The Call of AI for

Discrete & Continuous Manufacturing

Co-created by

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The manufacturing industry has long relied on telemetry data to measure, evaluate, and draw conclusions about the way we produce goods. Artificial intelligence—and more practically machine learning algorithms—promise to introduce profound changes to what we can do with the data we collect from a large number of real-time telemetry sensors, video streams, and audio streams. Through machine learning that leverages new capabilities in computer vision and deep learning, discrete and continuous manufacturing processes race to take full advantage of rising digital technologies. The future of manufacturing awaits those who can successfully deploy these technologies 24/7/365 in real-time in "dirty" industrial and operational environments.

What Is Telemetry Data?

The word 'telemetry' derives from Greek words that mean remote measurements, which, simply put, is how we remotely sense and gather measurements of something. Before the introduction of AI, the use of telemetry data in manufacturing had evolved over many years and even centuries. After all, while the term "remote sensing" only dates from the 1960s, kites were used as early as 1882 for remote photography and evolved to satellite remote sensing in 1972. Also, more than a century before than the official start of the Industrial Revolution in 1769, which was enabled by the rise of automatic mechanical control systems, Cornelis Drebbel developed an automatic temperature control system for a furnace.

In the industrial world, manufacturing plants and industrial operations have also long relied on the so-called operational technology (OT) stack that comprises a vast array of industrial control systems such as Supervisory Control And Data Acquisition (SCADA) systems, Programmable Logic Controllers (PLCs), and Distributed Control Systems (DCS) to collect real-time measurements

For decades, researchers relied on simple thresholds and assumptions when working with telemetry data. They built controls around its collection and storage for very specific processes and, typically, in very static environments. These controls limited its applicability. Not so, any longer.

How Is Telemetry Data Used?

Today, data scientists deal with industrial telemetry data from an even greater range of sensors. Data engineers put devices and systems in place to convert the data to digital format and stream it. Alternately, they may store it in databases, data warehouses, or data lakes. Data pipelines are then engineered to reliably process and serve that data for downstream AI-enabled processes and other business or advanced analytics needs.

> *"Now that we have seen the advent of machine learning and AI models over the last decade, we can use data or self-play with simulators to learn optimal control —instead of relying only on thresholds. This opens new possibilities for industrial companies and manufacturing processes. This has been the genesis of clients coming to us to look at telemetry data and how they can leverage it. They want to find the golden nuggets to do more and become more efficient over time."*

Remi Duquette
Vice President at Maya HTT Ltd

Engineers track advances in AI technology and telemetry data analytics to find the right fit and build the right roadmap for industrial clients, ensuring they increasingly establish data-driven decision-making as part of their DNA. To help them succeed in the longer term, engineers put a fresh focus on perennial subject areas like data ownership and data governance. In our client base and our industrial and manufacturing space, Maya HTT sees the need for agile assessments, business metrics, and evolution. Maya HTT stands ready to help our industrial and manufacturing clients during their entire digital transformation journey, not just for a quick PoC win that never gets into 24/7 production.

The Challenges of Telemetry Data

Challenges lie ahead. What happens when sensors get clogged? When dust settles on key components? When the lighting changes? Many factors can modify data and compromise its cleanliness, making it unfit for AI purposes. In industrial applications, a clean-up act needs to take place and it needs to be sustainable. Sometimes, the simplest and most obvious issues are what trip us up in life.

AI models are trained on data. If the data is made "pure"—artificially—just to achieve better results for AI training purposes, it will inevitably lead to implementation failures. Proper data pipelines that convert raw telemetry data into input data for AI model consumption are the key starting point…and this involves more than cleaning your past historical raw data! It involves building proper data pipelines that will convert your future data the same way it converted your past data for training the AI models. You must accept that your data pipelines will not catch 100% of data impurities, as the past data may or may not include examples of all problems. Additional safeguards may be needed and can be put in place on the AI input validation side to prevent the AI model from running a prediction in some cases.

In manufacturing, telemetry data can come from many sources, including:

- → Temperatures
- → Pressure values
- → Valve positions
- → Pumping forces
- → Conveyor speeds
- → Power voltages
- → Video streams
- → Audio streams

Manufacturing equipment and other industrial assets incorporate many different sensors that collect and push raw data to centralized locations, whether those are on-premise or in the cloud. A familiar challenge remains, however:

> *"As you collect that industrial data," says Duquette, "you will likely realize that your data is dirty until proven clean. Whatever the source of the issue, you will inevitably get data from various sources and at different levels of cleanliness."*

Another challenge for data analysts lies in the frequency at which data is collected and how to reconcile highly variable time frequencies.

> *"In industrial and operational environments, you will always get data from various time scales," Duquette continues. "Some sensor data will be collected in millisecond frequency. In other situations, like PLC controls, you will probably get an output every second or so, and for SCADA systems, at minute intervals. Then, for the manufacturing operations management system, sensor data may be collected every hour. Finally, ERP systems will provide you with daily updates."*

These large differences in frequency become a big concern for data integration downstream. Data scientists must develop the skills needed to combine the different timescales, flag analyses, deal with missing data, and extract the frequency of content from time series in ways that can be ingested correctly for the AI prediction to run.

In the end, data scientists must collaborate with process engineers or SMEs to ensure they have used the right data pipelines and guardrails around their data, and that these parameters will be sustainable and practical in industrial environments that are operational 24/7/365. This is a systematic approach to ensure they do not follow a manual, one-time clean-up of the "garbage in" in training their AI models. "Garbage in" is a real and continuous reality of industrial data and neglecting this will certainly lead to "garbage out" for operational predictions. A systematic approach establishes clean-up methods for future data as the past data is processed for model preparation. This potential pitfall reinforces the need for physics-based insights. It also highlights the efforts required in data fusion or data merging while combining various data sources and different timescales and aligning them so they will continuously feed the AI model. Engineering data pipelines that reliably serve clean data will give you the full benefits of AI technologies and lead to successful data analytics initiatives.

With industrial telemetry data, AI partners need to bring the engineering knowledge necessary to set up AI properly, clean the data, and prepare it for analysis. **The right AI partner will not just be an AI expert, but an expert in engineering too.**

AI Telemetry in Discrete Manufacturing

Discrete manufacturing and AI telemetry applications meet at a paradox. In discrete manufacturing, each process is defined by multiple steps or stations, and workers assemble or machine together components before sending them to the next process step.

> *"Historically, people have optimized each of these operations in siloed stages. They look at the steps separately," advises Duquette.*

The paradox arises with AI applications because they are native to businesses that need to understand combinations of data across manufacturing steps, and not just for one step. For many industries, optimizing just a single step does not seem to promise the ROI that can justify the investment. Some industries serve as exceptions, however, like the semiconductor industry. **"A 0.1% impact improvement in one station might mean a savings of $100 million per year,"** says Duquette.

Where Do AI Applications Deliver Value in Discrete Manufacturing?

AI applications deliver the best ROI where they can predict quality issues upstream in the manufacturing process. By training AI algorithms on telemetry, they can detect and avoid quality defects early in a manufacturing process and reduce lost time and resources. Also, AI can optimize strings of machines working together across a discrete manufacturing process, and not have to focus on each machine by itself. Many manufacturers can assume—fairly—that each machine by itself was optimized for its respective purpose. What's often missed are the complex combinations and interrelationships between machines, which can still yield quality issues.

Imagine the following scenario:

Machine 1 runs hot, but it's within its operation's safety limits, so it sets off no alerts.

Machine 2 applies pressure that's close to maximum pressure, but, again, it's within the acceptable limits.

Machine 3 runs colder than usual, but, again, it's within the limits.

While all three of these machines pass their individual operating thresholds, an AI algorithm can consider everything together and guide technicians who may be able to fix, or reject, the resulting onset of a defective product. This can prevent lost time and resources down the line at Machines 4, 5, 6, and 7.

> *"Human beings are very good at focusing on one or a few scenarios or machines that they're driving or optimizing," says Duquette, "But, when it comes to multiple machines, multiple people, that's where an overlay of data-driven AI algorithms can help augment the overall process and assist everybody along the food chain."*

AI Speeds Discrete Manufacturing

In discrete manufacturing, AI can also find ways to accelerate production time while keeping production quality constant. In thermal-driven processes where workers soak specific items at specific temperatures for a specific duration, technicians and engineers have long relied on black magic numbers that set those values.

Process engineers have accepted these values as best-practice benchmarks and they have stayed constant and within defined range limits. However, these values may not consider the highly varying properties of the raw materials or environmental conditions that could reduce or speed up soak times.

> *"Accelerating soak times is where we've done some truly interesting AI work on reducing product quality defects or increasing manufacturing production yield for discrete manufacturers—whether it's producing aircraft parts or manufacturing lithium batteries for electric cars."*

Remi Duquette
Vice President at Maya HTT Ltd

Using physics-based simulations of temperature-driven discrete manufacturing processes, data scientists can build AI models and algorithms that self-play against environmental factors, product variability, and properties. Process engineers can collaborate with data scientists to simulate the real world and provide levers that show how these conditions impact the manufacturing process.

With AI placed into a process loop, its algorithms can fine-tune a machine's soaking time based on the telemetry data it has been fed—even if technicians initially set those values based on notifications to move a knob. In this reduced-order modeling approach, physics-based AI models learn from the physics first and then apply their ML-informed decisions to help the process adjust soak times for factors like humidity and temperature, thus accelerating the process or increasing the product quality as dictated by business metrics and goals.

AI Telemetry in Continuous Manufacturing

AI's contributions to manufacturing-industry telemetry data extend to continuous manufacturing. "When you think about it," says Duquette, "in continuous manufacturing, we think we have a simpler process. We are talking about continuously feeding raw materials into the process at their respective inlets. And we get the final product after many machines are strung together end-to-end with conveyor belts and other transport mechanisms."

Where Do AI Applications Deliver Value in Continuous Manufacturing?

Consider the case for producing French fries from potatoes or large rolls of paper from pulp and resins, to name a few examples. As Duquette further points out, "in those manufacturing environments, sensor telemetry, video streams, and other data sources can be leveraged to train AI models and reduce the variance in the resulting French fry production process. This could include, for example, how much peel is left, the length of the fries, weight per volume, etc. Conversely, AI models can also help reduce wasted raw products, improve startup conditions, or enhance the many quality parameters of large paper rolls. In some larger facilities where a process relies on heavy equipment, machine vision can help with employee safety."

While there's little difference across the continuous manufacturing processes, there are many hidden variations. As Duquette explains, "the tricky part in feeding an AI model with the correct data is to align the telemetry data collected that is representative of the end product. For instance, when the material starts flowing and gets pressed down for a few minutes and then, five minutes later, is temperature-soaked, all the data values are linked not in time, but to the product's transformation lifetime as it passes by the sensor. This is technically called lag analysis. For AI purposes, this can be a nightmare, as it can be quite dynamic because the continuous process often changes in speed and duration."

In Pursuit of the Elusive "Golden Batch"

In continuous manufacturing, technicians often talk about golden batches. They feed raw materials to a few machines. Whether they are making French fries from potatoes or large rolls of paper from pulp and resins, they string machines together and package the final products. These machines could run 24/7 indefinitely as long as conditions permit and the raw material to feed them stays available. In these environments, the telemetry sensor is often augmented by video stream or audio sources so it can be leveraged to produce AI models with increased business value.

In the French fries example, for instance, the manufacturer might employ AI machine vision video stream data to determine how much peel remains, the length of the fries, their min-max values, how many fries go into each bag, other telemetry for their weight per volume, and any contamination from moldy potato content.

In paper production, manufacturers might be concerned with reducing wasted raw products —especially when technicians start the machine and begin production from a cold start. In paper mills, a few rolls may need to be sacrificed to get to passing quality with paper flexibility, thickness, and density. When the same machinery produces toilet paper and cardboard, AI models can track and adjust parameters, providing a good first use case for continuous manufacturing companies looking to start on their journey towards a more digital factory.

Before AI, machine vision components provided rough sizing from an image and manufacturers relied on manual checks based on sampling methodologies.

> *"For instance," explains Duquette, "there might be five or even twenty quality parameters that you want to check for. You're not likely going to check all those parameters in real-time as the sensors might be too expensive or not accurate enough for real-time processing. And you would certainly not want to have human beings check every sheet of the roll of toilet paper. Hence, manufacturing companies would typically put aside a few samples from a batch and run very accurate quality testing on these small-batch samples."*

The shortcoming of a sampling approach comes in hoping that each series will be roughly the same and not experience drastic changes. With AI, the quality control process gets a continuous real-time feed across all the rolls or fries (or batch), removing some of the reliance on a sampling methodology. Samples are still typically required for the quality parameters that cannot practically or economically be recorded in real-time.

“Maybe, in the past,” says Duquette, “the process was running fine and within tolerance. It would pass quality sampling checks, and unfortunately, some clients might be unhappy, but overall, the product was good, so the manufacturer kept going. That said, now with AI, you’re able to tweak and fine-tune those quality and batch parameters in real-time, which can have a big value in terms of the product quality itself as well as the reduced raw material waste you’re going to end up with. It means your customers will be a lot happier while the cost of goods will be lower. All in all, when done right, it brings measurable business value, which is important when you get going with AI implementations.”

Conclusion

Today's manufacturing business leaders seek to make the most of their industrial telemetry data as they increasingly turn to AI to solve their business challenges and inform their strategies. The past three to five years have shown AI early adopters the value and specific benefits that machine learning and computer vision can offer.

Regardless of whether you face challenges in a discrete or continuous manufacturing process, Duquette advises, "Start small, but dream big. Start from business issues, challenges you have, and align the industrial data that you have to support these business challenges."

Choose an AI partner who understands not just AI, but also telemetry data. Ask questions to vet a potential partner's engineering experience and expertise. Compare the potential benefits of the AI proposal against the time and effort required for deployment.

The best first projects start with small implementations that accomplish a few objectives. This delivers value by:

- → Establishing a baseline data pipeline that can be scaled as you grow.
- → Showing the value that AI predictions can bring and how it augments humans in the loop.
- → Getting business stakeholders, subject matter experts, and technicians on board with AI's long-term promise.
- → Increasing AI fluency within the organization.

The importance of the cleanliness of the raw input data going into the data pipelines cannot be overemphasized. **"Check if you have the right data and ensure your data pipelines produce clean data,"** advises Duquette. **"Make it reliably clean. And make sure you start tracking your business metrics on the as-was process before you deploy your AI models and preferably before you advance too much with your project."**

“Put those metrics and real-time monitoring on a dashboard so you can clearly and truly see the as-new AI-based process results.” Those early AI-based process results become important on the business metrics tracking side where it is critical to showcase small gains.

Lastly, AI project leaders need to involve stakeholders early. They need to train them so they understand the technology, its implications, and all it offers. They need to know the project plan. Project leaders need to tap into their knowledge from the daily workings of the process, especially in industrial and manufacturing applications. When they’re engaged, **“they will embrace what’s coming down. They will feel part of it, and they will feel augmented by it,”** explains Duquette. **“When that happens, that’s a win for everyone in the organization."**

About Maya HTT:

Maya HTT is an industry leading software developer and engineering services provider of multi-physics simulation, computer-aided engineering (CAE), computer-aided design (CAD), computer-aided manufacturing (CAM), Product Lifecycle Management (PLM) and industrial artificial intelligence (AI) applications and solutions. Maya HTT's expertise in industrial AI, industrial internet-of-things (IIoT) and low-/no-code apps boosts performance, enhances overall equipment effectiveness (OEE), improves manufactured product quality, drives down costs, reduces inefficiencies, and increases energy efficiency for clients across multiple industries. Maya HTT helps clients harness the potential of digitalization to capture the business value of their data and improve operational efficiency. Operating behind the scenes, Maya HTT's experts provide the insight and innovative solutions engineers need to tackle the most difficult and obscure issues in business today. As a technological partner, software editor, and provider of Siemens solutions, Maya HTT's extensive experience in design, analysis, systems integration, manufacturing, asset operations, and software deployment helps clients and partners optimize products and find cutting-edge, best-fit solutions for modern problems.

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Emerj Artificial Intelligence Research is a market research and advisory company focused exclusively on the business impact of AI.

Companies that thrive in AI disruption run on more than just ideas. They leverage data and research on the AI applications delivering return in their industry today and the AI capabilities that unlock true competitive advantage into the future - and that's the focus of Emerj's research services.

Leaders in finance, government, and global industries trust Emerj to cut through the artificial intelligence hype, leverage proven best-practices, and make data-backed decisions about mission-critical priorities.

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