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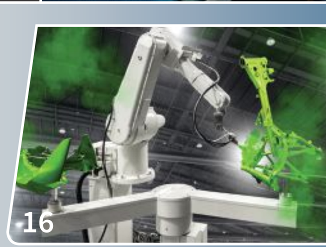

TECHNICAL EXPERTS

INNOVATIONS

NEWS / COLUMNS

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IIoT, Industry 4.0 and AI for Coatings Operations

Learn why "controlling everything" with automation, AI and smart manufacturing isn't practical and how to prioritize the parameters that truly matter.

BY MICHAEL BONNER SAINT CLAIR SYSTEMS

These days, every manufacturer is hearing about the Industrial Internet of Things (IIoT) or Industry 4.0, artificial intelligence (AI) that empowers these concepts and their promise to revolutionize how we make products. So, if you ask any expert, "What parameters should I actually be controlling?" you'll often get a quick "all of them!" answer. But that's a cop-out. It's easy to say, but it isn't practical.

The fact is, despite the proliferation of sensing technologies that have endowed us with the ability to monitor virtually every aspect of our environment and our process, implementation comes with a cost. And it's not just about the sensors themselves. It's also about the supporting network. And the processing. And the effort and energy costs. Unfortunately, these often get ignored during the upfront planning stages, and this can result in some unpleasant surprises at the back end of the project.

Though the hype and promise of AI has a powerful allure, the benefits can only be realized if it is truly understood and carefully implemented. And when it comes to AI, data is king

— which can present some significant issues when we are talking about manufacturing processes. As with any project, it is essential to balance the cost and effort with the return. Nowhere is this more apparent than with the application of paints and coatings, which often involve the most expensive, energy-intensive and environmentally sensitive processes in the manufacturing plant.

IIoT and Industry 4.0 defined

You're undoubtedly familiar with the Internet of Things (IoT). In your home alone, through what we've all come to know as "smart devices," your lights, thermostat, refrigerator, garage door openers — virtually everything — can be connected to the internet to facilitate monitoring and control via your computer, tablet, cellphone and watch.

IIoT is a subset of IoT, focusing on industry, or the "industrial internet of things." This has given birth to Industry 4.0 — the Fourth Industrial Revolution. While these terms are often used interchangeably, they are indeed separate. In fact, Industry 4.0 followed from, and could not exist, without IIoT.

According to IBM.com[1]: *"Industry 4.0, which is synonymous with smart manufacturing, is the realization of the digital transformation of [industry], delivering real-time decision making, enhanced productivity, flexibility and agility to revolutionize the way companies manufacture, improve and distribute their products."*

That's a powerful draw for manufacturers!

This means getting the information relative to your process into a shareable form, so it is easily accessible to all areas of the company (and the AI model), and this is often extended to mean "from anywhere" or "any device." The goal is to make it easier to analyze and control all aspects of your manufacturing process — to be more responsive — to be able to manage change as it occurs.

Sensor technology

The problem is, it's an analog world, from virtually all of the parameters that define our outcomes — like color, gloss, orange peel, mottle, run and sag, just to name a few — to the parameters that determine these outcomes, like temperature, humidity, pressure, flow and viscosity. To take advantage of "smart technology," all of these things need to be converted to a digital format so they can be stored and analyzed.

From need comes opportunity, so there has been a proliferation of sensing technologies that have endowed us with the ability to monitor virtually every aspect of our environment and process. There is the temperature of things like air and paint, humidity of the air, flow (again of both air and paint), pressure, viscosity, level, speed, voltage (for electrostatics) and velocity (of the air and the robot) — and the list goes on. Then there's quality control (QC) parameters like film build, color, gloss, orange peel and mottle, which are all measurable. And then there's visual defects like run and sag, blister, pop and so on, which are more subjective. The list is nearly endless but implementing these comes with a cost. First, there's the sensors themselves, then the installation

Process	Sensor	Install	Software	Total per Point
Ambient				
Temperature/Humidity	$2,000	$1,200	$250	$3,450
Air Flow	$1,580	$1,200	$250	$3,030
Paint				
Temperature	$1,350	$1,200	$250	$2,800
Viscosity	$10,000	$1,200	$250	$11,450
Pressure	$1,010	$1,200	$250	$2,460
Flow	$2,100	$1,200	$250	$3,550
Level	$3,470	$1,200	$250	$4,920
QC				
Film Build	$3,010	$1,200	$250	$4,460
Color	$12,630	$1,200	$250	$14,080
Gloss	$5,380	$1,200	$250	$6,830
Orange Peel	$31,950	$1,200	$250	$33,400
Mottle	$30,500	$1,200	$250	$31,950
Adhesion Tester	$1,770	$1,200	$250	$3,220
Hardness Tester	$1,060	$1,200	$250	$2,510
Impact Tester	$1,850	$1,200	$250	$3,300
Rub Tester	$2,140	$1,200	$250	$3,590

FIGURE 1. Installed paint shop sensor cost examples. *Source (All Images) | Saint Clair Systems*

Mix Room	Qty	Unit Cost	Total Cost
Ambient Temperature/Humidity	1	$ 3,450.00	$ 3,450.00
Paint Flow	10	$ 3,550.00	$ 35,500.00
Paint Pressure	10	$ 2,460.00	$ 24,600.00
Paint Temperature	10	$ 2,800.00	$ 28,000.00
Paint Viscosity (Tank)	10	$ 11,450.00	$ 114,500.00
Tank level	10	$ 4,920.00	$ 49,200.00
Totals:	51		$ 255,250.00

FIGURE 2. Installed mix room sensor cost example.

Circ System	Qty	Unit Cost	Total Cost
Paint Flow	10	$ 3,550.00	$ 35,500.00
Paint Pressure	10	$ 2,460.00	$ 24,600.00
Paint Temperature	10	$ 2,800.00	$ 28,000.00
Paint Viscosity	10	$ 11,450.00	$ 114,500.00
Totals:	40	Total:	$ 202,600.00

FIGURE 3. Installed circ system sensor cost example.

Prime Booth (2 Robots)	Qty	Unit Cost	Total Cost
Ambient Temperature/Humidity	1	$ 3,450.00	$ 3,450.00
Booth Air Flow	1	$ 3,030.00	$ 3,030.00
Paint Flow	2	$ 3,550.00	$ 7,100.00
Paint Pressure	2	$ 2,460.00	$ 4,920.00
Paint Temperature	2	$ 2,800.00	$ 5,600.00
Totals:	8	Total:	$ 24,100.00

FIGURE 4. Installed Prime Booth sensor cost example.

Basecoat Booth (4 Robots)	Qty	Unit Cost	Total Cost
Ambient Temperature/Humidity	1	$ 3,450.00	$ 3,450.00
Booth Air Flow	1	$ 3,030.00	$ 3,030.00
Paint Flow	4	$ 3,550.00	$ 14,200.00
Paint Pressure	4	$ 2,460.00	$ 9,840.00
Paint Temperature	4	$ 2,800.00	$ 11,200.00
Totals:	14		$ 41,720.00

FIGURE 5. Installed Basecoat Booth sensor cost example.

Clearcoat Booth (4 Robots)	Qty	Unit Cost	Total Cost
Ambient Temperature/Humidity	1	$ 3,450.00	$ 3,450.00
Booth Air Flow	1	$ 3,030.00	$ 3,030.00
Paint Flow	4	$ 3,550.00	$ 14,200.00
Paint Pressure	4	$ 2,460.00	$ 9,840.00
Paint Temperature	4	$ 2,800.00	$ 11,200.00
Totals:	14		$ 41,720.00

FIGURE 6. **Installed Clearcoat Booth sensor cost example.**

QC	Qty	Unit Cost	Total Cost
Film Build	3	$ 4,460.00	$ 13,380.00
Color	1	$ 14,080.00	$ 14,080.00
Gloss	2	$ 6,830.00	$ 13,660.00
Orange Peel	2	$ 33,400.00	$ 66,800.00
Mottle Tetster	1	$ 31,950.00	$ 31,950.00
Adhesion Tester	2	$ 3,220.00	$ 6,440.00
Hardness Tester	2	$ 2,510.00	$ 5,020.00
Impact Tester	1	$ 3,300.00	$ 3,300.00
Rub Tester	1	$ 3,590.00	$ 3,590.00
Totals:	15		$ 151,330.00

FIGURE 7. **Installed quality control (QC) sensor cost example.**

and also the supporting network. Next comes the energy, the processing and the ever-increasing cost of storing the data. Unfortunately, these are often ignored during the upfront planning stages, and, as I've already mentioned, this can result in unpleasant surprises at the back end of the project.

The sensors used in a paint shop are expensive. Often, they must be ruggedized and intrinsically safe. They must be easy to clean and often must be designed so they can be cleaned in place. As shown in Fig. 1, by the time they are installed and we can "see" their output, they can cost from $2,500 to $35,000 or more per point!

These add up in a hurry. Let's take a simple 10-color paint shop as an example. Since our focus is on process control, we're going to skip the warehouse and inventory and look directly at the painting process, starting in the mix room as shown in Fig. 2. This shows 51 sensors at a cost of more than $250,000 and represents the bare minimum we could expect.

From the mix room, the paint is sent to the application points via the circ system. The sensors and costs are shown in Fig. 3, which depicts a minimum of 40 sensors at a cost of over $200,000.

Looking at Figs 2 and 3, we've not yet sprayed a part and we're already into nearly half a million dollars!

In a small shop such as this, the Primer Booth has just two painting robots. Most of the spray parameters are monitored and/or controlled after the color changer or "color stack" so there are fewer of them here — really just eight (four/robot) at a cost of about $24,000 as shown in Fig. 4. Of course, this doesn't take into account the host of robot parameters that are available from the robot controller.

Next is the Basecoat Booth which, as shown in Fig. 5, has four robots. As with the Primer, most of the spray parameters are monitored and/or controlled after the color changer or "color stack," so there are just 14 sensors here at a cost of about $42,000. And as with the Prime Booth, this doesn't take into account the host of robot parameters that are available from the robot controller — twice the number in the prime booth.

The Clearcoat Booth also has four robots, so there are the same 14 sensors required at the same $42,000 cost, and the same considerations as the Basecoat Booth also apply.

In order to focus on the process of applying paint, we omit the curing ovens and associated remediation systems. However, to assure the integrity of the application process, the QC process is essential. As shown in Fig. 7, in QC the cost of sensors go up again. Though the data points seem small at just 15, the tools are more expensive, so those 15 points cost more than $150,000 to implement. In addition, the datasets they create can be huge.

When talking QC, there are a host of other parameters that might make the list but run and sag, and blister and pop are primarily visual assessments. Though there are vision systems to detect these, the cost and data generation is over the top of everything we have discussed so far!

Adding them all up, as shown in Fig. 8, we can see that we're approaching $3-4 million — just for the sensors. So why would we consider this?

	Sensor Count	Sensor Cost
Mix Room	51	$ 255,250.00
Circ System	40	$ 202,600.00
Prime Booth (2 Robots)	8	$ 24,100.00
Basecoat Booth (4 Robots)	14	$ 41,720.00
Clearcoat Booth (4 Robots)	14	$ 41,720.00
QC*	12	$ 119,380.00
Totals:	142	$ 716,720.00

FIGURE 8. **Installed sensor cost summary.**

The promise of AI

As we've already noted, the promise to reduce operating costs, remove bottlenecks and magnify output, accelerate revenue growth, streamline customer experience, improve compliance, sustainability and risk management, reduce supply chain friction, eliminate downtime, reduce waste, eliminate operator judgment and intervention, and finally realize a true "lights out" factory is just too enticing for most manufacturers to ignore.

But AI is not without its drawbacks and limitations. First, it requires large data centers, and at $7/terabyte/month there's a significant and continuously growing storage cost. And all that high-end processing requires lots of expensive chips — Nvidia's Blackwell chip currently costs between $30,000-40,000 each! And of course, the huge energy requirements have been all over the news of late. As shown in Fig. 9, data centers already use more electricity than some countries — and they're swiftly gaining on others! Which means it's only going to get worse. And as shown in Fig. 10, McKinsey & Co. projects that data center power consumption will continue to average a 10% CAGR, exceeding 35 gigawatts by 2030.

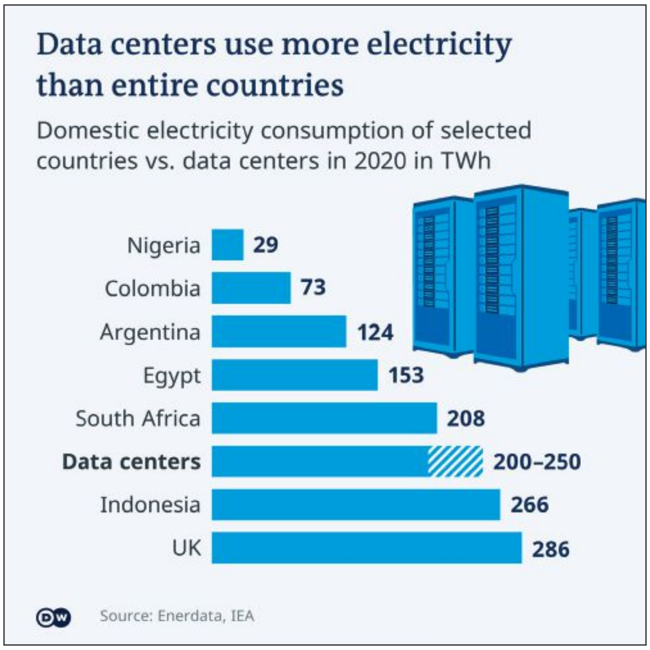

FIGURE 9. Data center power consumption versus select countries[2].

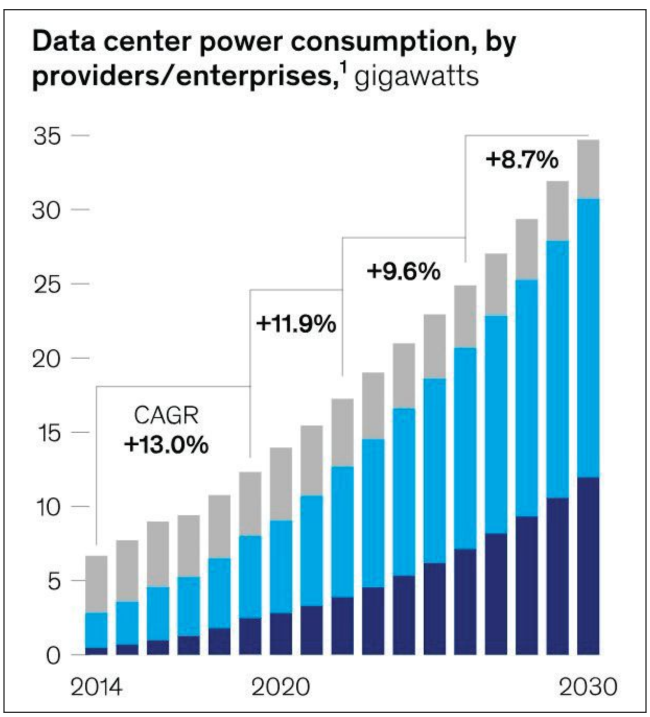

FIGURE 10. Data center power consumption trend and projection[3].

The process data conundrum

AI is a predictive tool. It looks at large amounts of data to determine what the next most likely event will be — the next

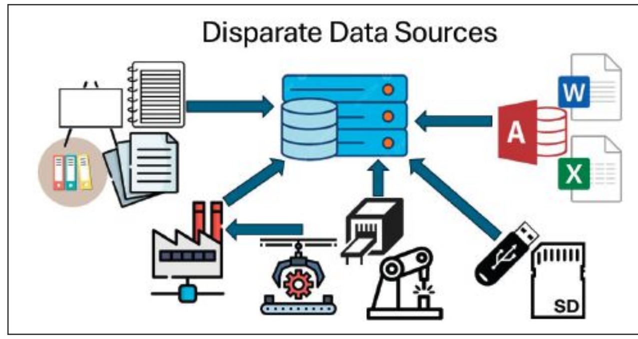

FIGURE 11. Disparate process data sources.

word, or sentence, for instance. It achieves this through large language models (LLMs). For words, meanings, implications and structure are fairly well-defined and have been generated in volume over centuries and moved to the web over the last three decades.

Manufacturing, on the other hand, is more about large data sets (LDSs), and the problem here is that the data is often not readily available. As Jennifer Heathcote, VP of business development at GEW UV, noted at the RadTech Winter Meeting in January 2025: "The problem is process datasets simply don't exist!" The conundrum is that, in many cases, process data comes from a host of disparate sources as shown in Fig. 11.

The hardest of these to deal with are handwritten sources like whiteboards, paper, notebooks or printed sources like books and magazines. The data may be in digitized documents like Word or Google Docs, or in spreadsheets like Excel or Google Sheets. Or, it may even be in a database like Access. But these can be on individual computers and not always accessible.

Other difficult-to-deal-with sources include disconnected storage like USB sticks or SD Cards. These can be lost or overwritten, or they can pose security threats.

In other instances, the data only exists on the machines themselves, in limited storage (first-in/first-out) or is lost forever whenever the machine is powered down. If we're lucky, these machines are logging to a Factory Information System. Regardless, all of these must be moved into a centralized database in a form that the AI can access. This can mean that your first six to 12 months may be nothing more than collecting and correlating data. That kind of delay hits an ROI calculation hard.

Hallucinations

Of course, no conversation about AI would be complete without a discussion about hallucinations. According to Electronics360 News Desk:

"Artificial intelligence (Al) algorithms produce outputs that are not based on training data, are incorrectly decoded by the transformer or do not follow any identifiable pattern. When an [AI] platform delivers outputs that are nonsensical or inaccurate, this is considered an AI hallucination."[4]

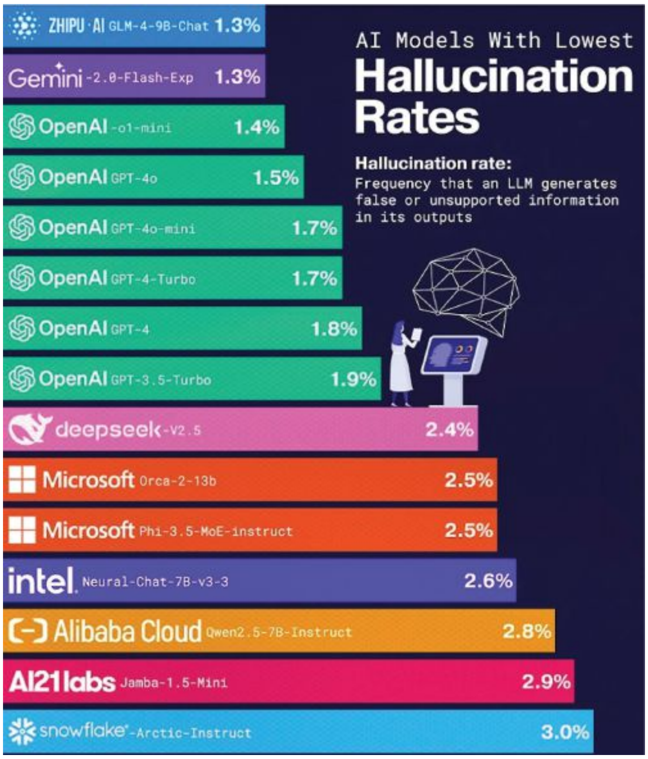

FIGURE 12. Hallucination rates[4].

When trying to produce a product with a first pass yield (FPY) greater than 99% — and for many products, especially those with narrow margins, this target can be greater than 99.99% — it is extremely important to understand the frequency of hallucinations that can be anticipated. According to Electronics360 News Desk, the top 15 AI models with the lowest hallucination rates, along with their documented hallucination rates, are shown in Fig. 12.

This implies that we must accept an error rate of between 1.3-3.0%! These errors can be attributed to errors in encoding and decoding, high model complexity and other factors like bad data. And while this may be acceptable for a term paper or a blog post, it is woefully inadequate for manufacturing quality.

The unique case of viscosity

In the case of paints and coatings, there are many data types that are difficult for AI systems to deal with. We've already talked about visual criteria like run and sag or blisters, but there are process variables that present equally difficult issues. Take viscosity for instance. It's the "poster child" for everything wrong with process data. To start with, most of the time it is a manual measurement made with a dip cup and a stopwatch as shown in Fig. 13.

The accuracy truly depends on the operator here — specifically with regard to motor coordination and attention to detail. It is obviously prone to variation. Another issue is that it takes time, so it is often taken infrequently — sometimes hourly, but more often once or maybe twice a day. This makes it very difficult to tie a measurement to a specific finish defect. And with regard to data storage, because it is manual in nature, viscosity is often recorded on paper, or a whiteboard. Even if it is transferred to a database, the frequency (or rather the lack thereof) and the inherent inaccuracy make it impossible to correlate viscosity variations to defects — and yet it is known to be one of the most important factors in coating outcomes.

Then there's the almost infinite selection of measurement tools and measurement units. Fig. 14 shows nearly 50 unit of measurement options, and it's not an exhaustive list. Moreover, though there are conversions and conversion tools available, they are notoriously imprecise — not like converting temperature from Farenheit to Celsius. This, too, makes data correlation and analysis difficult.

Fig. 15 shows a great example of the problem. The bottom two traces show the manual readings recorded for temperature (green) and viscosity (red). In addition to the long time interval between readings, it's also evident that the readings are not taken at the same time intervals — in fact, over the weekend (Feb. 8 and 9) there were no readings recorded at all. This makes it virtually impossible to identify if there is any interaction between these variables (and we know there is), for a person or an AI system.

To address these shortcomings, this company added Saint Clair Systems' in-line viscosity temperature sensor (VTS). Of key importance here is that viscosity and temperature data are recorded directly into a database in real time. Both

FIGURE 13. Manual viscosity measurement.

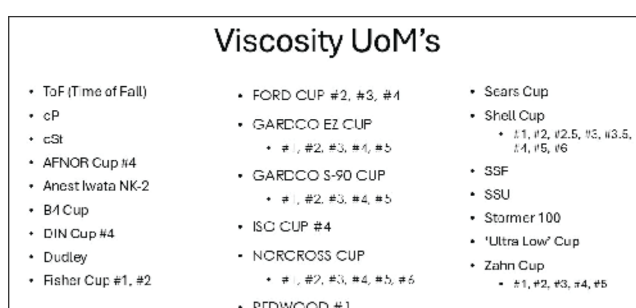

FIGURE 14. Viscosity units of measure.

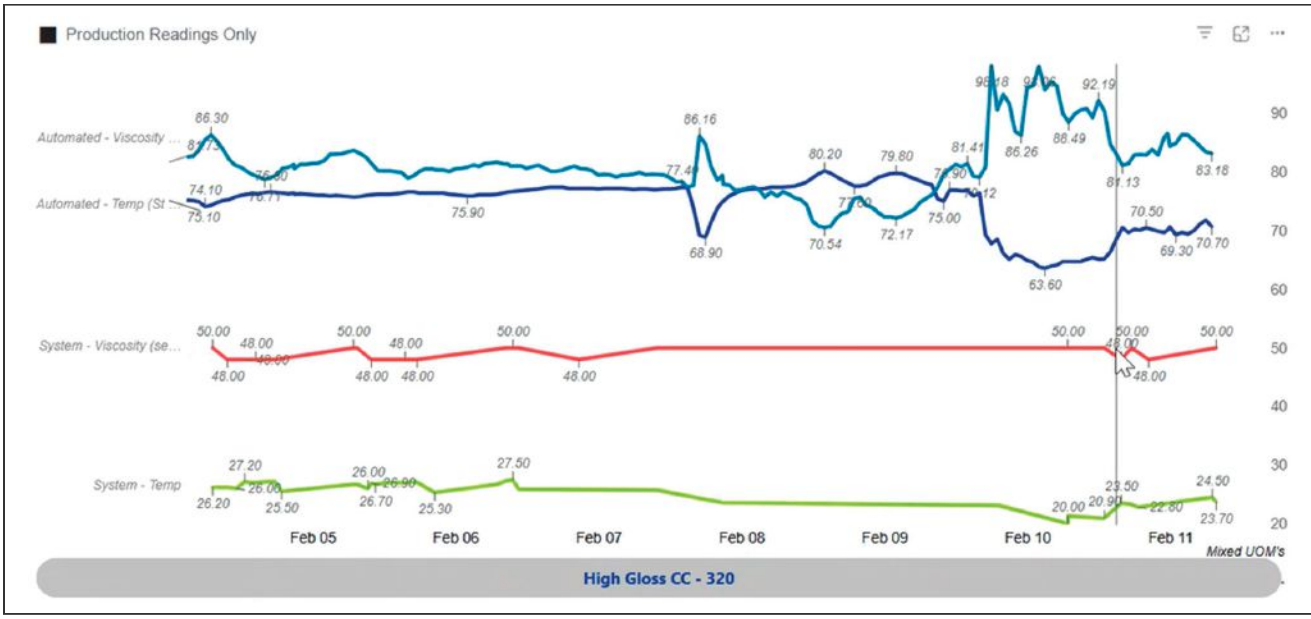

FIGURE 15. **Manual versus automated viscosity measurements.**

measurements are made synchronously on the same time base without operator intervention, so recordings can continue through the weekend. These simultaneous readings make it easy to correlate the inverse relationship between temperature and viscosity. We can see the relationship we expect with the viscosity decreasing as the temperature increases and vice versa.

Both an operator and AI can work with a complete dataset like this, making the correlation between viscosity and temperature and predicting how they will interact in future situations. If tracked to the rack level with viscosity-based defect data like color, gloss, orange peel, mottle or run and sag recorded on the same time base, it is equally easy to attribute these defects to viscosity variations and viscosity variations to temperature changes in a cause-effect relationship.

To control or not to control? That is the question!

To determine what parameters to control, it is imperative to first know your market and your customers. Know what outcomes are important to them. Next, focus on the process parameters that affect those critical outcomes. That will produce the dataset you require.

From that dataset, first identify those process parameters that directly affect your (or your customers') critical outcomes, then identify the cost/benefit relationship between those parameters. You can then classify those relationships in order of importance to you and your customers — a Pareto analysis — then install monitoring on only those parameters you intend to control. Anything else is a waste of time, effort, energy and, of course, money.

To decide which parameters to control, and when, start by identifying your budget and implementation capacity. Then, working from your cost/benefit analysis and order of importance to your outcomes, implement control on those parameters in that order. Then, as you build your database, establish critical cause versus outcome relationships between those parameters. Only then should you consider implementing AI in your process.

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ABOUT THE AUTHOR

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