IIoT & Industry 4.0

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Introduction

AUTOMATION 2021 VOL 5

IIoT & Industry 4.0: Keep the Ball Rolling

As Industry 4.0 initiatives continue to accelerate, advances in sensors, data analytics, artificial intelligence and more are enabling real-world benefits. For example, creating a secure wastewater management system in the cloud was seen as impossible not long ago. Predictive maintenance (PdM) strategies continue to rapidly evolve, underpinning a fundamental shift in the drive to become more efficient and demonstrating the benefits of digital transformation. PdM itself encompasses a range of Industrial Internet of Things (IIoT) and Industry 4.0 technologies that are reflected in this edition of AUTOMATION 2021. Deep-learning neural networks and artificial intelligence are two that show a lot of promise. MQTT/Sparkplug B can reduce bandwidth usage, ensure delivery of important system actions, and eliminate systemic limitations. Smart phones and portable sensors can simplify vibration data collection and analysis, while ultra-long-life lithium batteries power the remote wireless devices operating at the edge and in the field. Now is the time to upgrade and enhance automation and control systems with technologies that are showing benefits.

Renee Bassett
Chief Editor

About AUTOMATION 2021

The AUTOMATION 2021 ebook series covers Industry 4.0, smart manufacturing, IIoT, cybersecurity, connectivity, machine and process control and more for industrial automation, process control and instrumentation professionals. To subscribe to ebooks and newsletters, visit: www.automation.com/newslettersubscription.

AUTOMATION 2021 is published six times per year (February, April, June, August, October, December) by Automation.com, a subsidiary of ISA—the International Society of Automation. To advertise, visit: www.automation.com/en-us/advertise.

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Why Predictive Maintenance Is So Hard

By Alexander Hill, Senseye

Predictive maintenance may not be new, but it’s continuously and rapidly evolving; it is underpinning a fundamental shift in the drive to become more efficient

Most maintenance practices are based on service-interval schedules, a preventive and reactive approach that doesn’t take actual machine usage and health into account, and which is insufficient in reducing unplanned downtime. Predictive maintenance (PdM), on the other hand, is a more proactive approach, enabling machine failures to be dealt with before they stop production.

PdM is achieved by using machine learning and artificial intelligence (ML/AI) to analyze huge volumes of available machine and maintenance data to decode the machine health and enable maintenance staff to optimize their activities.

By predicting when machines will break down, companies can eliminate sudden failures, reduce unplanned downtime, optimize maintenance practices, and reduce the routine replacement of parts.
that may be perfectly healthy. They also improve energy efficiency and increase the sustainability of their asset operations.

Why is the implementation and deployment of PdM so misunderstood and littered with failures?

**Predictive maintenance, then and now**

PdM has been around for a lot longer than you might think. During WWII, scientist C.H. Waddington observed that a plane’s rate of failure or repair tended to be at its highest immediately after an inspection or maintenance session (Figure 1). Known as the “Waddington effect,” this phenomenon resulted in the adjustment of maintenance processes to correspond with a plane’s physical condition and the frequency of its use, with adjusted inspection cycles based on analysis of the resulting data. In short, it was the beginning of PdM.

It could be argued that aerospace remains the leading sector for PdM, deploying techniques such as condition monitoring, diagnostics, and prognostics. The proven success of integrated vehicle health management (IVHM) and health and usage monitoring systems (HUMS) in helicopter maintenance over the last 25 years are testament to this.

HUMS is an effective illustration of a successful PdM system. The Fourth Industrial Revolution and the advent of Industry 4.0 has seen

![Figure 1: B-24 “Liberator” bomber.](image-url)
technological breakthroughs occurring at such a rate that they’re disrupting almost every industry in every country.

These breakthroughs have led to significant improvements in sensor, network, data acquisition, and storage technologies, which, along with the access to a wealth of computing power and data made available by recent advances in AI technology, have seen PdM become increasingly applicable to wider industry.

Today, the key benefit of PdM remains its capacity to inform decisions. Responsible for overseeing many machines across one or more sites, maintenance professionals are extremely busy people. By providing them with a better understanding of the ongoing health of their machines, a PdM solution can help them make better use of the limited time and resources available to them.

Given its heritage and the clear advantages it offers, why has it been so hard for so many to achieve success in PdM?

“Maintainers typically have only a few minutes at the start of each shift to identify which among their thousands of assets most need their attention.”

Three common mistakes

The truth is, many vendors have jumped aboard the PdM bandwagon despite having little appreciation of what is, essentially, a unique and highly skilled domain. Some have tried to “supercharge” legacy monitoring tools, while others have applied conventional data science approaches to a problem space that is far from conventional.

Without the necessary understanding of exactly what a PdM system is, and how it works, many new solutions won’t even make it to the marketplace. Consequently, few businesses will achieve success at scale. In 2018, McKinsey released a report stating that more than 80% of data analytics (including PdM) projects fail.
Much of this lack of understanding—and subsequent PdM failure—comes down to three fundamental mistakes that vendors and their customers continually make.

1. Again, the concept of PdM is not new. Techniques such as condition monitoring, maintenance credits, and prognostics have been in existence for many years. But a lack of ability to scale these techniques beyond critical machines has meant that their deployment has been limited to just critical machines.

2. PdM is not a big data problem for which there are millions of data points and labels on which to train models. A factory environment is highly dynamic and noisy with a range of variables, including machine maintenance, different production speeds, and even the behavior of different machine operators. Every machine is unique. Despite this, many organizations will still take a data science approach to PdM.

3. It’s important to remember just how busy maintenance professionals are. If a PdM system’s user experience doesn’t reflect this, there’s a risk it won’t engage its target users. The valuable information and insight it generates will be ignored, and an organization’s investment in the system will be wasted (Figure 2).

Figure 2: A PdM system needs to address the needs of maintenance professionals.
The importance of the user experience cannot be underestimated. We’ve seen so many in-house PdM projects fail for which data scientists created some algorithms, connected them to an off-the-shelf dashboarding tool, and were then surprised when user engagement was lacking. The unsatisfactory user experience offered by their off-the-shelf dashboard failed to engage the system’s end user—the maintenance engineer—and the system was ignored.

**Performing PdM at scale**

What have we learned over the decades? We’ve learned a lot about deploying PdM and related technologies across a variety of sectors. It has been and continues to be a learning experience, especially as we encounter different sectors and different levels of customer maturity. Predictive maintenance is hard.

It’s important to appreciate not only what’s needed for PdM to work well, but also why it matters. We’ve learned that it can be hard to explain the value of PdM, even when it’s delivering a substantial return on investment. After all, implementing a PdM strategy requires a whole business transformation. Involving a shift in mindset from everyone from the board room to the shop floor, it’s a move that can’t be undertaken lightly, and can often require some serious justification.

**What are the key takeaways?**

*Don’t treat PdM as another data science problem.* That PdM is “big data” is something that’s become increasingly apparent as we talk with more people who share their experiences about previous failed projects. Big data solutions work best in context-rich environments, which are severely lacking in PdM. Many machine failure modes aren’t linear in nature and, if they don’t follow a clear pattern, can be difficult for established machine learning algorithms to accurately predict.

In a lab environment with high-quality, curated test data, specific accuracy figures will be achieved that can be pleasing to data scientists. But, if you factor in that each machine and each instance of a failure
mode is different, along with severe data quality issues in a live environment, low-quality sensor data, the highly dynamic nature of factories, and the dearth of available crucial context information, you’ll appreciate the inappropriateness of a generalized approach.

You should ask tough questions of anyone who tries to attach an accuracy figure to their solution; it’s probably never been used at scale and in the real world.

**Know your users.** Maintainers will typically have only a few minutes at the start of each shift to identify which among their thousands of assets most need their attention (Figure 3). Keeping the design of the software and its output simple and intuitive saves valuable time. Maintenance engineers do not want to spend hours diagnosing graphs and mining raw data for valuable insights. Yet, many vendors supply traditional dashboarding- or business intelligence-type interfaces that are generic and do not factor in the specifics of the user’s workflow.

![Figure 3: Maintainers typically have only a few minutes at the start of each shift to identify which among their thousands of assets most need their attention.](image-url)
**Know your users’ place along their digital acceleration journey.**

Businesses—and often areas within the same business—will be at different levels of data and cultural readiness. At the lower end, a company may do little more than carry out periodic route-based condition-monitoring checks, while, at the other, a company will combine robust, automated condition monitoring with the right PdM solution to give accurate predictions of time-to-failure and mode of failure for each of its assets. Each type of customer needs a completely different support and deployment package.

Most businesses will be somewhere between the two extremes. Increasing their maturity level relies on a greater understanding by their management and buy-in from their information technology team.

**Looking ahead**

The global PdM market is maturing rapidly, largely driven by a rise in the need to improve equipment uptime. Worth an estimated $4 billion in 2020, its value is forecast to reach more than $18 billion by 2025. What needs to happen to achieve that level of growth?

The market remains fragmented, with difficulty in separating the wheat from the chaff. This will take time to resolve itself. We believe solutions that take an integrated, user-centric, and holistic perspective will prevail.

A solution integrated with respect to broad sources of information, user-centric in the sense of having conversations between users and the system to capture key knowledge and experience, and holistic to algorithms and models; there is no single master algorithm, so there will always be a need for data scientists and custom models. The future belongs to a system that can integrate all this variety into a single product.

PdM is only one building block to a company’s wider Industry 4.0 initiative. As such, it’s important to think big: IIoT platforms such as PTC’s ThingWorx, Siemens’ MindSphere, and Schneider Electric’s EcoStruxure will play an increasingly pivotal role in enabling this (Figure 4).
Growth may yet be hampered by a lack of skilled staff, concerns around data privacy and security, and difficulties in deploying at scale. Many businesses are still nervous and confused by the marketing hype and their companies’ own internal direction around PdM. It is these issues that will take longer to resolve but have the biggest impact on how steep that growth curve will be.

ABOUT THE AUTHOR

Alexander Hill (alex@senseye.io) is a co-founder and chief global strategist of Senseye, a provider of scalable predictive maintenance. His background in digital systems engineering and early work on one of the largest wireless sensor networks in the world has enabled him to bridge the gap between the real world and the promises of the Industrial Internet of Things (IIoT) with a successful career developing software for condition-based maintenance in industries as diverse as aerospace, defense, manufacturing, and transportation.
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Formally organized in 1834, Waterford Township is located geographically in the center of Oakland County, Mich., and is home to more than 72,000 residents. It is known regionally for its 34 lakes, from which it earns its name.

Within municipal public utilities, Waterford is known for its leadership and persistent innovation in water/wastewater management. With 360 miles of water main and 355 miles of sanitary sewer, water management in Waterford is no small task. The Department of Public System integrator Perceptive Controls helps one community make the leap into an MQTT Sparkplug-based SCADA infrastructure.
Works (DPW) operates and maintains 19 production wells, 3 storage tanks, 11 treatment plants, and 63 sewer lift stations.

To run all this, it invested years ago in integrating core applications, including geographic information systems (GIS), asset management systems (AMS), enterprise content management (ECM), and supervisory control and data acquisition (SCADA), all of them sharing data to enable seamless operations.

That system has delivered a lot of value over the years, but nothing lasts forever.

**Time to upgrade**

In 2017, Russell Williams, Director of Public Works, and Frank Fisher, Engineering Superintendent, at Waterford DPW started on a routine maintenance project to upgrade the core SCADA infrastructure. At the time, they used a serial polling program to request updates from their many sites through a network of remote telemetry units (RTUs) that communicated over licensed radio frequency (RF) transmitters (Figure 1).

![Figure 1: Waterford DPW's legacy infrastructure relied on a network of RTUs and RF transmitters communicating to SCADA workstations in the office.](image-url)
A year later, they had begun replacing these RTUs and radios with Opto 22 SNAP PAC S2 controllers and DIGI 4G LTE industrial cellular modems communicating through a private Verizon network (Figure 2).

However, that same year, they attended a conference announcing the release of Opto 22’s groov EPIC edge programmable industrial controller, and it changed the scope of their plans. As Russ tells it, “We were talking about it on the ride back and said, ‘If this does what it’s supposed to, it changes the whole layout of everything.’”

They were particularly excited by the idea that the EPIC’s native support for message queuing telemetry transport (MQTT) Sparkplug publishing could help them eliminate some long-standing systemic limitations. With more than 90 controllers on their network, the polling mechanism they used, combined with the limited bandwidth of their radio network, meant that data from each site would update only every three to five minutes. Sometimes a lift station would run briefly between polling cycles, creating gaps in their reporting and inhibiting operators’ ability to detect issues until alarms eventually made their way through. For each input/output (I/O) point they added to the system, this latency only grew worse.
It seemed clear to them that MQTT (formerly IBM’s MQ Telemetry Transport, now available in open source) could reduce bandwidth usage and ensure delivery of important system actions. That’s because, as opposed to cyclic polling, MQTT follows a strict report-by-exception publishing rule. Instead of waiting to be commanded by the central server (called, in MQTT parlance, the broker), field devices and other MQTT network clients send data on their own if and only if there is a change in a monitored value.

“We have many lift stations that will spend most of their time sitting,” Russ said. “Why transfer data all the time?”

With no dependence on a central polling program, they saw the possibility to eliminate a systemic bottleneck and potential failure point. MQTT Sparkplug’s payload format takes resilience one step further by enabling edge devices like groov EPIC to store updates locally, in the event of a network interruption, and forward them to the broker as historical tags when the connection is restored.

“It just looks too simple. You’ve got to question it,” Russ said.

But, willing to test the premise, Russ and Frank purchased three EPICs to play with over the summer, and soon they had the evidence in hand.

“We disconnected a controller and within a millisecond the system reported the failure. It really is that easy: change a variable and it shows up in the broker, then on your mobile phone,” Frank said.

“It is that simple,” Russ agreed.

**From proof-of-concept to in-production**

To help them execute their vision, Waterford DPW engaged Perceptive Controls, a Michigan-based system integrator and long-time Opto 22 partner specializing in industrial and process control applications for the water/wastewater, food and beverage, and oil and gas industries. But building an MQTT system for the first time came with a learning curve, according to Kevin Finkler, Software Engineer at Perceptive.
“This was the first time I had done something that wasn’t strict client-server,” Kevin said. “The topic system and how you can subscribe to a particular topic is pretty different … When you first jump into MQTT, you understand that clients connect to brokers, but how do you actually send data?” He adds, “You can browse through the broker and see it there but understanding how it’s functioning is hard.”

MQTT’s publish-subscribe communication model is a departure from that of traditional industrial protocols in a few key ways:

▶ Field device connections originate from the device, not the broker.
▶ Each field device connects only to the broker, regardless of where its data needs to go.
▶ When using Sparkplug payloads, each device publishes (sends) a list of its available data items, called topics, upon establishing a connection to the broker.
▶ Other MQTT clients may also connect to the broker, see the available topics, and then subscribe to (request) updates on those topics when published by field devices.
▶ When a field device publishes an update, the broker forwards that update to all subscribing clients.

Understandably, the first challenge Waterford faced was integrating this new communication model into its existing SCADA system, but this proved to be a nonstarter. At the time, Waterford had two workstations running an older version of GE Proficy iFIX, and the system lacked the ability to work with the MQTT protocol.

“To help them execute their vision, Waterford DPW engaged Perceptive Controls, a Michigan-based system integrator and long-time Opto 22 partner specializing in industrial and process control applications for the water/wastewater, food and beverage, and oil and gas industries.”
After experimenting with a few popular SCADA packages, they decided on Ignition by Inductive Automation because it offered very tight MQTT integration, including the ability to serve as an MQTT broker. Even though MQTT caused Kevin some work at first, establishing communication was straightforward in the end.

“It kind of happens automagically,” Kevin said. “You basically define a few parameters [in Ignition] to set up the broker. And each of the EPIC devices was pretty simple. You just point it at the broker, and it starts sending tags.”

No “send data” commands to worry about after all.

“I love that both of these sides have embraced MQTT,” Frank Fisher said. “It makes the connection seamless.”

**Building defense-in-depth**

Earlier, as Frank searched for the components to build Waterford’s new SCADA infrastructure, he experimented with hosting an MQTT broker on Amazon Web Services (AWS). With the new cellular network already under construction, it seemed like an opportunity to leverage cloud computing for greater fault tolerance and scalability.

Having successfully tested the concept, when Waterford decided on Ignition as its broker and SCADA, it chose to deploy the new system directly on AWS. With that done, Kevin and Frank began building out the mechanisms to secure the new infrastructure.

First, Frank configured the firewall on AWS to accept traffic only from his groov EPIC controllers and specific Ignition clients in Waterford’s and Perceptive’s offices. Firewalls on the cell modems and EPICs also were configured to accept only trusted IPs.

Then Frank installed a client SSL certificate on each EPIC, so Ignition could authenticate and encrypt the connection, protecting against man-in-the-middle attacks that could expose data or permit unauthorized control.
Every authorized user is required to create strong passwords to access any groov EPIC controller or Ignition client in the system, but besides this, every user login is tracked and reported throughout the system also.

Frank and Kevin even integrated physical site security into Ignition. Each lift station is secured with an outer door—under lock and key—and a physical switch on the door is connected to the local EPIC. Ignition monitors the switch state to detect when someone enters, and if a user login is not registered within a specific time with access privileges for that specific room, Ignition generates a global alarm (Figure 3).

![Figure 3: One of Waterford's new lift station control screens. The station security panel is shown at center-left.](image_url)

**Return on investment**

After completing upgrades on all 63 of its sewage lift stations and six of its clean water sites, the groov EPIC-Ignition MQTT infrastructure has reduced field updates from multi-minute cycles to sub-second
event-driven publications. With that kind of speed, Waterford no longer misses system actions or alarm notifications (Figure 4).

Figure 4: Waterford DPW’s modernized infrastructure publishes data from groov EPIC controllers to a cloud-hosted Ignition SCADA and MQTT broker over a 4G LTE cellular network.
In Kevin’s opinion, “Ultra-low latency is probably the biggest benefit. The latency between the controller and the Ignition gateway is less than 200 ms. That’s across the cellular network with all [the EPICs] communicating to a server in the cloud.”

For most sites, it’s closer to 50 ms (Figure 5).

Because of MQTT’s report-by-exception behavior, in combination with analog I/O deadbanding in each groov EPIC, the new infrastructure also has reduced bandwidth consumption. This allows Waterford to publish even more data than before. They have access to communications and controller diagnostics like update latency, connection timestamps, message size, firmware version, and more, which wasn’t possible in the old system.

Ignition takes advantage of all this data with a more user-friendly look and feel, highlighting critical elements like wetwell level, run time, and pump flow totals in each lift station, so operators can quickly spot problem indicators. With cell-enabled tablets, operators can stay
connected from anywhere through Ignition’s mobile-ready human-machine interface (HMI).

Waterford’s cloud-based infrastructure also enables greater flexibility and reliability. Perceptive can perform controller updates over the air, which has reduced travel time and allowed them to continue project development unabated throughout the COVID-19 pandemic. If there is ever an issue at the Ohio, USA data center that hosts the new SCADA server, in 30 minutes, Frank can have the entire system up and running on a snapshot of the same server hosted in an Oregon, USA data center. In time, he will likely set up full server redundancy.

Russ recognizes that Waterford is leading digital transformation in the public sector. “I was at a FEMA training session not that long ago, and they were adamant about not having an Internet connection on your SCADA system,” he said, “but everything we are looking at will be more secure than we could do from [the office because then] you make a building a single point of failure.”

In fact, a recent Internet outage at the Department of Public Works offices provided an unexpected test of their new system, which kept on working without interruption.

“We only lost the old system,” Frank said. “Our internal stuff couldn’t reach out, of course, but our iPads could connect through Verizon … and I was able to get back in touch. In a situation like this, the old system couldn’t send out alarms because it depended on a local connection. The new system didn’t even notice or care because it’s not running anything local.”

**Looking ahead**

Waterford will continue to manage a few sites through its legacy SCADA system until the end of 2022, by which time it expects to complete all remaining upgrades.

But, with huge increases in bandwidth, the low administrative overhead of MQTT Sparkplug, and *groov* EPICs providing spare data processing at the edge, Waterford can continue expanding its system
for a long time. Each new device or application they add only needs a connection to the MQTT broker to produce or consume data for/from the whole system.

By integrating residential meter data, for example, they could help the system stay balanced against demand. If they can talk other agencies and neighboring counties into sharing data, they see the potential to build an advanced warning system that would improve their reaction time to system disturbances.

“We are still trying to figure out what else we can do with this,” Frank said. “We have a lot of other instrumentation we want to be able to pull data from out in the field that wasn’t really feasible before … not just at our lift stations and our treatment plants but throughout the organization. Where can we use it with flowmeters? Where can we use it throughout all our assets to give us a better overview? We’re just beginning that journey.”

When asked what he thought other engineers needed to understand most about MQTT, Kevin Finkler pointed out that “the client-server communication is handled for them. Before there was [a lot of code] that handled all the communication. It was a lot of work to maintain. Now you just mark a tag as ‘public’ [in groov EPIC] and that’s all handled for you. It’s less work, so it’s less money spent on engineering time.”

Less money spent on engineering time means teams can tackle bigger challenges, moving critical infrastructure closer to a true digital transformation.

ABOUT THE AUTHOR

Josh Eastburn is the director of technical marketing at Opto 22. After 12 years as an automation engineer working in the semiconductor, petrochemical, food and beverage, and life sciences industries, Eastburn works with the engineers at Opto 22 to understand the needs of tomorrow’s customers. He is a contributing writer at www.blog.opto22.com.
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Case Study: Simplifying Vibration Data Collection and Analysis

An Android phone and MATLAB make an easy solution to acquire data in the field and analyze in the comfort of the office

By Marco Peres, IMI Sensors

What makes the USB Digital Accelerometer (Model 633A01) a great device for data acquisition? Extreme portability.

Why not use a device most people already carry around? The smart phone.

An Android phone and MATLAB make an easy solution to acquire data in the field and analyze in the comfort of the office (Figure 1).

Figure 1: An Android phone and MATLAB make an easy solution to acquire data in the field and analyze in the comfort of the office. Courtesy: IMI Sensors
Since vibration measurements often occur in hard-to-reach places, lugging a laptop to acquire data may not be a convenient option. Recording data directly onto a phone and analyzing that data with a quick MATLAB program becomes an easy task with little user interaction.

**In the field**

Developing a graphical user interface (GUI) in MATLAB optimized to read .WAV files with Model 633A01 calibration information was straightforward. The Android data recorder app is optimized for use with Model 633A01. The USB digital accelerometer proves how feasible data collection on a phone has become. The phone can capture data from Model 633A01 and analyze it via computer in a few short steps. All that’s needed is a USB-to-micro-USB connector, a sensor, and a phone.

The USB audio recorder app by Daniel Sobe and Dr. Jordan is free and easy to use. This app can facilitate the acquisition and exportation of the collected data. In this application, the user placed the sensor on an air compressor and set up the app acquisition settings. The sensor had a magnetic base for mounting (Figure 2). This is one of many options that could be used such as bolting or gluing the sensor. Although a magnetic base allows the user to collect data on metal surfaces, the tradeoff for convenience is the accuracy of the higher frequency response.

After selecting a USB device, the app prompts for sample rate and sample resolution. The app offers a broad spectrum of sample rates and serves as a simple interface for quick data acquisition. All sample rates are supported by Model 633A01.
The user selected 8,000 Hz, deducing the vibration would be low frequency and 24 bits for best accuracy. Even better, the app writes complete calibration data into the .WAV file to ensure data scaling would be problem free.

After collecting initial data, the .WAV file, including the embedded full sensor calibration along with the measured data, was sent via email to a computer for MATLAB analysis. All files were placed in the same folder as the .WAV file analyzer. This is what makes the phone method of acquisition so appealing—it’s portable and there are many optional ways to transfer data.

The user then ran the .WAV file through the script, ‘633A01_Data_Analyzer.m’ for analysis. The GUI is user friendly and requires minimal input. It automatically does all scaling necessary to provide data in calibrated engineering units (Figure 4). The program reads information from the WAV file, including the scaling for engineering

![GUI](image)

Figure 4: The GUI is user friendly and requires minimal input. It automatically does necessary scaling to provide data in calibrated engineering units. Courtesy: IMI Sensors
units such as Gs and serial number, and can display them according to the user’s input settings. The scaling is traceable back to national standards.

Afterward, the user may input the desired settings and click on ‘Select File & Analyze’ to choose the data file. Although this requires the user to do little for the inputs, the GUI will still display accurate and precise data.

The GUI extracts the calibration information embedded in the .WAV file then displays the serial number, sample rate of the data, date of calibration, the length of measurement in seconds, sensitivities for the separate channels, average and instantaneous frequencies and magnitudes, the average and instantaneous frequency spectra, and the wave function. The program immediately displays scaled data according to the sensor’s sensitivity and creates readable graphs. The

Figure 5: Little effort was put into the data acquisition and analytical processes that can now be repeated for numerous test situations. Courtesy: IMI Sensors
return on the investment of time is huge. Little effort was put into the data acquisition and analytical processes that can now be repeated for numerous test situations (Figure 5).

The Android app makes it easy to record data with a phone instead of toting a computer around. This is especially appealing for users taking several tests at several different sites. The luxury of using the phone for recording is convenient and the GUI allows a quick analysis in the comfort of one's own office.

ABOUT IMI SENSORS

IMI Sensors, a division of PCB Piezotronics, Inc. manufactures industrial vibration monitoring instrumentation, such as accelerometers, vibration transmitters and switches that feature rugged stainless steel housings and survive in harsh environments like paper and steel mills, mines, gas turbines, water treatment facilities and power plants. Visit IMI Sensors at www.pcb.com/imi-sensors.
Remote wireless devices connected to the Industrial Internet of Things (IIoT) run on Tadiran bobbin-type LiSOCl₂ batteries.

Our batteries offer a winning combination: a patented hybrid layer capacitor (HLC) that delivers the high pulses required for two-way wireless communications; the widest temperature range of all; and the lowest self-discharge rate (0.7% per year), enabling our cells to last up to 4 times longer than the competition.

Looking to have your remote wireless device complete a 40-year marathon? Then team up with Tadiran batteries that last a lifetime.

* Tadiran LiSOCl₂ batteries feature the lowest annual self-discharge rate of any competitive battery, less than 1% per year, enabling these batteries to operate over 40 years depending on device operating usage. However, this is not an expressed or implied warranty, as each application differs in terms of annual energy consumption and/or operating environment.
Ultra-Long-Life Lithium Batteries Lower the Cost of Ownership

Ultra-long-life lithium batteries are being deployed throughout the IIoT to energize low-power remote wireless devices across all external environments.

By Sol Jacobs, Tadiran Batteries

Extended-life lithium batteries are supporting the Industrial Internet of Things (IIoT) by powering advanced functions that include supervisory control and data acquisition (SCADA), automated process control, and machine learning, to name a few. These technologies monitor structural stress, environmental quality, asset tracking, tank level and flow monitoring, energy usage, and more. Ultra-long-life lithium batteries are essential to powering these applications to reduce the cost of ownership by increasing system reliability, ensuring continuous data flow, and eliminating battery change-outs.

Primary batteries predominate

There are two types of low-power devices: Those that operate mainly in a “stand-by” state while periodically drawing pulses in the multi-amp range for an average current measurable in micro-amps, typically requiring an industrial-grade primary (non-rechargeable) lithium battery; and those that draw average energy (background current...
and pulses) measurable in milli-amps, typically requiring an energy harvesting device in combination with an industrial grade Lithium-ion (Li-ion) rechargeable battery.

Remote wireless devices are typically powered by primary (non-rechargeable) battery chemistries including alkaline, iron disulfate (LiFeS$_2$), lithium manganese dioxide (LiMnO$_2$), lithium thionyl chloride (LiSOCl$_2$), and lithium metal-oxide (see Table 1).

<table>
<thead>
<tr>
<th>Primary Cell (AA-size)</th>
<th>LiSOCl$_2$</th>
<th>LiSOCl$_2$</th>
<th>Li Metal Oxide</th>
<th>Li Metal Oxide</th>
<th>Alkaline</th>
<th>LiFeS$_2$</th>
<th>LiMnO$_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bobbin-type with Hybrid Layer Capacitor</td>
<td>Bobbin-type</td>
<td>Modified for high capacity</td>
<td>Modified for high power</td>
<td>Lithium Iron Disulfate (AA-size)</td>
<td>Lithium Manganese Oxide</td>
<td></td>
</tr>
<tr>
<td>Energy density (Wh/Kg)</td>
<td>700</td>
<td>730</td>
<td>370</td>
<td>185</td>
<td>90</td>
<td>335</td>
<td>330</td>
</tr>
<tr>
<td>Power</td>
<td>Very high</td>
<td>Low</td>
<td>Very high</td>
<td>Very high</td>
<td>Low</td>
<td>High</td>
<td>Moderate</td>
</tr>
<tr>
<td>Voltage</td>
<td>3.6 to 3.9 V</td>
<td>3.6 V</td>
<td>4.1 V</td>
<td>4.1 V</td>
<td>1.5 V</td>
<td>1.5 V</td>
<td>3.0 V</td>
</tr>
<tr>
<td>Pulse amplitude</td>
<td>Excellent</td>
<td>Small</td>
<td>High</td>
<td>Very high</td>
<td>Low</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
<tr>
<td>Passivation</td>
<td>None</td>
<td>High</td>
<td>Very low</td>
<td>None</td>
<td>None</td>
<td>N/A</td>
<td>Fair</td>
</tr>
<tr>
<td>Performance at elevated temp.</td>
<td>Excellent</td>
<td>Fair</td>
<td>Excellent</td>
<td>Excellent</td>
<td>Low</td>
<td>Moderate</td>
<td>Fair</td>
</tr>
<tr>
<td>Performance at low temp.</td>
<td>Excellent</td>
<td>Fair</td>
<td>Moderate</td>
<td>Excellent</td>
<td>Low</td>
<td>Moderate</td>
<td>Poor</td>
</tr>
<tr>
<td>Operating life</td>
<td>Excellent</td>
<td>Excellent</td>
<td>Excellent</td>
<td>Excellent</td>
<td>Moderate</td>
<td>Moderate</td>
<td>Fair</td>
</tr>
<tr>
<td>Self-discharge rate</td>
<td>Very low</td>
<td>Very low</td>
<td>Very low</td>
<td>Very low</td>
<td>Very high</td>
<td>Moderate</td>
<td>High</td>
</tr>
<tr>
<td>Operating temp.</td>
<td>–55°C to 85°C, can be extended to 105°C for a short time</td>
<td>–80°C to 125°C</td>
<td>–45°C to 85°C</td>
<td>–45°C to 85°C</td>
<td>0°C to 60°C</td>
<td>–20°C to 60°C</td>
<td>0°C to 60°C</td>
</tr>
</tbody>
</table>

Table 1. Comparison of primary lithium cells
Among lithium chemistries, bobbin-type LiSOCl$_2$ is overwhelmingly preferred for long-term deployments because it delivers the highest capacity and energy density, the widest temperature range, and the lowest annual self-discharge of all, especially well-suited for extreme environments (Figure 1).

Figure 1: Bobbin-type LiSOCl$_2$ batteries are preferred for remote wireless applications, delivering high energy density, up to 40-year service life, and the widest possible temperature range, making them ideal for use in inaccessible locations and extreme environments. Courtesy: Tadiran Batteries

**Keeping self-discharge low**

IIoT-connected devices, especially those that expend additional energy to power two-way wireless communications, need to conserve energy wherever possible. Energy-saving strategies include the use of a low power communications protocol (WirelessHART, ZigBee, Lora, etc.), low-power chipsets, and proprietary techniques to minimize power consumption during “active” mode. While useful, these schemes are typically dwarfed by energy losses resulting from self-discharge.

Self-discharge is common to all batteries as chemical reactions exhaust energy even when a cell is disconnected or in storage. The rate of annual self-discharge is affected by the cell’s current discharge
potential, the quality of the raw materials, and, most importantly, the passivation effect.

Passivation is unique to LiSOCl₂ batteries, as a thin film of lithium chloride (LiCl) forms on the surface of the lithium anode to limit reactivity. Bobbin-type cells are better able to harness the passivation effect than spiral wound cells that allow for greater energy flow.

Whenever a load is placed on the cell, the passivation layer causes initial high resistance and a temporary dip in voltage until the discharge reaction begins to dissipate the LiCl layer—a process that keeps repeating each time the load is removed. Passivation can be affected by the cell’s current capacity, length of storage, storage temperature, discharge temperature, and prior discharge conditions, as removing the load from a partially discharged cell increases the level of passivation relative to when it was new.

Passivation is essential to limiting annual self-discharge. However, too much of it can be problematic if it overly-restricts energy flow. Experienced battery manufacturers know how to optimize the passivation effect using higher quality raw materials and proprietary manufacturing processes.

**Powering two-way wireless communications**

Standard bobbin-type LiSOCl₂ cells are unrivaled for harnessing the passivation effect. However, the tradeoff is the inability to generate the high pulses required for two-way wireless communications due to their low-rate design. This challenge can be overcome with a hybrid battery that combines a standard bobbin-type LiSOCl₂ cell that delivers...
nominal background current in combination with a hybrid layer capacitor (HLC) that delivers periodic high pulses (Figure 2).

Figure 2: Bobbin-type LiSOCl₂ batteries can be combined with a patented hybrid layer capacitor (HLC) to deliver up to 40-year service life along with the high pulses required for two-way wireless communications. Courtesy: Tadiran Batteries

Other design considerations include the amount of current consumed in active mode (along with the size, duration, and pulse frequency); energy consumed while in “standby” mode (the base current); storage time (as normal self-discharge diminishes capacity); extreme temperatures during storage and in-field operation; equipment cut-off voltage — as battery capacity is exhausted, or in extreme temperatures, voltage can drop to a point too low for the device to operate (Figure 3).

Figure 3: Bobbin-type LiSOCl₂ feature the widest possible temperature range, modifiable for use in the cold chain, where temperatures can dip below -80°C. These batteries can also be modified to handle +125°C heat for specialty applications such as the autoclave sterilization of medical devices. 

: Courtesy: Tadiran Batteries and Awarepoint
Battery quality

Major differences exist between seemingly identical bobbin-type LiSOCl₂ cells. For example, a superior quality bobbin-type LiSOCl₂ battery can feature a self-discharge rate as low as 0.7% per year versus an inferior quality cell with a higher self-discharge rate of up to 3% per year, losing 30% of its capacity every 10 years to make 40-year battery life unachievable. By contrast, the higher quality cell can retain more than 70% of its original capacity, even after 40 years.

Specifying an ultra-long-life lithium battery can be difficult because the impact of higher self-discharge can take years to discover, and predictive models often underestimate the effects of passivation as well as long-term exposure to extreme temperatures. Where extended battery life is essential, it pays to perform added due diligence by demanding fully documented long-term test results along with historical in-field test data involving comparable devices under similar loads and environmental conditions (Figure 4).

Pay more attention when comparing batteries and pay less over the operating life of remote wireless devices.

Figure 4: Resensys structural stress sensors mounted beneath bridge trusses require extended life bobbin-type LiSOCl₂ batteries to reduce the need for costly and dangerous work to replace batteries in such hard-to-access locations. Courtesy: Resensys

ABOUT THE AUTHOR

Sol Jacobs is vice president and general manager of Tadiran Batteries. He has more than 30 years of experience in powering remote devices. His educational background includes a BS in engineering and an MBA.
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WITH OUR FULLY AUTONOMOUS MATERIAL HANDLING VEHICLES YOU CAN:
Machine learning (ML) methods based on deep neural network models have made breakthrough strides in the automated perception of data including the interpretation of images, speech, and text. Research results hold a promise of the next leap in automation levels, but there are also challenges concerning data, engineering, processes, and communication important for successful adoption of this technology. Addressing these challenges will be key to getting technology beyond pilot phases and into operational deployments.

Industrial factory automation relies on various sensors like cameras, light detection and ranging (LiDAR), light curtains, radio-frequency...
Identification (RFID), and encoders to provide the needed perception capabilities for numerous applications (i.e., sorting, robot picking, and quality inspection). Computational algorithms, broadly referred to as artificial intelligence (AI), process raw sensor data to extract relevant information and form decisions. Traditional algorithms consist of rules and mathematical operations designed and parameterized by human experts. For example, one application is to discard a produced item if a hole dimension is not within a given tolerance threshold (Figure 1). The mathematical operations to extract the hole dimension from an image and to set the tolerance threshold value are design questions for human domain experts.

**Machine learning advantages**

ML offers a different algorithmic approach to the previously mentioned inspection problem in which the human handcrafting is replaced by an optimization of the parameters in a machine learning model that maps the raw sensor data as input to the desired output decision to reject the item or not. What is ultimately left for a person to complete is giving examples of correct mappings (i.e., to supply training images of holes with the right and wrong dimensions).

An advantage of the ML approach is that the underlying mathematical optimization procedures can handle millions of model parameters, something a human worker would not have the capability to do. It also can find solutions not obvious to a human. However, a consequence of this advantage is the ML solution often becomes a black box where the internal decision mechanisms cannot
be fully understood, which has potential consequences for lifecycle management and general trust in the system.

The use of deep neural network models has been shown to outperform human handcrafted algorithms within the machine vision and speech understanding domains (Figure 2). A deep neural network is an artificial neural network with multiple layers between the input and output layers. These networks assist with deep learning capabilities for quality inspection applications.

For factory automation, one application of deep neural networks is to mimic the outstanding human visual perception by optimizing the neural network to reproduce human responses to visual data for tasks like visual defect inspection, localizing objects in the camera field-of-view, sorting based on visual appearance, or spotting foreign items in food production. Related disciplines also are seeing strong development, including robotics, data connectivity, Internet of Things (IoT), miniaturization of computing power, and cloud technology.
Opportunities for advancing deep learning technology

Regarding identifying different types of opportunities for advancing deep learning technology, with a special focus on sensor technology, an emphasis is placed on opportunities expected to become reality within the next decade, based on already demonstrated algorithmic improvements. Long-term predictions in the AI domain are difficult, given the complexity of the problems and the current development pace.

Opportunity 1: Sensor perception. The most obvious way deep neural networks may contribute to more efficient production processes is by automating tasks that have not been possible by means of conventional algorithms. Until now, such tasks have required the interpretation skills of a human or were not possible at all.

Applications where camera and LiDAR sensors are used can be characterized by the need to recognize spatial relationships, such as shape and distances. In other applications, temporal relationships may carry the information, like a vibration pattern. Deep neural network architectures for such applications can draw on results and research within the speech recognition field. There are several industrial sensors producing measurements that can be analyzed as a time series, including sensors for acceleration, motion, flow, temperature, pressure, distance, and proximity.

Opportunity 2: Measurement utilization. While predictions around AI typically often revolve around solving new automation applications, an overlooked aspect is to use improved perception skills to simplify existing applications with a more efficient utilization of the measurement data. A straightforward example would be to replace high-resolution 2D cameras with lower resolution ones, but one also can foresee examples where a 2D camera plus improved AI can accomplish the same task as a larger 3D camera.

Trends in this direction can be seen within the robotics domain where deep neural networks trained on CAD models can estimate the six-dimensional pose, 3D location, and 3D orientation of an object from a 2D image. A practical consequence may be that one can make lighter and small-sized sensor solutions that fit in more narrow spaces.
Opportunity 3: A new configuration paradigm. A key property of ML and deep neural network approaches is that they are configured in a fundamentally different way compared to a traditional algorithmic approach. This is typically done through a well-defined procedure from collecting the raw data, annotating the raw data, training, and finally deploying a neural network.

“A deep neural network is an artificial neural network with multiple layers between the input and output layers.”

Opportunity 4: Post-deployment improvement. There also is a clear path of how the performance of a deployed deep neural network system may be improved by continuously increasing the training data set and retraining the network models. This can be especially useful in cases where there is an imbalance in the training data.

For example, in a machine vision defect inspection system, it is common to have an abundance of training data from the “ok” class, but fewer examples of defects as they occur less frequently. A deployment can be made using an initial training data set and then, subsequently, be improved upon as more examples of the defect class are collected. However, current deep neural network systems do not adaptively self-tune during operation, but a retraining with new human-labeled data is needed.

Opportunity 5: Sensor data quality. Deep neural network applications mentioned so far operate on output data from an industrial sensor. Inside most sensors, there is a low-level measurement core where processing is carried out to produce the output measurements. 3D reconstruction in time-of-flight and stereo cameras are high-level examples of such processing.

As low-power edge computing becomes more powerful, deep neural networks and other ML models can be applied deeper into
the sensors with the aim of producing higher quality measurements. Further use could be sensor self-monitoring to detect operation anomalies such as dirt or moisture on a camera lens.

**Challenges with deep neural networks**

Reaping the benefits of deep neural networks, AI does not come without challenges.

**Challenge 1: Managing expectations.** The scientific AI field has experienced several so-called “AI winters,” during which funding and interest went down significantly due to overinflated promises and expectations that could not be realized. While the latest AI results are directly applicable in industrial manufacturing systems, a challenge for the coming decade is to maintain the readiness to invest by communicating balanced predictions and descriptions that set realistic expectations.

**Challenge 2: Energy efficiency.** Deep neural network models are computationally intensive and consume significant amounts of energy to train and use. To scale up AI in a sustainable way and to be able to deploy deep neural networks within small, embedded hardware, attention to energy efficiency is required. There are two ways to address this, both of which are being pursued currently: To shrink the deep neural network sizes, both in terms of the number of parameters and in terms of numerical precision; and to design dedicated energy efficient hardware, ASIC, FPGA, and similar, for deep neural networks.

**Challenge 3: Labeled data.** Deep neural network systems are configured by training data sets. Data management and human data labeling are bottlenecks in the adoption of AI and deep neural networks. Research efforts are ongoing into methods to reduce the amount of data needed for training deep neural network models, for example, the ability to use a network pre-trained for some other tasks and adjust it for a new task.

Reducing the model network sizes works toward this end as well. Even if the amount of labeled data needed for network training can be reduced, there also is the need for labeled test data to verify the accuracy
of the trained neural network. For example, say one manages to train a deep neural network for a machine vision inspection task using only 50 labeled example images. The network still needs to be verified using many more test images before deciding to deploy it into real operation.

**Challenge 4: Fusion with other models.** In industrial automation systems, there are already plenty of geometric and mathematical models in use that describe prior knowledge of sensors and the production process. Examples include CAD models, camera calibration models, or the laws of physics. It is an open research question how a deep neural network can incorporate the information represented within other more specific models. For example, how can a deep neural network be used to find deviations in a produced item relative to a reference CAD model? Currently a deep neural network must re-learn the information encoded in other models through observations, which is inefficient and prone to errors.

**Challenge 5: Batch size one.** The ability to manufacture individually designed products with the same efficiency and quality as in mass-production lines is a central vision in the digital transformation (Figure 3). Using deep neural networks in such a setting raises the question of coping with the product variability: How can quality assurance be automated when every manufactured object is different?

Figure 3: Coping with product variability in the production line is a challenge for AI and deep neural networks. Example industries include textiles, car manufacturing, and electronics. Courtesy: SICK
Challenge 6: Lifecycle maintenance. Industrial systems have a long lifespan compared to consumer electronics and applications; more than 10 years of operation is not unusual. Considering the fast-moving pace AI is developing including the architectures and software used for training and deploying deep neural networks, a question to ask is: How can AI solutions deployed today be maintained over a 10-year period or more?

Challenge 7: Safety-critical systems. Like self-driving cars, there are industrial applications that include aspects of human safety such as anticollision systems for mobile or collaborative robots (Figure 4). Given the black box nature of deep neural networks, how are they tested and certified for safety-critical applications? One aspect of this issue is to get standardized qualification processes in place.

Figure 4: Self-driving cars use deep learning to find objects in the environment. With availability of data, computational power, and open-source algorithms, adoption has increased. Courtesy: SICK
Another issue is to make deep neural networks pass the tests applied by making them fault-tolerant to unusual events and disturbances in inputs or in hardware. A special kind of vulnerability is adversarial attacks, which are intentional modifications of the input data. One example is to put specially designed patterns in the view of a camera that are known to confuse an already trained deep neural network to make erroneous predictions (Figure 5). Another example is to contaminate the training data set with the purpose of making a deep neural network trained on it misclassify or ignore certain patterns in the data. Keeping the training data secure and reviewed is important.

Figure 5: One way to make deep neural networks fault-tolerant to unusual events and disturbances in inputs is to put specially designed patterns in the view of a camera that are known to confuse an already trained deep neural network to make erroneous predictions. Courtesy: SICK
Looking ahead

Soon, deep neural network research results will be transferred into operative factory automation deployments. The main driver is improved sensor data perception capabilities through which more tasks and decisions can be automated. To maintain the current development momentum and to realize more opportunities, attention must be paid to the challenges that exist with deep neural network technology.

New types of jobs will be created within factory automation with the tasks to create labeled data sets, maintain, test, improve, and retrain deep neural networks or other machine learning models to new situations or products. Industrial automation is characterized by myriad specialized tasks. Consider the different manufactured products that can be quality-inspected at various production steps, each requiring its own labeled data set. Bringing out deep neural networks in factory automation will be a more decentralized effort that takes place closer to the individual applications.

ABOUT THE AUTHOR

Divya Prakash is the director of business consulting and Industry 4.0 at SICK. With more than 30 years of experience in the industrial automation industry, he has expertise in engineering and business consulting with an emphasis on Industry 4.0 solutions. He has extensive knowledge in digital transformation, supply chain management solutions, and manufacturing operations management solutions.
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