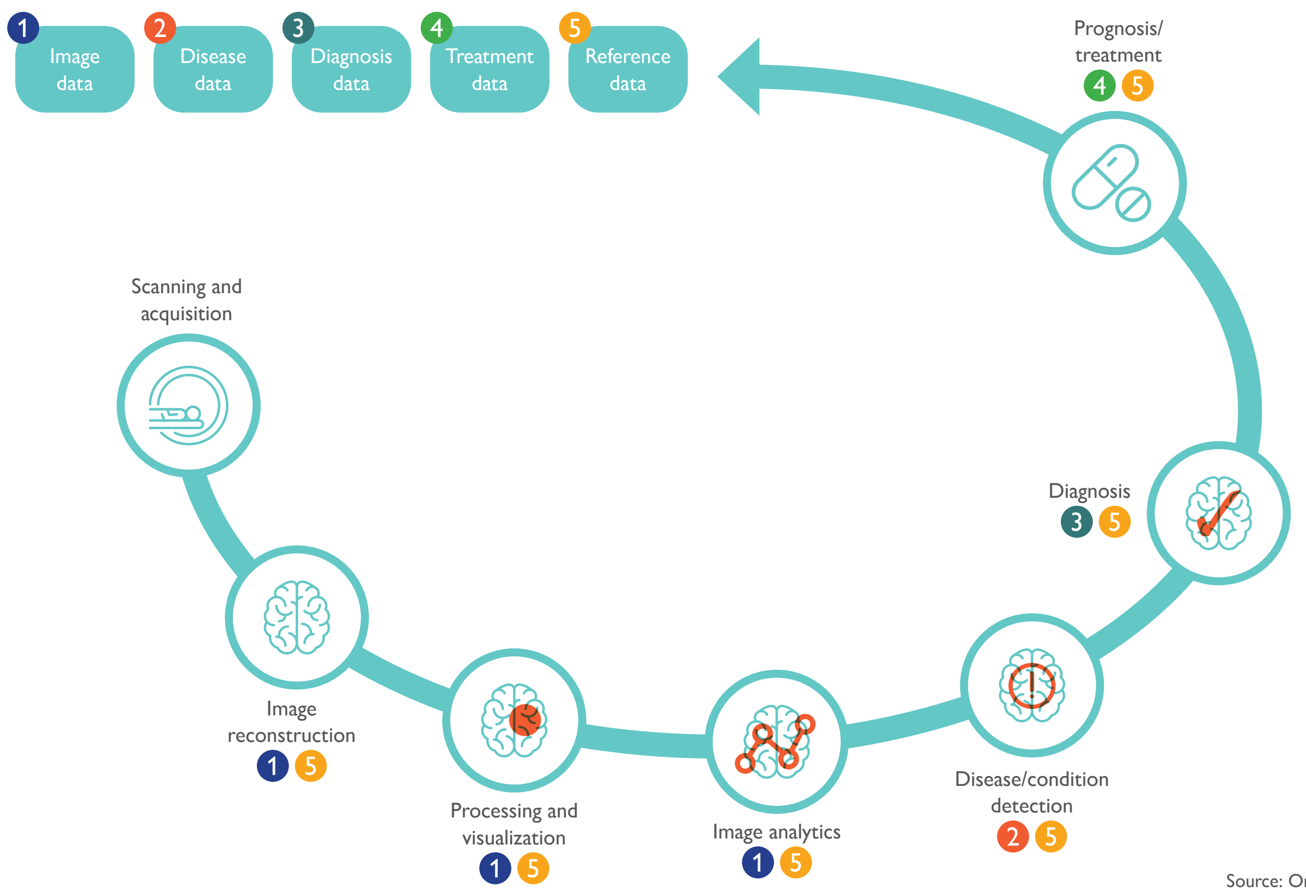
AI can be trained to mine large datasets and deliver advice, triage questions, promote medication adherence, or facilitate appointment scheduling for individual patients. Using NLP, DL, ML, and potentially CV (using patients' mobile device cameras, for instance), virtual assistants are not likely to replace human doctors, but can scale their ability to provide guidance.

Medical image analysis

Analyzing images is a strong application for DL and CV within the realm of patient data processing. DL is now being applied to automate the analysis and increase the accuracy, precision, and understanding of images down to the pixel. Some of the more common applications include 3D CV (images analyzed and rendered into detailed 3D models), autograding of eye diseases, and detection and segmentation of radiology images.

AI can improve the entire workflow of certain disciplines, such as radiology.

Figure 9: AI-enabled imaging workflow



Source: Omdia

One way that AI is being used is by training waste sorting robots for use at garbage dumps. Rather than having workers sort through garbage, these autonomous robots are trained using ML algorithms to identify and process waste based on the type of garbage.

Energy/electricity

One of the primary concerns facing manufacturers is managing energy consumption. From a pure financial perspective (electricity can account for a significant chunk of operational expenses), as well as a desire to reduce environmental impacts, a comprehensive approach to energy management should be a part of any manufacturer's strategy. Further, manufacturers of electrical equipment should be designing and incorporating energy management features into products to help customers monitor and manage energy use. AI can be used to address both issues.

Energy management

Energy management refers to the planning and operation of energy production sources, as well as the management of systems and devices that consume energy. The key objectives in an energy management plan are to conserve resources, maximize efficiency and cost savings, and whenever possible, address ancillary demands, such as environmental or economic mandates. ML can play a large role in making this process more efficient by capturing usage data from a wide range of customers, noting the amount of power consumed, the duration of peak use, the customer's location, and other power use signatures that can determine what type of device is drawing power. An algorithm can identify specific patterns of use by location, customer type, or other criteria, and then generate use predictions that can be fed to power production systems.

These predictions can allow energy producers to match power production to demand, creating (for example) a schedule for firing peaking plants or determining when power sources may be shut down for maintenance. Such patterns and predictions can also be used to help create conservation plans and incentives for customers, which are designed to reduce peak power usage through a reduction of power during the hot summer months.

Waste sorting, collection, and recycling

Waste sorting is the process of separating different types of waste so that material can be recycled, reused, or disposed of properly. There are several applications that are designed to use ML to enable smart waste applications.

One way that AI is being used is by training waste sorting robots for use at garbage dumps. Rather than having workers sort through garbage, these autonomous robots are trained using ML algorithms to identify and process waste based on the type of garbage. The algorithms are trained on images of various types of waste. Using CV, the robots are able to sort through waste and match garbage based on specific characteristics, much in the same way humans might compare pieces of garbage. Most importantly, the machines will continue to learn over time and are more efficient than humans.

The overall goal with using AI is to address waste management at all phases: at the initial point of waste disposal, during waste collection, and at waste processing plants. By using ML, DL, and CV technology, waste collection and management processes can be made more efficient and effective and can reduce the amount of human labor cost required to accomplish these tasks.

Industrial

Industrial companies are largely focused on improving the efficiency and management of assets and processes. Manufacturers can benefit by applying AI to their own assets and processes or by integrating AI tools, hardware, and software into products that can provide operational visibility and control within an industrial environment.

Predictive maintenance

Predictive maintenance uses data inputs from disparate streams to predict failures in machinery. Unlike preventive maintenance or condition-based maintenance, which is triggered by the occurrence of one or more indicators, predictive maintenance helps to predict failures beforehand. ML algorithms are used to identify failure patterns and detect anomalies, often triggering automated maintenance actions, such as setting up service upgrades, scheduling service engineers, or managing spare parts in inventory chains. Uses span several industries and equipment types, including airplanes, cars, construction equipment, factory equipment, manufacturing equipment, telecom networks, and infrastructure.

Video surveillance

Video surveillance can be used for a variety of different use cases within an industrial environment. However, these use cases generally can be segmented into a few key functional groups, all of which use a combination of CV and ML technology to identify objects, people, and actions, allowing greater surveillance and response with minimal human monitoring:

- ***Improve security and safety:*** *Video cameras can be combined with CV technology and ML to be trained to scan for people, objects, and actions, thereby helping to secure private spaces, such factory floors, storage areas, testing centers, and other buildings or spaces. By setting up real-time alerts based on object detection, facial recognition, or specific thresholds or no-go areas, safety operators can be automatically alerted when unusual behavior occurs.*

  In addition, companies can further leverage the video footage and related analytical findings and insights after an event occurs by using ML to recognize patterns and configure alerts to detect anomalies or suspicious behaviors.

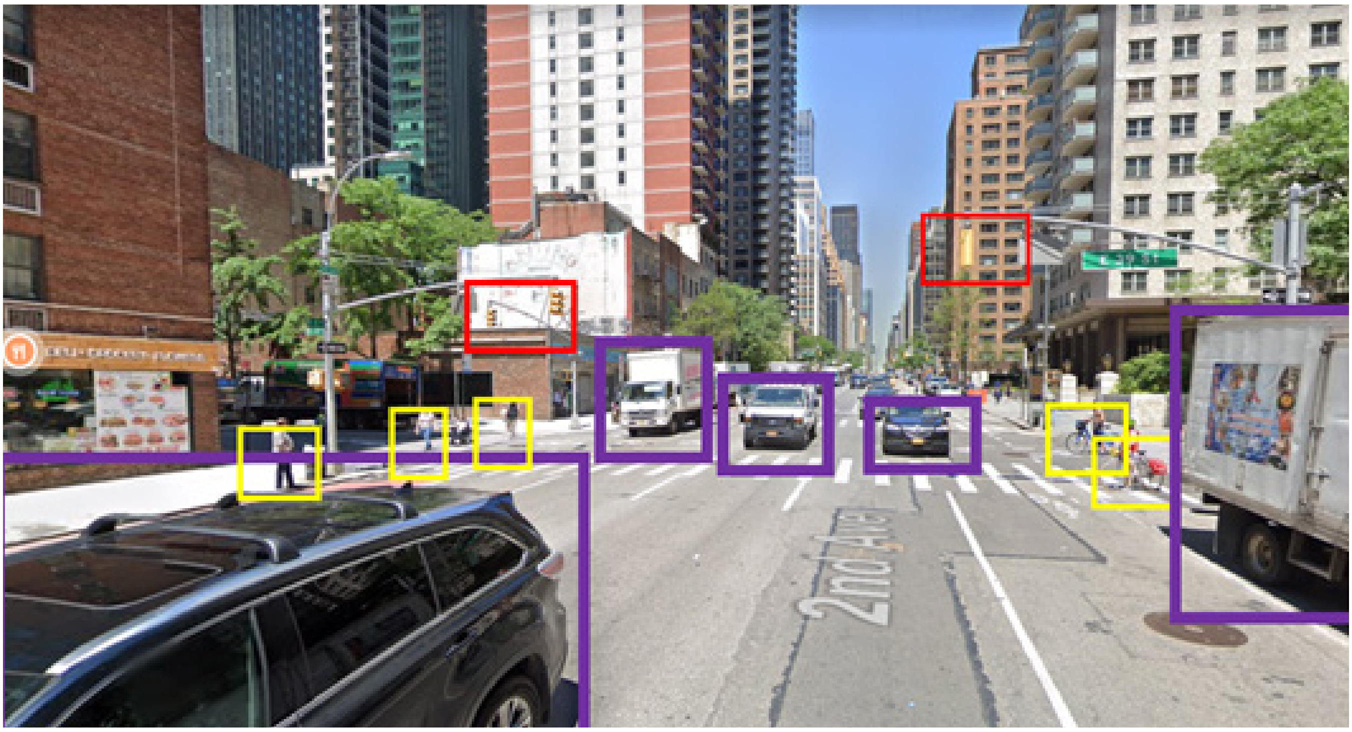
- ***Maximize efficiency:*** *One of the key challenges in running a manufacturing environment is ensuring that systems and services are run as efficiently as possible. Financial and labor resources are often limited, and operations managers are being asked to do more—without increasing operational budgets.*

  AI can be used to monitor and analyze manufacturing processes by examining the data to find hidden data patterns, data anomalies, or other markers that may indicate that a system is not operating as efficiently or optimally. Areas of inefficiency can be identified by looking at historical operational data and comparing it to optimal or simulated data. Video camera and CV technology can aid in this process by inspecting machines or the product itself during production, and then identifying anomalies or defects. Video technology can also often uncover root causes, such as a physical bottleneck, or a catalyst that would not necessarily be found by looking at operational statistics alone.

Buildings

AI can be used both to address a number of issues with buildings themselves (detailed in the ***Industrial*** and ***Energy/electricity*** sections above) and to manage the actual planning and construction issues surrounding development. AI can also be utilized to better manage compliance related to safety protocols on construction sites, which can reduce worker injuries or deaths.

Figure 10: AI for traffic optimization



Source: Google Maps; accessed September 10, 2020

Real estate planning and construction
Smart planning and construction software is designed to offer a platform where builders, subcontractors, and designers can plan and design in tandem with an accurate 3D visual representation of the site plan to validate costs easily and manage risks. The incorporation of AI can provide additional insights by mining troves of data sources and identifying anomalies or patterns in the data. Humans can then make better choices on which properties to develop, address building or construction issues in real-time based on analysis of in-progress site construction data, and ensure adherence to all safety regulations. These processes will allow city agencies to more closely and accurately monitor development and ensure a safer and more transparent approach to development.

Safety enhancement
Employers have an incentive to ensure better compliance with safety standards and protocols. One example of how DL is being used to help ensure better compliance includes tools that allow employers to leverage photos and videos to identify workers who are missing hard hats, gloves, or other safety equipment.

Transportation

Manufacturers should remain abreast of the many developments related to AI and transportation. While much of the focus is on self-driving vehicles, the technologies, approaches, and lessons learned can be applied to vehicles used in the manufacturing and production environment.

Traffic control and management
Traffic jams can cost millions of dollars in lost productivity, as well as make it more challenging for emergency services, public transportation, and private vehicles to navigate around the city. AI is being used to address traffic congestion, largely by collecting real-time traffic data, along with other relevant weather, time of day, or incident data, and then processing it using an edge server, incorporating an ML algorithm that can provide traffic predictions which can then inform future traffic signal models.

Fleet management and maintenance
AI is likely to become a key enabler in fleet management, particularly as ridesharing and autonomous shuttles, buses, and taxis begin to hit the road. By incorporating ML algorithms to schedule, control, and handle maintenance of fleets, greater efficiencies can be gained while keeping costs down.

Today's traditional vehicles are able to collect information about their activities, and semi-autonomous and autonomous vehicles are being designed to capture both operational and environmental data. By incorporating connected vehicle data, a wealth of information about how long a vehicle has operated can be collected, and specific data about the conditions and issues the vehicle has faced can also be captured and analyzed.

Analyses and recommendations

If deployed properly, AI can provide a number of benefits to manufacturers and industrial companies, both with respect to their internal operational practices (as well as to the products they make) and the customers they serve.

AI benefits

If deployed properly, AI can provide a number of benefits to manufacturers and industrial companies, both with respect to their internal operational practices (as well as to the products they make) and the customers they serve. Some of the general benefits that nearly any manufacturer or industrial company can reap are discussed in the following sections.

Quality assurance

Many manufactured goods are already constructed using precision techniques and materials. Analytics and sensors can be used to closely monitor the performance of machines and ambient factors that affect the production process. But ML and DL allow systems to review vast amounts of process data and identify variances, patterns, and other anomalies that may affect the efficiency of a process or the end quality of a product. This means that manufacturers can more easily modify processes at a granular level, thereby resulting in efficiency gains, improvements in quality, and a reduction of waste materials.

Efficiency

AI is useful for managing and combining smart technologies and services and can be used as a catalyst for integrating disparate networks and cutting costs. By incorporating ML and DL, systems can identify patterns in the data generated by machine logs, system logs, and data from the larger production ecosystem, identify inefficiencies or problems, and then apply an optimal solution based on historical data patterns or simulations.

Safety

Using a combination of machine vision and ML, images from video surveillance cameras can be used to recognize humans, vehicles, or objects. Machine vision incorporates a series of algorithms that compare the object seen with hundreds of thousands of stored reference images of objects in different postures, angles, positions, and movements. Once trained, the algorithm can determine whether the observed object moves like the reference images and whether it appears like the reference images (as well as other characteristics, including speed and gait). It combines all the values to ascertain what the object is, and can apply various preprogrammed rules to safety alerts when the object or its attributes fall outside of the accepted norms.

Marketing and sales

AI is increasingly being used to drive marketing and sales processes, allowing manufacturers to better understand, engage with, and satisfy both existing and new customers. Through the use of ML algorithms and enhanced data analysis, more detailed and granular analysis of engagements, activities, and purchasing can be conducted. Such analysis enables a more one-to-one relationship with each customer, as well as enhanced automation of interactions and responses.

One way in which AI is being utilized to improve engagement with prospects and customers is by utilizing virtual assistants that incorporate ML and NLP to guide them through the marketing funnel and answer queries about products, service, or parts. Because the virtual assistant is linked to an ML algorithm, it can offer personalized suggestions based on customers' buying history or customers that are similar in terms of any criteria (type of company, size, geographic region, etc.). By allowing a virtual assistant (which can be set up to handle inquiries on a 24/7 basis) to handle a first-call inquiry, it reduces the possibility of a lost sale or inquiry due to a prospect or customer dropping off and seeking out another manufacturer.

Another way to utilize AI is to capture data about customer behavior at each touchpoint of the customer journey. By analyzing this data to find specific patterns, a more personalized and customized experience can be created, allowing the relevant delivery of specific content, product recommendations, consumable reminders, or other marketing messages. Some manufacturers may choose to provide links to their retail or distribution partners to ensure the proper purchasing and distribution channels are maintained, even if the customer is interfacing with the manufacturer.

The goal with any AI-driven marketing and sales strategy is to improve the accuracy and responsiveness of routine tasks, thereby freeing up humans to handle higher value interactions. By intelligently automating initial or routine customer touchpoints, operational efficiency should improve, which would enhance customer experience and retention.

AI's impact on electrical manufacturers

Workforce

One of the most contentious aspects of AI is the specter of job displacement. Within the manufacturing segment, the scars of automation are deep; many workers have lost their jobs as automation has become commonplace, particularly those who hold jobs that had limited training requirements or featured highly repetitive and repeatable actions.

Over the next four to five years, the limitations of ML systems, combined with the reluctance of managers to totally trust machine-based decisions, will mean that AI's impact on jobs will not be one of replacement. Rather, it will be one of transformation. It is likely that analysts and operations professionals will need to pivot to take on a more strategic role, as the day-to-day analysis and operations activities likely will continue to be automated using AI and traditional automation techniques.

Distribution channels

Most manufacturers utilize a network of distribution partners, which can include distributors, wholesalers, and retail stores, that are charged with selling and servicing products. While AI can provide significant benefits to manufacturers, a well-designed plan for rolling out AI that includes benefits for these distribution partners must be implemented in order to maximize the chances for a successful rollout and sustainable, long-term business model.

Distributors

Manufacturers need to ensure that distribution partners are properly incorporated within the sales and marketing process when AI is incorporated. For example, insights derived from customer behavior tracking should be shared with distributors so they can ensure their downstream supply chains can dovetail with product demand cycles. Further, manufacturers that can integrate the output from customer support technology, such as virtual digital assistants, with their distributors can further streamline the problem resolution process or provide more data to feed into a continuous feedback loop.

Retailers

The increasing use of technology within stores, including in-store shopper tracking, mobile and e-commerce integration, and delivery services, is serving as a catalyst for the way the industry operates. Armed with a digital trail on how customers research, purchase, and pick up/receive products, retailers can better tailor their product offerings, individually target customers with customized marketing and support offers, and physically readjust their stores to maximize profitability.

Further, the use of richer and more granular datasets permits companies to optimize pricing, promotions, and recommendations, which can lead to increased customer satisfaction and repeat business. This approach applies to B2C and B2B customers, both of which are provided with a multitude of options for purchasing goods and services. Retailers are faced with a choice of deploying advanced technologies that allow them to act nimbly or risk losing out to savvy, more technologically advanced competitors.

Customers

The benefits of AI for customers are also going to be seen in the more advanced self-service tools that are being rolled out by manufacturers, distributors, and retailers. From real-time order and delivery tracking to more intuitive, image-based or natural language, intelligent search capabilities, it will be easier for customers to find the products they need through the web, on an app, or via a call with a digital assistant.

The likely applications for this technology within manufacturing will be interactive product guides and repair manuals, using augmented reality (AR) and virtual reality (VR) technology. These will allow technicians to conduct a repair or maintenance procedure without needing to refer to a paper manual. AR- and VR-based googles will provide hands-free access to these materials. Driven by AI, they will also allow voice-based searches and queries in real time.

Implementation guidance

Current challenges/obstacles in implementing AI across operations

While there is general agreement about the need for guidelines or regulations surrounding the use of ML, CV, data, and other related technologies, there are concerns that the implementation of these regulations or controls may stifle innovation and the implementation of new technology. Whereas many regulations that apply to commercial entities are often focused on balancing protections for customers against commercial interests, the regulation of manufacturing-related AI technology may be more focused on safety, data privacy, and security.

Managing data overload

One of the critical issues involved with the use of data is preventing or managing data overload. It makes little sense to capture and process data that will not result in greater visibility, productivity, or efficiency. Essentially, the goal of business analysts and data scientists is to assess which data (whether operational or ambient, internal or external) is critical to feeding an algorithm that can solve a problem. Any non-pertinent data should be excluded from processing and storage to reduce the load on the communications and processing infrastructure.

Privacy issues

Privacy remains a major concern of both individuals and those organizations responsible for collecting, using, and storing personal data. Certain jurisdictions have taken the lead on the issue of data privacy in terms of developing regulations. In the EU, for example, the General Data Protection Regulation (GDPR) was enacted to ensure that entities that have access to personal data are properly protecting, securing, and disposing of that data within a reasonable timeframe.

From both a commercial and public safety perspective, the trends and tides are shifting toward collecting and using more data. This will require the use of specific regulations to ensure that personal privacy rights remain protected.

Liability concerns

One of the key concerns about the use of algorithms to enhance the performance or efficiency of a system or service is determining liability if something goes wrong. If someone is injured or aggrieved by a system that used AI, there likely would be liability assigned to the company that deployed the algorithm. However, in a legal scenario, it is likely that additional liability may be sought; the vendor that supplied the software, platform, or algorithm may also share some liability.

Figure 11: Strategies for managing human capital objections

Choose simplicity	Cumbersome, complicated tools that require extensive training and research will be met with major resistance and may never really get off the ground. For example, Falkonry's software easily integrates with existing data infrastructure and control loops and does not require additional sensors, data management, or dashboards. Thus, the existing workflow is not disrupted, and the solution can be up and running in a day and delivering results in as little as a few weeks.
Sell it!	PLM tools can benefit from advanced data validation and cleaning, a process that is required when data is prepared for processing by an algorithm. This process will eliminate or reduce existing invalid data that may be negatively affecting the PLM system.
Build a coalition of the willing	A significant portion of useful data that feeds into PLM tools is unstructured, and there is a need to leverage this unstructured data for better product digitization.
Give people a reason to use AI	Most integrations with PLM systems are hardwired. Incorporating AI integration via an API will allow more flexibility in how two systems talk to each other.

Source: Omdia

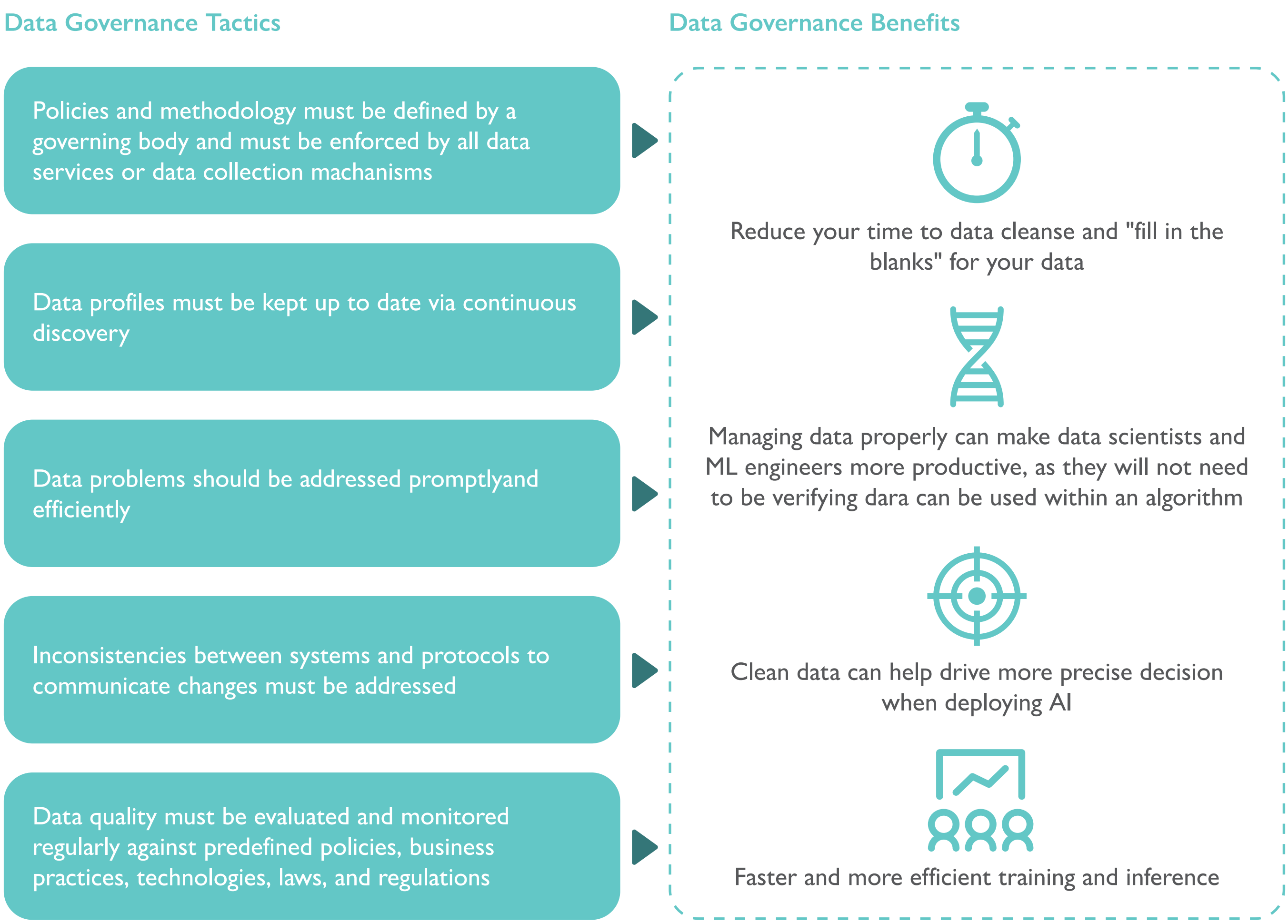
As a result, some companies may be less inclined to incorporate new algorithmic technology for certain use cases until legal protections are in place to shield or limit the liability of the vendor and end user. One of the criteria used to evaluate algorithms likely will be proof or verification that the algorithm was devised in good faith and has been trained using data that has been reviewed to remove as much bias as possible.

Human capital objections
There are several ways in which organizations can motivate employees to adopt new technology. Each strategy shown in Figure 11 is mapped to a tactic being used by vendors servicing the manufacturing market.

Regulations
Within the manufacturing sector, there are a few specific regulations that are likely to affect the use of AI. Data protection and privacy regulations, such as the EU's GDPR, and regional regulations, such as the California Consumer Privacy Act, will continue to affect manufacturers. Determining which customer data is captured, stored, and utilized within algorithms will remain a major compliance challenge for companies. While some larger manufacturers are able to handle these legal questions internally, outside expertise and counsel are recommended for manufacturers that cannot hire compliance staff that are solely dedicated to these regulatory issues.

Managing data governance and data infrastructure
Modern manufacturers, regardless of whether they are utilizing AI, need to practice good data governance, which helps an organization better manage data availability, usability, integrity, and security. Good data governance is even more critical when incorporating AI, which is reliant on clean, relevant, and sustainable data.

Figure 12: Data governance tactics and benefits



Source: Omdia

The key elements of good data governance include the following:

- ***Data security:*** *For regulatory, competitive, and operational integrity, data must be protected from unauthorized access and use.*
- ***Data loss prevention:*** *Similar to data security, data must be protected from loss or misuse, particularly customer data. If improperly accessed, the latter can be used by competitors or malevolent third parties.*
- ***Data integrity:*** *Data integrity refers to ensuring that the data being collected and used is accurate, relevant, and usable across all systems. If data integrity is not assured, the results of any process or algorithm using that data are likely suspect.*
- ***Data integration:*** *Data that is captured but not able to be processed or utilized efficiently by operational or IT systems is of little value. Particular attention needs to be paid to ensuring that data can be easily integrated into all relevant systems without compromising efficiency or security.*
- ***Data traceability:*** *Particularly when utilizing AI, the original source of the data, including which operational asset and systems are generating that data, as well as the path it travels throughout the system, must be identifiable and traceable. This ensures that any AI algorithm can be adequately explained, for both regulatory and verification purposes.*

Data and system privacy and security

Manufacturers themselves will need to ensure specific regulations and controls that govern the access to, control over, and security protocols of both systems and data used within AI algorithms. The most common regulations include the European Commission's GDPR, which covers entities that operate within the EU or have customers that are residents of the EU, and the California Consumer Privacy Act, which covers citizens of California. Due to the expansive nature of these regulations, many manufacturers are defaulting to these two regulatory statutes in order to simply compliance costs. That said, given the complexity, it is often wise to consult with outside legal experts to ensure specific issues are resolved, such as which entity owns the data, which party is responsible for the security of that data, and which entities may access that data.

Suggestions for future activities

The future success of AI is largely dependent upon innovation and companies' willingness to discover novel ways of solving problems that may be years or even decades old. Manufacturing associations such as NEMA should take the following approaches to supporting the growth of AI across their respective members and partners:

- ***Consider setting up working groups*** *to test new use cases/approaches, thereby diluting the initial risk of vetting use cases. Much of the company-specific work will be undertaken in single-company POCs. However, much of the underlying work around understanding what data is needed, how it should be captured, and how it can be applied to a specific process or industry group can be undertaken by a consortium of companies.*
- ***Consider setting up an association-led vendor database,*** *allowing members to directly compare specific vendors' offerings, thereby speeding up the process of identifying and selecting appropriate outside vendors.*
- ***Consider partnering with research institutions*** *with strong AI/data science programs to build a direct link between future AI talent and the manufacturing industry. As AI becomes more ubiquitous, there will be a need for an increasing amount of data science talent within manufacturing organizations.*

Conclusions

Enterprise demand for AI technology is growing, particularly among manufacturers that are trying to streamline operations, reduce costs, and improve profitability. Based on the interviews conducted with NEMA members and other manufacturers, the high priority areas for AI initiatives over the next two or three years include the following:

- ***Leveraging AI*** *for more granular customer and market insights that allow more personalization, just-in-time fulfillment, and better overall customer service, which can be used to drive sales and improve customer retention.*

- ***Utilizing ML*** *to improve the quality of manufactured goods, as well as enhance the operational aspects of production, which can create more top-line and bottom-line revenue.*

- ***Applying ML, NLP, and other technology*** *to back-office and administrative procedures to support greater automation and AI-enabled decision-making, removing repetitive human tasks.*

- ***Incorporating AI technology*** *into manufactured products to aid in increased visibility into the use of products, allowing more accurate predictions of product usage trends, along with increased opportunities for customer touchpoints, service calls, and upsells.*

- ***Deploying AI technology*** *across a variety of organizational functions, allowing AI to become a key operational success linchpin across operations, sales, marketing, support, and customer service functions.*

Methodology

NEMA retained the services of Omdia for this white paper project, which was developed through a combination of primary research, including telephone interviews with NEMA member companies, interviews with other manufacturers, interviews with AI vendors, and conversations with industry consultants and experts. Additional insights and research were gathered via trade publications, industry conference findings, and business journals, as well as ongoing technology briefings provided by AI vendors and consultants.

Author

Keith Kirkpatrick, AI & Intelligent Automation
keith.kirkpatrick@omdia.com

An expanded version of this eBook is available via NEMA.

AI Business
eBook Series

National Electrical Manufacturers Association

Founded in 1926, NEMA is an ANSI-accredited Standards Developing Organization made up of business leaders, electrical experts, engineers, scientists, and technicians. NEMA convenes a neutral forum for Members to discuss industry-wide concerns and objectives under a legal umbrella by trained NEMA staff.

In association with:

OMDIA

For more info