Unlocking the Value of Artificial Intelligence and Machine Learning to Transform the OEM Aftermarket

The Aftermarket Business Guide to Applying Artificial Intelligence

5 PRACTICAL USE CASES

Press “1” for Service

At the start of the 21st century, inbound phone calls used to be directed to the new sales side of the automobile dealership. The automated phone systems that fielded these inquiries instructed callers to press the number “1” on their phone’s keypad for sales and “2” for service.

That sequence was significant because new vehicle sales used to be the primary focus. At that time, the service department, while necessary, was largely second class to the grandeur of new sales. Everything was designed to shepherd customers toward buying new vehicles.

In the mid-2000s, that model began to change. It used to be the sales department that had all the information and you had to talk to them to get it. With the proliferation of the Internet, consumers could now get that information online and check consumer reports, manufacturer’s maintenance reports, and other previously “guarded” information. Soon enough, used car dealers started to achieve scale online, such as CarMax.

Combine these factors with automotive companies themselves understanding that potential aftersales revenue was increasing, and the sales versus service model had been turned upside down. Dealerships invested in service departments, building state-of-the-art facilities, implementing new technologies, and creating high-touch customer relationship programs. Accordingly, around 2010, the order of the phone system directory changed too: callers today are directed to press “1” for service and “2” for sales.

Things are still moving toward the service model and away from the old sales model. Consider how companies like Carvana are selling cars online from what is essentially a giant vending machine. Tesla doesn’t have any franchise dealerships at all. Car sales tend to be cyclical, pricing of vehicles is under constant pressure, and the margins on services are higher. The service department is an opportunity for growth and profit.

The shift proved to be a better model for the end-customer, too. Vehicles serviced by the dealerships are maintained to manufacturer specifications. As such these tend to run better, last longer, and have a higher trade-in value. In effect, the service department was fostering stronger customer relationships with the goal to drive more repeat purchases and greater lifetime value from those relationships.

The Business Case for Servicing the Aftermarket

Auto dealerships are just one small part of a larger story that's unfolding in the aftermarket for original equipment manufacturers (OEMs). Across the board, manufacturers in industries such as auto, agriculture, construction, industrial equipment, and mining sectors are focused on capturing a slice of the service market.

In each industry, the case for pursuing aftermarket services is similar: sales tend to be cyclical, pressure on pricing is continuous, and margins are being squeezed by factors such as high research and development (R&D) costs. In comparison, services offer three key benefits – growth opportunities, higher margins, and greater customer satisfaction.

The marginal profit rates are especially compelling.

Our research suggests that while services account for an average of just 30% of revenue, the margins are more than double compared to the sales of parts. For example, the profit margin on the sale of replacement parts alone is roughly 9%. By contrast, the average profit margin on servicing that equipment is 23%.

Estimates and forecasts might vary by industry, but the central theme is the same. And that's attracting greater competition – a trend that is likely to accelerate. As technology continues to advance exponentially, the digitization of data has created mountains of information that can be analyzed and used to make better business decisions.

The human brain does not have the capacity to evaluate and interpret terabytes of information. However, computer software with artificial intelligence (AI) and machine learning (ML) capabilities does – within seconds. Being able to do this at scale is a significant step toward turning quantitative and qualitative data into actionable insights

Algorithms as a Competitive Edge

The secret to success in service is to have a deep understanding of the customer. To understand the customer, you have to understand the data. And OEMs have large volumes of data – sales, inventory, service records – housed in enterprise resource planning (ERP) and related systems. The challenge is most struggle to analyze it and derive actionable insights.

It's here that AI and ML have the potential have the potential for outsized benefits. According to McKinsey & Company, "Successfully implementing AI-enabled supply-chain management has enabled early adopters to improve logistics costs by 15%, inventory levels by 35%, and service levels by 65%, compared with slower-moving competitors."

This is because these technologies are highly effective at sifting through large volumes of data to identify anomalies, gaps, patterns, and trends in sales, demand, and performance that escape the human eye. Importantly, these tools aren't replacing humans, but rather eliminating rote work and supporting decision-making to provide OEMs with a competitive edge in delivering services to the aftermarket.

This guide will examine several practical examples of how OEMs are using this technology, not just today, but as the gold standard in the years to come.

The Difference Between AI and Machine Learning

Before diving into the examples, it's first necessary to describe the differences between AI and ML. These terms are often used interchangeably in casual conversation, and while they are associated, they also have meaningful differences.

Artificial Intelligence

AI refers to the broad discipline of computer science to develop and maintain an algorithm or set of algorithms, engineered to imitate human intelligence. AI is programmed with a set of rules that allow it to solve problems independently. This problem-solving ability is human-like – or "intelligent."

Machine Learning

ML is a specific subset of AI that describes an algorithm's ability to learn based on experience. These algorithms are typically "trained" on historical data – and use what it learns to find new relationships in the data, execute certain decisions that meet thresholds set by the OEM and extrapolate forecasts.

How AI and ML Work at a Basic Level

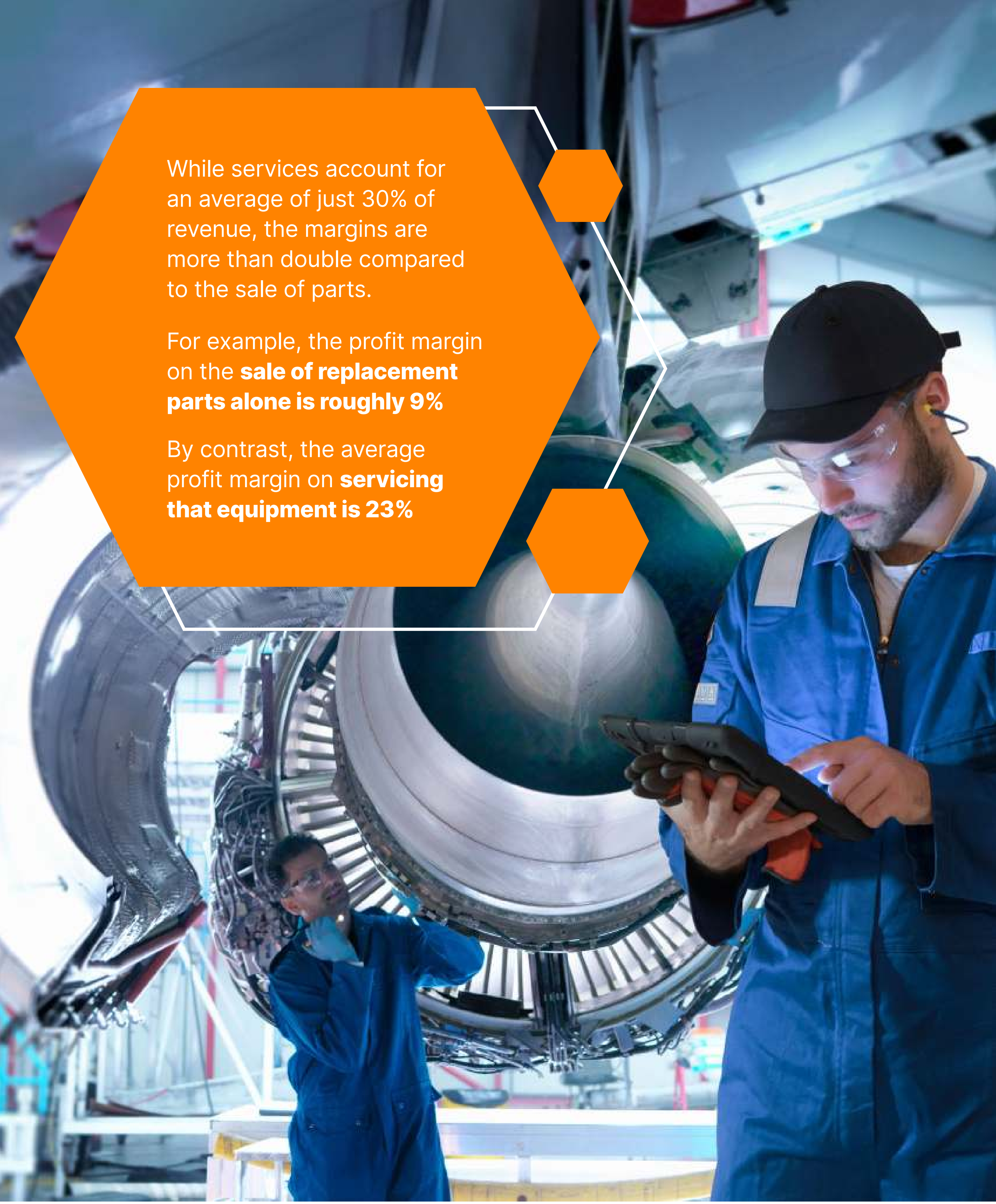
Understanding how AI and ML work at a basic level goes a long way to understanding the value these sophisticated technologies deliver in specific use cases. At a basic level, the "rules" in artificial intelligence work on an "if this, then that" basis. This means if a certain condition is met, then the algorithm should take a specified action.

Sophisticated AI programs have thousands of complex rules that are engineered around defined problems. These algorithms have many uses for forecasting inventory or analyzing sales trends, for example. Most importantly, AI allows OEMs to analyze datasets on an order of magnitude larger than the capacity of any human using a spreadsheet.

ML is a bit different in that it's designed to learn. If you show an ML algorithm 1,000 pictures of a truck and 1,000 pictures of a car, it will learn to identify the attributes associated with cars and trucks in detail. Once it understands the attributes, it can identify images of cars and trucks you show it in the future. If you show it a picture of a pickup truck, a tractor-trailer, or a dump truck, it will correctly categorize the image as a "truck" with a high level of statistical confidence.

There are some caveats too – ML algorithms are limited by the data and training they receive. For example, if you show a picture of a plane to an algorithm trained to identify cars or trucks, it's going to label the plane as either a car or a truck, albeit with low confidence.

You can, however, train the algorithm to identify planes, too. ML can be trained to make nuanced distinctions. For example, it can learn to recognize the difference between a sports car and a sedan – or basic hose and a hydraulic hose. As we will see on subsequent pages, that knack for nuance plays an important role in the use cases.



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Use Case 1:

From Preventative Maintenance to Predictive

Despite a diligent preventative maintenance program, a contractor had an excavator go down at a construction site for a commercial building. The critical component, whether it's a motor or a fuel pump for example, is known to be generally reliable – this was an anomaly – so the builder didn't keep a spare one on hand.

The contracting company called the dealer where the excavator was procured – but the dealer didn't carry the part either. The component was also expensive, and the dealer didn't want to tie up cash with inventory that was typically stored in a warehouse for months.

The issue was compounded by supply chain challenges. The shipping ports were backed up and the manufacturer was experiencing delays getting parts into the country. The best estimates suggested it would take six weeks to obtain a replacement part.

Without it, the excavator remained inoperable, which meant losses in productivity and profit on that construction project. The risks of unplanned downtime on equipment are high. One study by Deloitte found unplanned downtime costs upwards of $50 billion each year.

Preventative maintenance and condition-based monitoring

Most equipment makers follow a mix of preventative maintenance and condition-based monitoring (CBM) to keep fleets or equipment in operation. Both are based on field knowledge and historical data. By observing what's gone wrong in the past, a team can set parameters for identifying known performance issues when these conditions are present.

This is effective for known issues. However, when there's an anomaly or emergent problem, there's no historical record to set the conditions that would trigger an alert. So, as in the case of a hydraulic motor holding up a construction project, these issues go undetected until the machine is out of commission.

Machine learning and predictive maintenance

More and more machines and critical parts today are manufactured with sensors and telematics embedded. These sensors provide diagnostic data streams on performance and equipment uptime. ML can monitor this data at scale and identify anomalies that may indicate potential degradations and failures before they occur.

It works by monitoring sensor readings for dozens of characteristics like engine torque, fuel consumption, airflow rates, and manifold pressure. The algorithms learn what normal readings look like and when these start to deviate, the algorithm triggers an alert for review.

In the anecdote above, the OEM will see the degradation and contact the customer to bring that hydraulic motor in for service before it goes down, as well as ordering the part in time to avoid machine downtime. In other words, the uptime technology can forecast failure and predict when maintenance will be required. This gives the customer some latitude to choose when to bring the equipment in for service or when to order parts.

Knowledge, inventory, and design optimization

The ability to predict potential future issues and notify a customer ahead of needed maintenance is valuable on its own. It wards off costly downtime and improves customer relationships. However, there are other inherent benefits as well.

First

The problem ML identified augments the existing CBM program. It adds to the parameters and field knowledge that will enhance the overall program for condition monitoring.

Second

The early warning allows an OEM to optimize inventory. For example, it can search the dealer network to locate a replacement part in stock and initiate the transfer of a part. Alternatively, a replacement hydraulic motor, for example, can be ordered and shipped faster.

Third

The OEM will glean performance data over time that can improve quality control – or even shorten the R&D process for introducing new parts.

In total, the ability to move from reactive or even pre-emptive maintenance – to predicting failure – is one of the strongest applications of AI in the OEM service transformation.

Use Case 2:

Contract Pricing Properly Adjusted for Risk

A truck manufacturer had an opportunity to bid on a public tender for 300 vehicles. The winning bid would both deliver new vehicles and service them for the next five years. While services represent a growth opportunity, it's also fraught with risk.

Historically, coming up with such pricing for contracts involved numerous parameters to consider, such as parts consumed, labor, distance from dealer to customer, terms of use, etc. It is often based on complex, multi-tabbed spreadsheet analysis that require advanced knowledge to navigate and calculate. Even hiring a consulting firm would result in a similar outcome. These manually calculated estimates can still prove to be profitable or financially disastrous.

Today, the OEM has a more viable option. It used advanced algorithms to analyze historical service contracts, part warranties, and technician hours associated with service calls. Based on this data, the technology modeled the potential failure rates and connected costs – both in terms of probability of occurrence and severity of impact – for the vehicles under contract.

The process of analyzing and modeling the data sparked new thinking as well. The manufacturer realized it could apply other factors within its control to set pricing for this contract.

- One factor was using the known historical failure rate to adjust pricing to match the part warranty. In other words, they could structure the contract to incentivize proactive part purchases consistent with a comprehensive preventative maintenance program.
- Another factor was bundling parts into packages to bring the cost down. For example, the contract would discount noncritical parts with critical parts purchases.
- Finally, the sensor readings driving predictive maintenance would allow the manufacturer to more accurately forecast optimal inventory requirements. Accordingly, it could price the total project more competitively.

“What-if” style simulation

The AI also provided the manufacturer with a way to change variables and simulate the outcomes. This yields a “what-if” style analysis that allowed the team to change the assumptions and look at a range of probable outcomes from best to worst. The result was a more scientific and data-driven approach to pricing that helped them develop the winning bid.

Use Case 3:

Current Value-Pricing for Millions of Parts

A construction machinery company has over 1 million SKUs with more than 20 thousand added annually. The volume of parts to be managed and priced is complicated and involves comparing reams of data across multiple systems.

When new SKUs are added they need to be segmented and, more often than not, item segmentation is completely manual – identifying the item attributes (size, length, etc.) and then assigning it to the appropriate segment. Not only is this process time consuming and tedious, it is also prone to human error due to its manual nature.

The company realized they had enough data within their current systems that this process could easily be automated using machine learning. They trained the engine using their existing data and for new SKUs coming in, and they were able to automatically analyze the item attributes to suggest or automatically add those items to their appropriate segment.

Once they segmented their items accurately, they needed to set the right price. Another complex and maintenance-heavy process, but by implementing artificial intelligence, they were able to define approval thresholds based on their desired "rules" to help minimize the amount of time spent on reviewing and approving prices.

The thresholds were defined based on the business impact a price change would have. For example, if you were to change the price of an item and the business impact is below the defined threshold, it would automatically be approved and exported to external systems. However, changes that would bring a higher business impact would still require approval. Not only did this remove much of the manual users' input and save time, but also made the price to market go much faster, resulting in increased sales.

Machine learning does this at scale – evaluating thousands of parts every day to update and automate pricing. It cuts the time it takes to segment and price parts in half for this construction machinery company.

Use Case 4:

Identifying Lost Sales

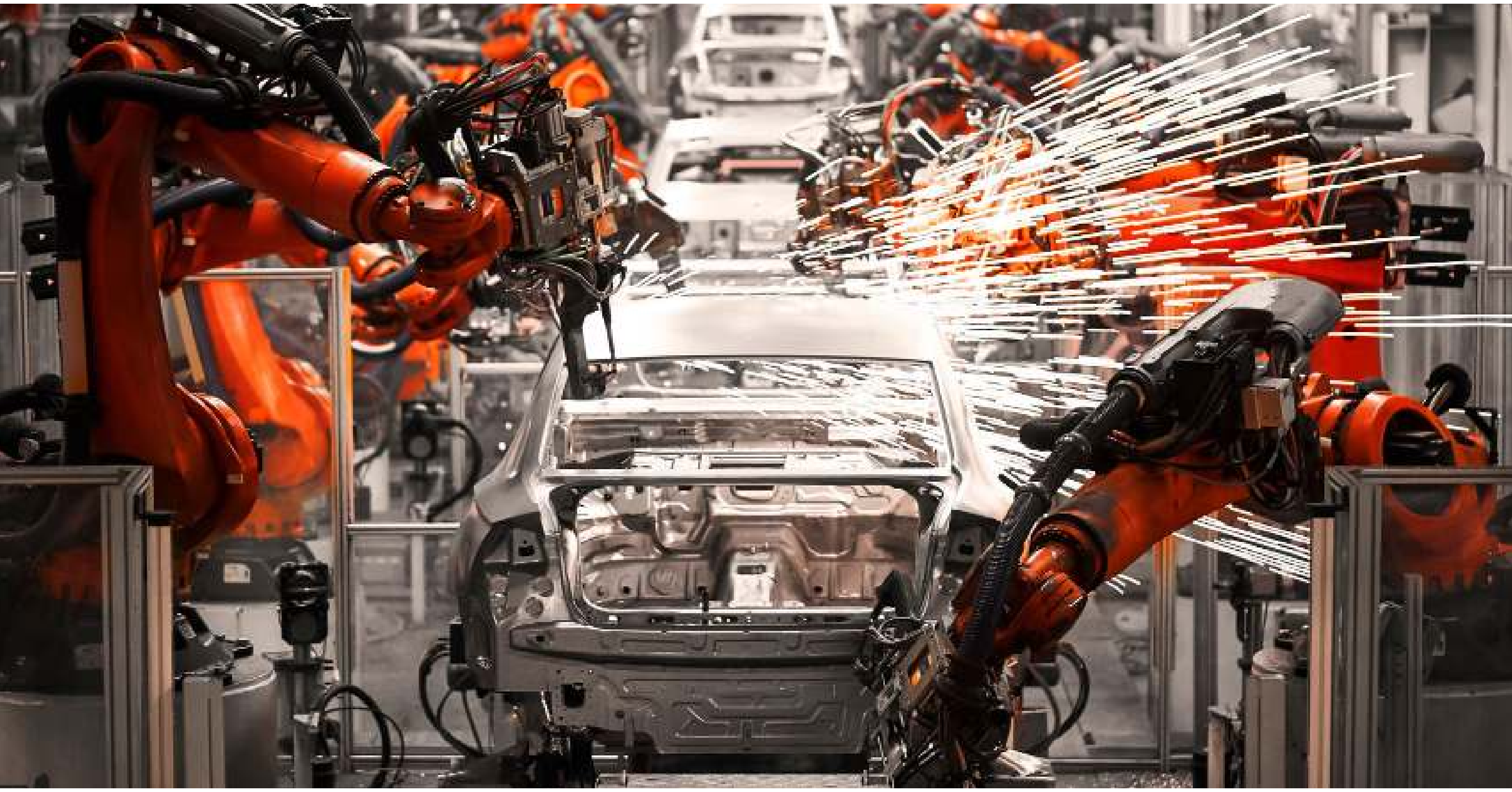
AI and ML algorithms can be trained to recognize millions of attributes about inventory and sales. Then it can classify, cull, and sort through reams of data to find trends, patterns, and correlations.

For example, a global car manufacturer used ML to group or "cluster" a set of customers responsible for 80% of their sales. This allowed them to understand what they were buying, and how frequently to make informed decisions about incentives such as pricing, and loyalty and rewards programs.

This clustering concept even permitted the algorithm to see patterns the inventory management team could not see – such as lost sales. For example, the ML could see one cluster of dealers all had similar buying patterns except one dealership. That one dealership in question wasn't buying windshields anymore.

The inventory manager deduced from the analysis that the dealer had found a new supplier. When the algorithm flagged this for review, the inventory manager could initiate a call or visit to the dealer to find out why and try to win that business back.

It's important to understand the ML algorithm determines the clustering, as this windshield example shows. It's very difficult to track parts that haven't been sold because there isn't a record for a business analyst to review. As such, ML will find trends across millions of data points and show findings for which a manufacturer hadn't thought to look.



Use Case 5:

Decision Support for Demand Forecast Simulation

Averages can be misleading – especially when it comes to inventory management and demand forecasting. For example, if a dealer sells 10 hydraulic motors one month, and five the next, how many motors should it keep in stock, given the average is five?

This is a perplexing question because too much inventory on hand ties up capital. On the other hand, too little inventory can mean a loss of customers when they come in for a part and it's not in stock. AI offers value here because it's a powerful tool for running simulations and testing assumptions to better gauge the probability of any given demand forecast.

One of the main benefits is that the technology detects patterns that aren't obvious to the human mind. Wheels for automobiles are a good example. We inherently know these always sell as a set of four. However, AI can show an OEM that this was true 90% of the time – and the other 10% of the time the tires were sold in differing bulks such as 427.

Such anomalies make reliable forecasting nearly impossible in a conventional spreadsheet. However, the advanced algorithms will identify and factor in these anomalies in a projection. In addition, ML will pick up such anomalies from multiple locations, such as other warehouses. This helps factor in seasonality, market density and other qualities that impact demand into the model to generate more accurate forecast models.

There are two primary ways this is being used for inventory analysis:

Retrospective.

This is a simulated analysis using historical demand data with new parameters. The goal is to understand the effects on forecasting if assumptions change.

Forward-looking.

This simulated analysis looks at trends over a certain time period and predicts future demand. For example, it might look at the rate of change in new car sales and predict the demand curve for tires in the future.

This application of AI and ML fits a notion the Boston Consulting Group calls a "bionic supply chain." A bionic supply chain "leverages the best of what both machines and humans have to offer." The consulting firm says use cases like this have "the potential to reduce manufacturing, warehousing, and distribution costs by 10% to 20% and working capital by 15% to 30%."

With the proliferation of internet-connected devices – sensors and telematics – there is potential for AI to enhance forecasting. An AI can monitor usages, such as the number of times a machine starts and stops, or the mileage being logged, or parts that are often being sold together, and factor this into the forecasting model and support decision making.

Conclusion:

AI and ML Offer Clear and Present Value

As an industry, the supply chain is collectively still in the early days of applying sophisticated technology like AI and ML to inventory, pricing, and maintenance. Advancements in natural language processing (NLP) are likely to add significantly to the data sources these algorithms can analyze. Moreover, the pace of such innovation is accelerating.

It's conceivable that in the not-too-distant future that a greater volume of unstructured sources of data about the supply chain will be factored into inventory management. This could include the effects of weather, pandemics, or even a ship stuck crosswise in a major shipping canal. In essence, OEMs will be better at serving their customers despite uncertainty.

To be able to take advantage of emerging capabilities in AI and ML, OEMs must get started now – and many are behind. Despite the substantial benefits, just 9% of supply chain management professionals have implemented AI for "inventory and parts optimization," according to a survey by McKinsey.

To that end, these technologies are already having a tangible impact today. AI and ML have a clear and present value in driving growth, profits, and customer satisfaction amid the OEM service transformation.

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