PLANT ENGINEERING 2020 eBook Series

CONTROL ENGINEERING 2020 eBook Series

kontron S&T Group

Contents

With AI, zero failure is more than a pipe dream

Improve confidence with a complete view of data.

Everyone in our business knows—or ought to know—about the pipeline maintenance crisis that puts billions of dollars, lives, property, and the reputation of mid-stream oil & gas industry at risk, leading some in the public to call it a "ticking time-bomb." Statistics indicate tens of thousands of miles of pipes decades beyond their predicted end-of-life, scattered so wide and buried so deep that just finding them on a map can be a problem.

No one is happy with this situation, but it's not easy to solve. Pipeline integrity teams already are asked to perform miracles with the data generated from traditional inline inspection (ILI) tools, to analyze vast spreadsheets that typically represent only 5% of the data collected. What if the answers are in the other 95%? What happens when new laser scanning technology increases the volume of data exponentially, without any new tools to make sense of it all? And what happens when the senior-level experts who have been keeping everything running for decades retire to spend their days playing golf and passing time with their grandchildren?

Those are the kind of problems keeping risk managers, CFOs, and CEOs awake at night. Today's expertise and technology is, at its very best, able to hold the line against catastrophic failures. Given the challenges ahead, is it even conceivable to imagine reducing failure risk to zero?

We think it is. Here's why.

Digital transformation for pipeline operators

Folks use the term "digital transformation" as a buzzword for the investments being made in technologies like artificial intelligence (AI), machine learning, augmented reality, robotics, and wearables taking place across the business world. McKinsey and Accenture recently estimated that digitalization has the potential to create as much as $1 trillion in value for oil & gas companies.

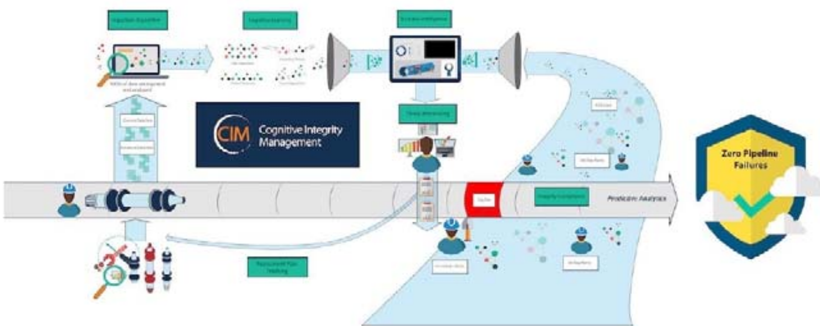

Figure 1: *Artificial intelligence is being applied to pipeline management based on its ability to identify patterns in data that are not always intuitively obvious to humans. Courtesy: OneBridge*

AI may be the technology promising the most impact—particularly when applied to pipeline management. AI systems aren't actually "intelligent," of course, but they are trained to recognize in Big Data sets patterns that look like problems or issues worthy of human attention. At scale, they can churn through billions of data records to spot everything from suspicious network activity to fraudulent financial transactions, if they know what to consider a problem. The more data these systems look at, the more precise and confident they become in finding what they're looking for.

That has a bunch of big payoffs for pipeline management. First, you will analyze 100% of your data, as compared to the likely 5% that organizations leverage today to assess safety risk, and can increase that analytical capacity at almost no marginal cost. In fact, costs will probably be reduced by freeing up analyst time and effort by automating the most time-consuming, repetitive parts of their job.

Second, depth of confidence improves based on a more complete view of the data. Think of the millions of dollars that pipeline operators waste every year because they don't believe their data and err on the side of safety by digging where they don't need to. Sure, it's better to be safe than sorry when it comes to risk exposure. On the other hand, there are financial costs to being over-cautious—costs that organizations can eliminate by having clear and precise data on the exact status of every square inch of pipe along thousands or tens of thousands of miles of run.

Bringing data into the business

When we first started OneBridge in 2015, we felt we had a good handle on the technology required to automate the repetitive tasks related to pipeline data analysis that experts hate. Now that we've spent several years working with some of the top companies in the business, more capabilities have been added to our system to benefit operators on everything from assessment planning to integrity compliance to threat monitoring. With each new release, including the latest, Cognitive Integrity Management 3.1, the product is getting smarter about how it analyzes and identifies problems, and smarter about how to make adoption easier for customers.

These capabilities take the platform beyond the basic ability to interpret pipeline data by bringing that data into the mainstream of the business. For workgroups and managers responsible for assessment planning, it's easier to automate, schedule, and monitor many of the project tasks associated with maintenance. Tools have been incorporated that enable regulatory compliance by monitoring a range of technical threats and documenting the integrity of business processes end-to-end.

> **"Listening to customers it's clear they want better reporting, data visualization, and integration with standard analytics tools like Microsoft Power BI."**

New monitoring and reporting features have been added that empower teams to collaborate around threat monitoring data, smoothing the path from insight to action. Listening to customers it's clear they want better reporting, data visualization, and integration with standard analytics tools like Microsoft Power BI. Along these lines, the ability of OneBridge to interoperate with other systems across the enterprise has been enhanced.

Moving forward, part of the mission will be looking for unique and exciting ways to get that data to field crews to make digs faster, more precise, and less costly, so operators can maintain their networks with greater confidence and less expense.

Getting to zero failures

For some people, AI can have sinister connotations, including the replacement of humans with computers. Rest assured, tools like OneBridge are about getting customers to zero failures, not zero employees. For the past 20 years, pipeline integrity experts have been waging a valiant battle against aging infrastructure with inadequate tools and inadequate resources, incurring the wrath of management when they fail, but garnishing little notice or attention in their daily triumphs, despite the odds.

As those people head toward a well-earned retirement, organizations need to embed their knowledge and experience in systems so that their successors can step into new roles without any reduction in operational excellence. Investing in AI-based tools can move that process forward while at the same time it delivers the other benefits of greater confidence, greater data coverage, and reduced risk. It also demonstrates to next-generation workers that the company is willing to invest in modern solutions.

No one can stop the hands of time as they affect our pipelines, organizations, or workforce, but interested parties can get out in front of the problem instead of giving everything they've got just to fight it to a standstill. AI is the industry's secret to stop playing defense and start moving toward the goal of zero failures. It's not a promise, a vision, or a pipe dream. It's here today and getting smarter by the minute.

Tim Edward and Rob Salkowitz
Tim Edward and Rob Salkowitz, OneBridge Solutions.

How automated anomaly detection can maximize production

Industrial artificial intelligence/machine learning (AI/ML) software and long-range sensors predict maintenance requirements across entire enterprises, increasing productivity and profits.

For product manufacturers, profitability requires safely maintaining efficient operation, minimizing expenses, and reaping as much production from plant equipment as possible. When plants are new, efficiency and reliability are not among highest concerns, but as equipment ages, unanticipated failures and the resulting reactive repairs often become problematic.

Plant personnel can address this issue by accessing equipment data to identify problematic equipment requiring maintenance. The problem is manually analyzing data to generate insights requires a great deal of time, expertise and operational knowledge. Custom artificial intelligence/machine learning (AI/ML)-enabled software removes most manual data analysis. The problem is this type of software can be cost-prohibitive to implement and maintain.

Off-the-shelf AI/ML software, such as data logging software, deliver automated anomaly detection and alerting, empower personnel to identify equipment issues before failures occur. This software often serves a second purpose as a centralized repository for multiple devices' data, including data captured by an Industrial Internet of Things (IIoT) long-range wireless sensor system. These types of off-the-shelf AI/ML software solutions increase operational efficiency, prevent equipment problems, and allow plants to plan maintenance prior to equipment failure.

Figure 1: *An AI package consisting of a sensor, software to collect and analyze data, and a recorder to visualize data. Courtesy: Yokogawa*

Three development goals for AI-enabled products

An off-the-shelf AI/ML software solution prioritizes achievement of three goals:

1. Maintain healthy conditions in equipment: Log all equipment output, including deviations from the baseline.
2. Anticipate equipment maintenance via abnormal sign detection: When equipment variables begin to stray from normal values, the software flags this behavior and alerts personnel to take maintenance measures prior to failure.
3. Make AI accessible: End users do not need to be AI experts or contract expensive consultants to configure the software as it is usable by personnel of many skill levels.

In the industrial automation space, a complete AI package includes sensors and controllers to gather data, PC-based software to organize and automatically analyze the data using AI/ML, and a recorder to visualize data (Figure 1).

AI/ML software orients personnel to normal operational levels based on past performance and notifies them when an anomaly is detected.

Anomaly detection and predictive maintenance

Warning, alerting, and alarming are nothing new by themselves, as control systems often possess user-adjustable high, low, deviation, and out-of-range setpoints. When equipment data exceeds the applicable setpoint, the user is notified.

Automated anomaly detection offers significant improvements beyond these automated functions.. When AI-enabled software is first deployed, it undergoes a learning phase during which it monitors the equipment conditions to build a baseline for known, normal operation. Time dedicated to the learning phase varies by application and can be user-defined.

Once the learning phase is complete and a normal operation baseline is established, the AI/ML software begins automatically monitoring the equipment, build reports for personnel review and generate anomaly alerts when operation deviates from its baseline. These alerts provide users advance warning of potential equipment problems.

AI/ML software should offer ease of configuration and user-friendly parameter changes, simplifying these and other types of adjustments. The degree to which current equipment data matches the normal baseline can be given as a health score, signaling advance notice of an abnormality if something is negative (Figure 2).

In addition to identifying abnormalities before equipment failures occur, AI-enabled software is ideal for creating predictive maintenance forecasts. As equipment data deviates from the baseline, AI/ML software shows a declining health score. Maintenance operators can use this indication to determine timelines for scheduled equipment maintenance prior to potential failure. These automated visual insights free up time for tasks besides data analysis and maintenance scheduling.

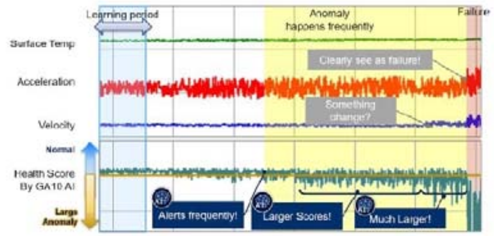

Figure 2: *An example of anomaly detection, in which an AI/ML software's health score indicated signs of an abnormality prior to equipment failure. Courtesy: Yokogawa*

AI-enabled software functions

Many software suites can wrangle data from multiple devices and measurement points on a network into one location, allowing users to visualize the data using graphs and charts. However, data visualization alone does not inform on the normalcy of the data being viewed. To deal with this problem, AI/ML software employs algorithms that automatically overlay trends and highlight anomalies on the graphical user interface.

With certain types of equipment data, such as temperature or pressure, it is often possible, if not always ideal, to use classical methods of high or low limit setpoint warnings to detect an abnormality. However, for data such as motor speed or the vibration of a machine, it is difficult to understand if the equipment data is normal without manual and meticulous historical data analysis. This manual analysis is time-consuming and requires a skilled data analyst with extensive expertise, but these experts are in short supply. AI-enabled software transforms this tedious manual process into instant automated insight, comprehensible by all staff (Figure 3).

AI/ML software uses a clustering algorithm to detect anomalies. This means anomaly detection is not limited to data following linear, quadratic or other basic functions. Advanced AI-enabled software creates correlations among multiple equipment data points when it determines a normal baseline, and detects when the relationships are abnormal during operation.

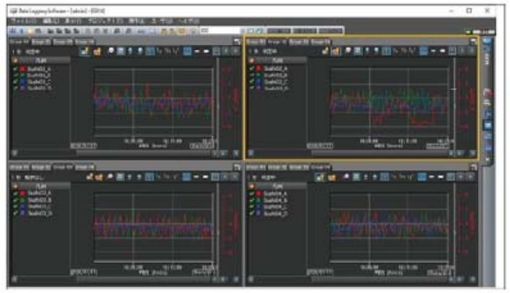

Figure 3: *AI/ML software highlights an anomaly screen at upper right with an orange outline. Courtesy: Yokogawa*

Automatic anomaly detection frees personnel from manual analysis, and it often detects problems missed by data examined using visualization tools such as charts and graphs. This added capability typically results in increased uptime and lower maintenance costs.

Long-range sensors improve data collection capabilities

In the age of IIoT, it is not practical to limit data collection to stationary and accessible processes and areas. Applications like mobile machines and vehicles, rural outpost facilities, and lengthy pipelines generate data worth gathering and analyzing, but also present obstacles regarding non-stationary, long-range and low power data transmission. Low power wide area network (LPWAN) systems address these and other issues and are being used across many enterprises to capture data in difficult applications.

A few noteworthy characteristics of LPWAN sensors are:

- They consume minimal power, hence batteries can last several years
- They provide long-range wireless data transmission, capable of transmitting data over several miles
- Highly efficient communication protocols, resulting in lower data usage requirements than 3G, 4G, and 5G.

Each sensor measures vibration, temperature, or pressure, delivering monitoring capabilities for equipment located just about anywhere (Figure 4). A long-range wide-area network (LoRaWAN, a subcategory of LPWAN) enables a connected enterprise without the necessary provisions for wired lines or IEEE 802.11 Wi-Fi.

Figure 4: *Yokogawa's long-range Sushi Sensor system can transmit equipment data wirelessly over long distances to a LoRaWAN gateway. Courtesy: Yokogawa*

Data transmitted by the sensors can be supplied to host systems, including AI-enabled software. By using the wireless sensors in conjunction with AI anomaly detection software, plant personnel receive a clear window into the operational health and maintenance needs of equipment, no matter where it is located (Figure 5).

Detecting anomalies

Detecting an anomaly does not guarantee a failure will occur, but it is almost always of interest to plant personnel. If anomalies were easily spotted or could be produced on

How automated anomaly detection can maximize production

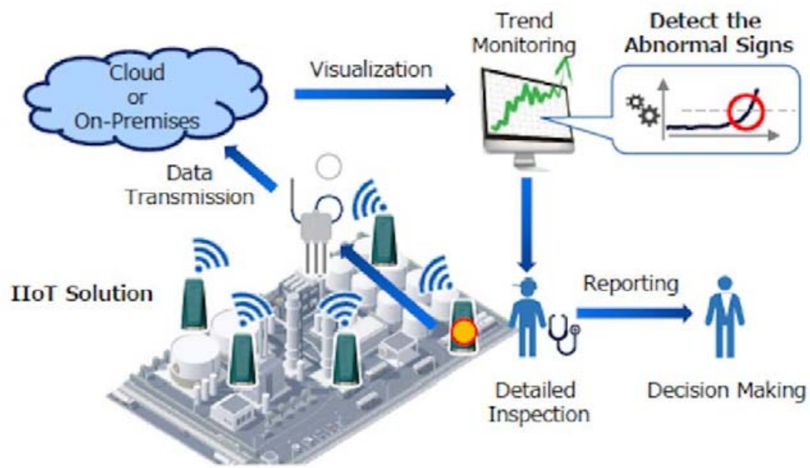

Figure 5: *This system uses the LoRaWAN communication protocol to wirelessly transmit data to a central source from equipment located almost anywhere. Courtesy: Yokogawa*

demand, there would be no need for AI anomaly detection. However, it is often difficult to produce and acquire abnormal data to create a manual reference point for identification. This challenge is addressed by AI.

After recording equipment conditions during its learning phase, AI-enabled software can detect the slightest anomalies, even if the software has never been exposed to abnormal data in the past. Maintenance personnel can identify which equipment requires maintenance or inspection from the detected anomalies.

How automated anomaly detection can maximize production

Although anomaly detection is already a helpful tool for plant personnel, AI/ML software feature development continues. Rather than only identifying anomalies, the goal is to develop AI-driven control to prevent them from occurring in the first place.

AI as an alternative to equipment replacement

As plants age, equipment becomes less efficient and reliable. At some point, maintenance and repair may become too costly and time-consuming, and equipment replacement may be necessary. This may be the best course of action in some situations, but AI/ML software can reduce maintenance costs to tenable levels.

Using AI-enabled software for analysis and anomaly alerting — in conjunction with reliable, adaptable wired and wireless sensors – extends equipment life, reduces maintenance costs, and increases uptime. Off-the-shelf AI/ML software is a cost-effective solution to provide quick insights into the sources of plant inefficiencies and failures. This capability can add years to an asset's life by predicting problems and allowing planned minor maintenance prior to complete equipment failure and costly repair or replacement.

Takayuki Sugizaki

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Quality is the key

AI-supported digital inspection systems ensure higher quality in production

In their quest for greater quality and productivity at reduced costs, manufacturers across all industry sectors are looking to harness the Internet of Things (IoT) to AI 'machine learning' and 'deep learning' quality inspection applications.

According to a recent survey by Deloitte, machine learning enables as much as 35% increases in quality. Analyzing production lines in real-time using visual inspection processes allows product quality issues to be highlighted and addressed proactively. This is in line with increasingly adopted Zero Defects manufacturing best practices which advocate no waste, thereby eliminating the real costs of defects: inspection and rectification, material wastage, additional labor, lost revenue, and customer dissatisfaction.

Next generation visual inspection systems

By applying machine learning to digital image processing, inspection systems are therefore playing an increasingly pivotal role in raising the bar on quality. By automatically processing, manipulating and interpreting information received from machine sensors and cameras, powerful software algorithms identify anomalies occurring during the actual production process, triggering alerts when necessary. Apart from being very fast, totally objective and immune to fatigue – unlike laborious, error-prone human visual inspection techniques – these next generation vision inspection systems not only improve quality but also boost productivity and reduce unnecessary materials wastage and costs.

Going even further, especially for production line applications where there are many variables or subtle nuances, 'deep learning' systems based on neuronal networks algorithms are also emerging. From the outset, as part of the training of such algorithms, thousands of images from many different angles and perspectives are used as reference examples. Applied to machine vision systems, these learn to differentiate and decide intuitively between 'normal' and flawed visual images - without human intervention. They are also very flexible, easily adapting between production runs and different products or components. Thus, automated visual inspection systems applying powerful AI technologies are set to become an integral part of many modern industrial-scale production processes, from food to aircraft manufacturing.

Focus – printing industry

The printing business today is more competitive than ever. Maximum productivity, minimum waste, consis-tency and high quality are essential with even the smallest defects during print production having the po-tential to impact the quality of entire print runs. The risk of defects is ever present, caused by a number of factors, from malfunctioning print nozzles on printers to ink splashes, scratches, paper creases, not to mention color and register deviations.

Kontron's new KISS V3 4U SKX server supports next generation AI inspection systems for production environments.

Typical challenges:

- Human error
- Faulty print nozzles
- Paper creases
- Color and register deviations

With so much at stake, the traditional visual inspection of individual sheets by humans has become increasingly unviable in recent years. Not only is this approach highly subjective and laborious, it is expensive in terms of labor. Automated computer vision inspection systems, equipped with innovative image processing technology utilizing line scan cameras or integrated contact image sensors (CIS), are therefore increasingly deployed.

CIS systems can be mounted in printing machinery close to the flat printing surfaces being inspected. Due to their compact design, they take up minimal space in space-constrained printing presses. The line scan cameras, on the other hand, can score with a higher speed as well as with a flexible and overall better resolution than the CIS scanners. Inspection data is processed in real-time, providing comprehensive reporting and alerting on print quality.

Industrial 3D Printing

Visual inspection technologies are equally applicable to industrial 3D printing. In fact they are seen as essential to driving future demand from many manufacturers looking for greater quality control assurances over component strength and reliability. After all, 3D printing may offer huge potential to produce previously impossi-ble designs, but the difference of a few microns in the geometry of a machine or vehicle component could at the very least prove disruptive, at worse, a matter of life and death.

Typical 3D printing challenges:

- Concerns over consistent parts quality
- Monitoring of multiple parameters
- Insufficient computing power

Quality is the key

Industrial 3D printing, also known as additive manufac-turing (AM), produces objects by layering materials such as metals, composites, or polymers to produce a three-dimen-sional part. Achieving quality control in AM involves greater command over parameters other than geometry. Among others, these will include laser power, laser scan speed and build chamber temperature. Each contributes to the outcome of a build and even the slightest change could impact final part quality. There-fore, for the avoidance of defects and ultimately to guar-antee quality, highly accurate simulations are necessary for creat-ing build plans that adjust input parameters dynamically.

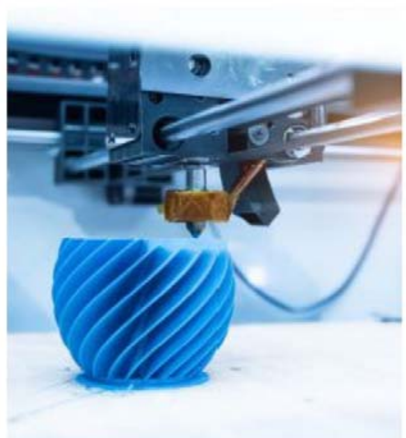
Until recently, specialized, high performance computing resources have been potential limiting factors in the future advancement of quality control for industrial 3D printing. Access to the computing power necessary has been a major obstacle, for handling the unprecedented volume of video data generated during real-time 3D printing pro-cess monitoring. However, as demand grows for AM in production environments, pur-pose-designed simulation software is becoming more widely available. Combined with new AI-enabled 'deep learning' capabi-li-ties and the latest powerful computer hardware plat-forms using high-perfor-mance GPUs, many more manufacturers can gain access to the real-time visual inspection and quality control systems they've been waiting for.

Powerful and reliable server solution for automated in-spection systems

Quality is the key

Kontron has recently introduced a new high perfor-mance industrial server for meeting the growing real-time processing and storage requirements of AI-enabled monitoring and inspection systems. The KISS V3 4U SKX server is well-suited to demanding pro-duction environments and therefore ideal for data- and graphics-intensive image processing and machine learning applications. The KISS V3 4U SKX features Dual Intel® Xeon® SP series processors, allowing real-time compute-intensive processes for analysing large amounts of data. Up to three double width high-end GPU cards (NVIDIA® TESLA® V100, NVIDIA® T-4 GPU) ensure extremely high GPU performance, and for extended storage, up to eight 2.5" storage trays can be installed.

Like the company's other KISS server plat-forms, the super-powerful KISS 4U V3 SKX can be used 24/7 and is based on industry standard components, enabling ease of configuration and ease of maintenance. The flexible, modular design also allows easy ad-aptation to custom-er-specific requirements. The consistent use of compo-nents with long-term availability (5+ years) ensures systems are well-suited to meeting manufacturers' needs for longevity. The KISS Rackmount Sys-tems optionally support TPM V2.0 encryption for secure cloud connection as well as the Kontron APPROTECT se-curity solution. The integrated security chip from Wibu-Systems in conjunction with a suitable software frame-



AI-enabled visual inspection technologies ensure highest quality in industrial 3D printing work protects IP rights and provides copy and re-verse engineering protection.

At A Glance

- Industrial grade for challenging environ-ments: robust, reliable and sustainable
- Maximum performance up to 8th Gen Intel® Core™ i3/5/7 or Dual In-tel® Xeon® processors
- Supports up to 3 double width high-end GPU cards for breakthrough 'multi precision performance' (e.g. NVIDIA® TESLA® V100, NVIDIA® T-4 GPU); alternatively 1GB/10GB Ethernet cards (e.g. for connection of IP cameras for surveillance systems)
- Powerful power supplies from 800W up to 1200W (sufficient for the operation of 3 high-end graphics cards)
- Extended storage possibilities with up to eight 2.5" storage trays
- NVMe interface for connecting SSDs via PCIe
- Supports Intel® Rapid Storage Technology enterprise Option RAID 0/1/10/5
- Remote Management by AST2500 BMC module
- Low noise level
- Modular and flexible concept for easy customization
- Long-term availability (5+ years)
- Tool-free replacement of fans, filter mats, or hard disk drives in the removable tray
- Microsoft Azure certified, TSN functionality optionally

"For ensuring consistently high quality and cost optimization in 3D printing, Kontron's latest KISS server complements our data-intensive build simulation software by supporting our growing need for high-end computing and stor-age. The high performance KISS server with high-end GPU cards is well-suited to many systems designers and OEMs developing and deploying AI image processing or machine vision solutions."
-Software Designer, Industrial 3D printing systems

About Kontron – Member of the S&T Group

Kontron is a global leader in IoT/Embedded Computing Technology (ECT). As a part of technology group S&T, Kontron, together with its sister company S&T Technologies, offers a combined portfolio of secure hardware, middleware and services for Internet of Things (IoT) and Industry 4.0 applications. With its standard products and tailor-made solutions based on highly reliable state-of-the-art embedded technologies, Kontron provides secure and innovative applications for a variety of industries. As a result, customers benefit from accelerated time-to-market, reduced total cost of ownership, product longevity and the best fully integrated applications overall.

For more information, please visit: www.kontron.com

AI-based maintenances improve pump uptime

Data-driven information supports advanced predictive maintenance.

Industrie 4.0 and digitalization offer optimization opportunities for operations and maintenance functions. Innovations such as digitalization, artificial intelligence (AI), machine learning (ML), neural networks, and cloud computing have raised the capability to collect, analyze and trend equipment condition/health in real time.

With these advanced monitoring equipment and analytics methods, reliability engineers can step up predictive maintenance (PdM) programs to achieve profitability goals, including:

- Optimizing critical assets' service life
- Minimizing unscheduled downtime
- Controlling maintenance costs
- Improving plant safety and operations.

Maintenance can be a profit center

Energy, power and chemical/petrochemical processing plants are very complex and complicated facilities. Numerous equipment and infrastructure items manage, contain and store feedstocks, process fluids and gases. Decreasing process unit and plant downtime due to unavailable equipment and systems are central to improving company profits.

Mechanical failure is the leading cause of processing industry accidents (Figure 1), while equipment failures result in 36% of unscheduled plant shutdowns (Figure 2). Creating better maintenance and planning programs increases operational excellence and facility uptime.

'Smart' maintenance profitable

According to a recent McKinsey report, PdM can increase asset availability (either process unit or equipment) by 5% to 15%. Optimized PdM activities lengthen the service life of key assets by 20% to 40%. More importantly, PdM effectively can reduce maintenance costs by 18% to 25%. Improved monitoring and early proactive maintenance significantly reduce repair and replacement costs for key processing equipment and minimizes unscheduled downtime and lost productivity. In addition, unexpected equipment failures may result in losses greater than the replacement value of the asset.

PdM benefits

In general, rotating and reciprocating equipment have the highest failure rates (Figure 3). Vibration problems are predominant root causes for rotating equipment failures, especially pumps. All rotating equipment vibrates, however, the changes in vibration levels over time are indicators of

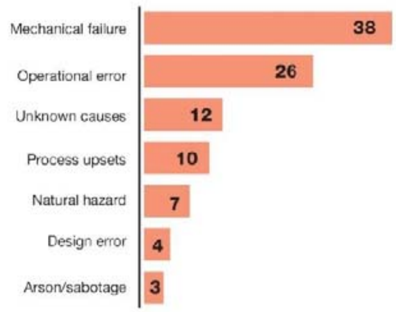


Figure 1: *Root causes for accidents and safety events occurring in the processing industry. Courtesy: Nanoprecise Sci Corp.*

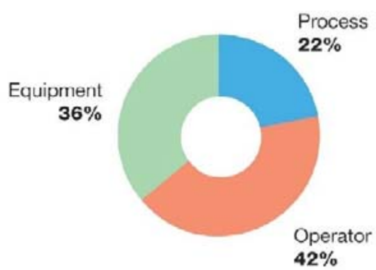


Figure 2: *Root causes for unscheduled downtime occurring in the processing industry. Courtesy: Nanoprecise Sci Corp.*

possible problems. In the hydrocarbon processing industry, about 7% of the pumps in use consume 60% of the money spent on pump maintenance and repair. Finding and addressing the root causes for vibration or temperature changes supersedes just treating the symptoms.

To avoid repeat failure, pump owners must push routine maintenance practices to a superior level. Increased use of smart manufacturing strategies and cloud computing can raise the integrity of PdM activities.

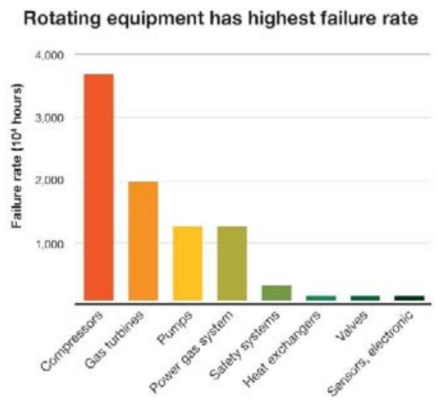


Figure 3: *Failure rates for major plant equipment. Courtesy: Nanoprecise Sci Corp.*

Not a new concept

Since the 1970s, maintenance and reliability engineers installed stress (piezoelectric) sensors to monitor and detect performance issues on pumps and motors. Unfortunately, these early methods encountered trending and continuity problems with data collection. These vibration sensors often operated at different frequencies and amplitudes and had their own baseline signatures.

Deciphering collected sensor data into usable information required interpretation by data scientists. Stress sensors often were lost or removed by routine maintenance actions. Early sensors were connected physically to minicomputers or terminals by

"In some cases, too much data decreased the ability to find key information on equipment health."

wires. Contaminants such as dirt and lubrication oil degraded sensor signals. Reliability and maintenance engineers found that early vibration-monitoring methods did not yield desired results.

Improvements in minicomputers, terminals and hand-held sensors improved equipment monitoring programs. However, real-time information and data connectivity remained limited due to computer hardware and software capabilities. Converting vibration sensor signals into useable information remained a tedious task. In addition, data trends and information were siloed in databases and not easily shared among users.

Remote monitoring methods were incorporated in preventive maintenance programs. The amount of data collected was never the issue. In some cases, too much data decreased the ability to find key information on equipment health. The long-standing problem remained understanding what the data were indicating about an asset's condition. Simply put, you can't effectively correct what you don't understand.

Vibration monitoring methods still struggle to provide and convert collected data into reliable real-time information. Too often, routine and preventive maintenance programs discover deteriorating conditions of rotating equipment after significant damage has occurred.

Real-time monitoring

Over the last 10 years, the use of wireless technologies, cloud computing, smart-field devices and AI enable the management of plant assets through advanced PdM programs. While preventive maintenance is done on the manufacturer's recommended schedule, PdM pushes maintenance activities to the next level. In PdM, real-time process and equipment data build trends and histories that be used to forecast changes within process equipment. Improving equipment availability and process uptimes through enhanced reliability/maintenance programs, such as advanced PdM, can increase operational excellence and plant safety.

Advanced PdM analytics

To be fully effective, PdM programs require robust and valid data and the analytics to develop information-driven decisions. Recent advancements in AI and ML enable analyzing and converting huge volumes of collected data into patterns. To monitor rotating and reciprocating equipment, advanced vibration sensors use cloud computing to upload real-time data in various formats. Innovative AI and ML algorithms, built on a combination of software and neural networks, convert and analyze wireless sensor data.

This information generates trends that identify normal and unhealthy operations. More importantly, the AI algorithms "learn" from the transmitted vibration data and discern between "normal" or unacceptable signals.

Using AI-based predictive analytics, ML and neural networks, correlations concerning the performance of critical equipment are possible. These validated analytics are instrumental in identifying true root causes for performance deviations of rotating and reciprocating equipment. Early fault identification enables optimum corrective actions to be selected before substantial asset damage or failure occurs, thus minimizing repair costs, reducing unscheduled downtime and ensuring safe operations.

Deteriorating conditions of pumps and compressors are not observed easily through visual or normal health checks. AI and ML algorithms identify patterns from the histories and detect performance decline as proven by deviations in asset trends. Equipment performance problems are identified much sooner than through traditional preventive maintenance methods. System-generated alarms alert maintenance engineers to conduct further investigations.

Also, AI-based predictive analytics go beyond failure notification. They use data and operating histories to estimate the remaining useful life (RUL) of failing equipment or a component item. With RUL, maintenance and reliability engineers have complete information to plan repair and replacement actions that have the least impact on process uptime.

Visualization of data

Data without refinement have limited value. The basis of PdM is visualizing the data. Advanced PdM uses AI-based analytics and neural networks to distill collected data into usable information. They usually include dashboards that enable users to quickly survey equipment condition data and review trends. With such graphics, engineers can interpret equipment/process unit health easily and make more informed, data-driven decisions. In addition, RUL estimates are combined into the graphics for centralized information.

Secure wireless technology and mobile apps connect advanced sensors to the cloud for analysis by AI and ML software. Fully applying Industrial Internet of Things (IIoT) and cloud computing, maintenance and reliability professionals continuously can review the health of critical process equipment. The ability to forecast the RUL and "time to failure" is invaluable. With such information, maintenance and operations groups can plan repair actions rather than react to an emergency shutdown or unscheduled outage.

Case history: L&T Nabha Power plant

The L&T Nabha Power facility is the company's first supercritical, coal-fired power plant and is one of the most efficient power-generation facilities in India. This facility operates two 700-MW supercritical thermal power units and is the major electricity provider to the state of Punjab in northern India. As the chief regional energy provider, reliability of the Nabha power plant is critical. Unplanned maintenance and shutdowns of this facility have dramatic and adverse effects on the productivity and profitability of regional businesses and residential customers. Unfortunately, this power plant experienced three unplanned downtimes in one year due to critical-service pump failures.

Figure 4: *This condensate cooling-water pump experienced chronic cavitation and vibration events that resulted in bearing failures and unscheduled downtime of the Nabha power facility. Courtesy: Nanoprecise Sci Corp.*

In power generation, pumps are key processing equipment. The condensate cooling-water pump is one of the critical-service pumps to maintain steady-state operations of the facility (Figure 4). It is a horizontal vane pump operating at up to 1,650m3/hour with a discharge of 9 MPa (62 psi) at 986 rpm. Each day that this pump is offline costs the power plant up to $250,000 in lost revenue. Unplanned maintenance and failure of this pump can incur repair costs exceeding tens of thousands of dollars.

AI-based maintenances improve pump uptime

The facility's condensate cooling-water pump had chronic unscheduled downtime due to bearing failures from cavitation events. As the primary electric power provider for the region, reliability of the condensate cooling-water pump was a top priority at the facility.

To resolve failure conditions and increase unit uptime, plant engineers elected to install a real-time vibration monitoring and advanced AI-based predictive analytics solution on the condensate cooling-water pump. The new monitoring strategy focused on early fault detection of the pump and its components. Besides fault detection, this monitoring solution included AI-based algorithms to provide reliable RUL estimates before service interruptions occurred. To solve the bearing failure problems for this condensate cooling-water pump, several advanced wireless sensors were installed to monitor:

- Non-drive-side bearing, electric motor
- Drive-side bearing, electric motor
- Drive-side bearing, pump
- Non-drive-side bearing, pump.

The monitoring system used secure Wi-Fi-enabled sensors to collect and upload vibration data continuously via the cloud. Cloud-based AI algorithms analyzed and tended the collected data.

Approximately six weeks after the installation of the advanced sensors and analytics system, the new monitoring program alerted maintenance staff that a vane fault had developed. It was causing cavitation problems for the condensate cooling-water pump. The plant's maintenance staff verified the fault with a hand-held vibration monitor and did a partial disassembly to visually confirm damage to the pump vanes. A temporary repair of the damaged vanes was done before putting the pump back in service.

Figure 5: *Using past maintenance work orders, plant engineers selected optimum locations to install advanced acoustic-vibration sensors. Courtesy: Nanoprecise Sci Corp.*

The advanced AI-based PdM system estimated a RUL of 25 days before total failure. This was sufficient time to schedule the pump replacement during an already planned maintenance outage. Applying AI-based predictive capabilities and advanced vibration monitoring, L&T Nabha Power avoided a serious pump failure and unplanned downtime. Early intervention reduced much needed repairs and minimized interruptions to facility operations.

Not just black boxes

IIoT, cloud computing and wireless technologies support AI-based data analytics as part of an advanced PdM program. Fully applying AI and ML methods, engineers can detect anomalies or faults in critical-service equipment well in advance of failure mode.

AI-based maintenances improve pump uptime

Advanced wireless vibration/ acoustic sensors support PdM programs in collection and uploading of real-time data.

Figure 6: *The advanced wireless acoustic sensors were installed using a strong magnet and a two-part epoxy to endure the rigors of this pump's operations. Courtesy: Nanoprecise Sci Corp.*

With AI, ML and neural-network algorithms, advanced analytics develop historical trends of monitored equipment or components. With a complete operating history, AI-based analytics identify changes in the trending data and estimate the RUL of the monitored asset. With the RUL, maintenance and reliability engineers can take corrective action well before failure and focus on preserving the asset and maintaining safe operations. Advanced PdM programs support better results-driven maintenance plans that improve operations uptime and safety.

Sunil Vedula and Don McClatchie
Sunil Vedula is the founder of Nanoprecise Sci Corp., and ***Don McClatchie*** is the company vice president. Nanoprecise Sci Corp is located in Edmonton, Alberta, Canada

How to use human and artificial intelligence with digital twins

Industrial Internet of Things (IIoT), artificial intelligence (AI), user interface technologies such as augmented reality and virtual reality can help the form and function of digital twins to improve training, operations and outcomes.

Human intelligence has been creating and maintaining complex systems since the beginnings of civilizations. In modern times, digital twins have emerged to aid operations of complex systems, as well as improve design and production. Artificial intelligence (AI) and extended reality (XR) – including augmented reality (AR) and virtual reality (VR) – have emerged as tools that can help manage operations for complex systems. Digital twins can be enhanced with AI and emerging user interface (UI) technologies like XR can improve people's abilities to manage complex systems via digital twins.

Digital twins can marry human and AI to produce something far greater by creating a usable representation of complex systems. End users do not need to worry about the formulas that go into machine learning (ML), predictive modeling and artificially intelligent systems, but also can capitalize on their power as an extension of their own knowledge and abilities. Digital twins combined with AR, VR and related technologies provide a framework to overlay intelligent decision making into day-to-day operations, as shown in Figure 1.

What's needed to form and feed a digital twin?

The operations of a physical twin can be digitized by sensors, cameras and other such devices, but those digital streams are not the only sources of data that can feed the digital twin. In addition to streaming data, accumulated historical data can inform a digital twin. Relevant data could include data not generated from the asset itself, such as weather and business cycle data. Also, computer-aided design (CAD) drawings and other documentation can help the digital twin provide context. AI and other analytical models can take raw data and process it into forms that help humans understand the system.

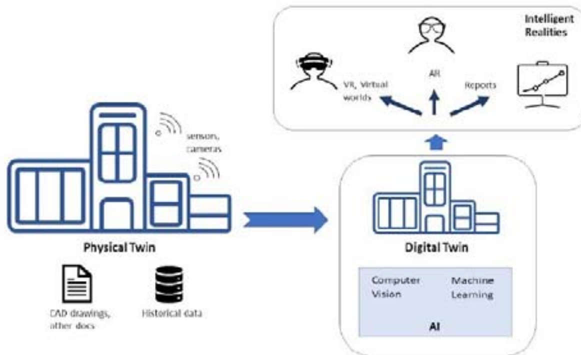


Figure 1: *A digital twin can be enhanced with artificial intelligence (AI) and intelligent realities user interfaces, such as extended reality (XR), which includes augmented reality (AR) and virtual reality (VR). Courtesy: SAS and IIC*

AI also can make intelligent choices of content on the user's behalf. Such guidance could be very welcome to users because user input facilities are very different from the typical keyboard and mouse. As displayed in the upper right corner of Figure 1, humans can perceive the system as an intelligent reality – a technologically enhanced reality that can aid their cognition and judgement.

With the blueprint in Figure 1 as a basis, it's possible to create digital twins that use AI and reality technologies to achieve operational benefits. Any number of operations could be enhanced with the techniques described here.

For example, the paper "Augmented Reality (AR) Predictive Maintenance System with Artificial Intelligence (AI) for Industrial Mobile Robot" details how a machine learning model can be used to classify the state of a robot motor which can then be presented to factory personnel with AR. This article applies the blueprint concepts to facilities management after first exploring each concept in depth. While the various data streams reach their conclusions in human perception, the starting point of a digital twin for a user is how it is perceived. Thus, the starting point for this exploration are user interfaces for digital twins, followed by a discussion of AI.

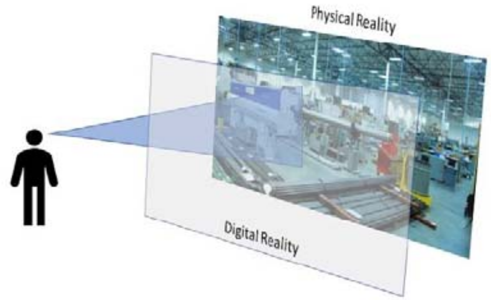


***Figure 2:** Digital reality is produced as a digital twin overlays the physical twin. Courtesy: SAS and IIC*

Human reality of digital twins

Humans have a long history of interfacing with data and data visualization, starting with William Playfair's inventions of line, bar and pie charts in the late 1700s. Digital twins can present data in such familiar forms, but the traditions of the late eighteenth century should not restrain the digital twin's power.

When using mobile technologies such as tablets, smart phones and AR headsets, the digital reality is overlaid on the physical reality into one view, as shown in Figure 2. AR headsets may be the obvious choice for this use case, but it is not the only one. Traditional interfaces rendering 3D models also allow workers to take advantage of digital twins.

The first step in considering the creation of intelligent realities for digital twins is understanding data visualization options across the user interface (UI) spectrum. Next, a reporting integration approach is considered which can operationalize analytics and AI without requiring a new hardware paradigm, like an AR headset. AR headsets have the potential to benefit operations, but only if applications are successfully designed for usability, which is the next consideration. An outline follows of how to build a digital twin interface for remote experts.

	Traditional Desktop	Smart phone or tablet	Monocle AR	Stereoscopic AR, including mixed reality (MR) devices	Fully Immersive VR
2D data visualization	Yes	Yes	Yes	Yes	Yes
3D data visualization	Yes	Yes	Yes	Yes	Yes
Augmenting a digital 3D model of a physical asset	Yes	Yes	Not practical	Yes, and model appears as 3D	Yes, and model appears as 3D
Augmenting a physical asset with charts, heat map overlay, etc. in physical space	Only if PC is in the physical space with the asset	Yes	Yes	Yes	No, but it could augment a virtual rendering
Heads up and hands free in a physical environment	No	No	Yes	Yes	No
3D rendering of a remote asset	Yes	Yes	Not practical or typical	Yes	Yes
Eye and hand tracking	Possible, but not typical	Not practical or typical	Not practical or typical	Yes for some products	Yes for some products

Figure 3 table: *Five technological approaches for rendering digital twins and their respective capabilities are traditional desktop; smart phone or tablet; monocle AR; stereoscopic AR, including mixed reality (MR) devices; and fully immersive VR. Within each class of device, capabilities vary, and the variance may significantly affect a product's viabilities for different use cases. Courtesy: SAS and IIC*

Visualizing digital twin output across the UI spectrum

In Cap Gemini's "Augmented and Virtual Reality in Operations" report, Jan Pflueger from Audi's Center of Competence for AR/VR encouraged a business-first approach for reality projects. "First, focus on your use case and not on the technology itself. After you identify your use case, focus on your information handling and data so you can deliver the right information to the technology."

Consider five technological approaches for rendering digital twins and their respective capabilities. These are traditional desktop; smart phone or tablet; monocle AR; stereoscopic AR, including mixed reality (MR) devices; and immersive VR. See figure 3 table for comparison.

Within each class of device, capabilities vary, and the variance may affect a product's viabilities for different use cases. This is especially true for AR headsets. Display resolution, field-of-view and computational power differ from product to product. In addition, design decisions about whether to put battery and compute units on the headset or on a separate tethered module can affect comfort and practicality. One practical concern for AR headsets is how they integrate with work clothing and uniforms such as those required for clean room and food processing operations.

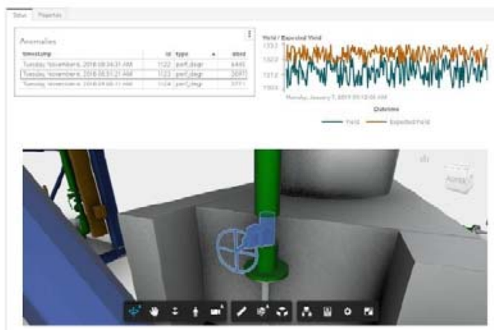


Figure 4: *Using SAS Visual Analytics and Autodesk Forge software can enable system integration. In this example, Autodesk Forge is integrated into the reporting interface of SAS Visual Analytics. Courtesy: SAS and IIC*

Reporting with a digital twin context

Given an interactive visual analytics application, intelligent reality reports can be created with integrated 3D models like the one shown in Figure 4. The digital twin presents a custom visualization that can interact with other objects in the report, including showing data in a table or graph.

This visualization approach adheres to long standing data presentation traditions without requiring new hardware beyond a regular desktop setup. The user interface is presented on a typical computer with a mouse and keyboard. Users need little additional training to use the power of the digital twin.

Usability and augmented reality

When moving beyond the desktop into AR headsets, application designers face a new set of usability challenges. Usability is the cornerstone for any technology to be a tool rather than a hindrance. While AR is a new interaction paradigm, the long-standing standards of usability still apply. These should guide efforts to integrate AR with a digital twin. A good interface is efficient, learnable, memorable, error-infrequent and pleasant to use. Leveraging domain knowledge with the advantages of AR and digital twins makes this space situated to maximize usability in many of these categories.

Learnability of augmented reality

Users on AR platforms show significant improvements with minimal instruction over a short period of time. Some users find AR is initially difficult because they cannot rely on their intrinsic knowledge to operate the system. This setback is temporary, however and users often improve. Learnability varies significantly based on the target audience. Tools made for experts have a higher learning curve but are more powerful overall, and expert efficiency should justify the extended training period.

Efficiency of augmented reality

AR has the effect of "embodiment" when the technology fades away and becomes an extension of our senses. When this happens, the technology extends our sensory, cognitive and motor limitations, so we spend fewer cognitive resources thinking about the interface and more on the task at hand. The information in the world combined with information in the program improves the efficiency of a task through embodied cognition.

Learning advantages of augmented reality

Users are more engaged with the content when accessing it in an AR system because of the novelty. Engagement is a key factor in thinking critically and remembering details. When a user comes back to the interface after a period of inactivity, they will be more likely to remember the content and the actions.

Low error rate of augmented reality

As with any application, the error rate is often affected by the interface design. A good interface designer will be able to create a user experience well within the limits of human factors, and this applies for AR. While the interaction paradigm is different from point and click, system designers have considered the kinds of inputs that can be recognized and limit the amount of irrecoverable errors during use.

***Figure 5:** Digital twin of a retail store created with the Unity gaming engine. In the blog post "Design, build and operate faster with the PiXYZ Plugin for AEC," Unity evangelist Kieran Colenutt outlines a way to perform a conversion from CAD to model formats supported by Unity. Courtesy: SAS and IIC*

Satisfaction of augmented reality use

Multiple studies have indicated users prefer AR over traditional interaction paradigms. Satisfaction is the culmination of learnability, efficiency, memorability and the ability to use the system without catastrophic errors. When the other categories of usability are well-balanced, the user will be satisfied with their experience.

Remote experts and digital twins

An AR device can help a field worker by overlaying their reality with digital twin output. The same AR device can also serve as a platform for remote expert assistance. The simplest way is to transmit the video feed from the AR device's video cameras to the remote expert; however, the video feed alone would not be able to go beyond what the field worker can physically access and does not contain live Internet of Things (IoT) sensor data.

Instead of relying on video, the remote expert could view the system as a virtual world. A VR or MR headset could be used, but a traditional flatscreen would also work well. The picture below shows a digital twin created with the gaming engine.

In this kind of VR system, the expert can change to a vantage point the field worker cannot see. For example, they could view the system from any angle, go through locked doors or even go inside of components.

Unlike the field worker's digital reality, the expert's reality must be created. It could be created by a 3D artist or with digital artifacts such as CAD drawings – or some combination of the two. An artist would have full control, but using CAD drawings would be more scalable.

While it is technically possible to convert CAD drawings directly for use in gaming engines, CAD drawings tend to be too detailed for real-time rendering in a gaming engine. CAD is purposed towards creating models that can be handed to manufacturing or building, while gaming engines pursue photo realism, believable lighting and low latency response to changes in camera position.

Tools exist to optimize CAD drawings for virtual engines.

From IoT sensors to artificial intelligence

With IoT, data is collected from sensors on a device, on neighboring devices, the environment around a device and whatever interacts with the device. The speed is real time, and connectivity often allows us to span distances instantly. Advances in streaming analytics now enable us to process this real-time data using machine learning and artificial intelligence.

While very simple systems can be twinned from raw data readings, AI and other analytical techniques are necessary to make a human-consumable digital twin of complex systems. When considering a vehicle only as an object on a map, then a digital twin can be very simple and easy to digest. There are only two variables, latitude and longitude, and the variables are easily understood by humans.

But when twinning the operation of the vehicle requires hundreds of megabytes of data per second and thousands of variables. While all that data is important for the operations of the vehicle, that much raw data would overwhelm the ability of a human to make sense of it. AI synthesizes the data so the digital twin can present it in a human consumable format. Conversely, AI enhances the digital twin experience by providing additional information about the environment not otherwise available to the user.

Underneath the umbrella term of AI are several specific categories of machine learning. Consider the next section a digital twin toolbox. First, the general architectural practices of AI are presented, and then specific deep learning techniques are reviewed.

Common practices of creating artificial intelligence

AI must become intelligent somewhere, and it's usually not "on the job." Deep learning models are trained on large databases and are almost always done offline. It is not unusual to take hours or days to train a model. Once the model is trained, the model application through inferencing is less compute-intensive but still requires more compute resources than is typical for digital-twin applications.

For some applications, near real-time or slightly delayed results are sufficient. For example, in the computer vision defect detection described below, it might be acceptable to hold a production batch while the defect detection is performed. In other cases, real-time inferencing is needed. Inferencing can be done in the cloud or data center where sufficient resources are available. For edge inferencing, edge gateways are becoming available with sufficient compute power, but that specialized need requires planning.

Recurrent neural networks

Recurrent neural networks (RNNs) are a special class of deep learning neural networks designed for sequence or temporal data. Within IoT and digital twins, there are many examples of such sequence and temporal data. Many sensors are collecting data over time. The sequence or pattern of the measurements over time can be used to understand interesting characteristics of the digital twin asset. One example is measuring energy circuits in a smart building or power grid. The pattern of the energy use

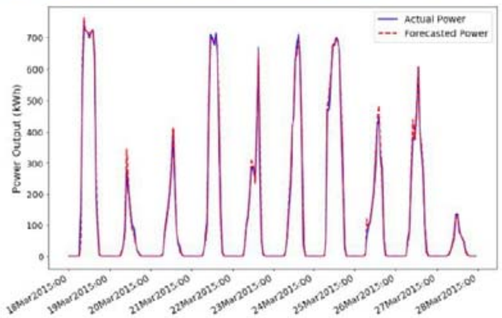


Figure 6: *A solar farm performance can be enhanced with trends shown in a power output chart, below. Courtesy: SAS and IIC*

on a circuit can capture the start or end of an asset operation such as a motor start, which signals an operation change in the digital twin asset. Another use of RNNs is for forecasting unusual time series data. An example is forecasting the energy output from a solar farm, shown in Figure 6.

In this case, there is a cyclical component that could be forecasted using traditional methods, but there is a less well modeled component of weather and cloud cover. With the large amount of data available from the solar farm and nearby solar farms, a deep learning RNN can capture the more sporadic aspects of the energy output.

How to train a recurrent neural network

The process for training an RNN is different when working with sequence data versus working with temporal data. The process for training the RNN with sequence data is as follows:

- Break the data into segments of sequential measurements. The length of the segment is determined by the time interval of the data and the expected duration of the precursor to an event. For the energy circuit example in smart buildings, the data is collected at 5-second intervals, and we use the previous minute of data.
- Create a target variable for the events of interest and use it to label the sequences where the event occurs. For our example, we are using motor starts and identifying weak motor starts indicating capacitor failure.
- Train the RNN. Bidirectional model fitting is not needed in this case because measurement data is always moving forward in time.

The trained model can then be deployed for inferencing. In most cases, the model inferencing function will be sufficiently fast to be used on the real-time measurement stream, either in the cloud, server or edge device.

Recurrent neural network forecasts

The second type of RNN is used to forecast. The example in this case is to forecast the energy output of a solar farm for short time periods in the future (1 hour). The key in this case is to create a set of lagged variables for the predictors and the response variable. The response variable is the energy produced.

To train this RNN, take the historical input database and create lagged variables for the predictors and response variable. The number of lags is determined by the time interval of the measurement data and the expected correlation of previous measurements on the forecast time horizon.

For the solar farm example, we are producing one-hour-ahead forecasts, and the data over the last few hours is sufficient to capture the primary effects for the forecast. There are a large variety of conditions possible throughout the year and previously-observed weather, even though the forecast horizon is short. Since we have a large amount of historical data of the various conditions, using an RNN is appropriate for this particular problem.

Since training and evaluating the RNN model is dependent on the sequence, partitioning the data requires more care than typical random partitioning. In this case, we need to preserve the sequence of the data for use in the model creation steps (training, validation, test). The easiest way to do this is to partition the data based on the time variable. Use the earliest historical data for the training data set. Then use the next time partition for the validation data set.

Finally, use the most recent data for the testing data set. This is sufficient if the performance of the asset has been consistent over the historical data sample. If there have been periods of degraded performance, it is best to eliminate that data from the data sets used to create the model.

Use RNNs for one-step-ahead forecasting where the forecast interval matches, or is less than, the desired forecast interval. This yields the most accurate forecast. In some cases, a multistep forecast may be required to project future time periods based on the near-term forecast estimates. These forecasts are often less accurate but can be tested to determine if they have sufficient accuracy.

Reinforcement learning, machine learning, HVAC

Reinforcement learning (RL) is a subfield of machine learning and deals with sequential decision-making in a stochastic environment. In any RL problem, there is at least one agent and an environment. The agent observes the state of the environment and takes and executes a decision. The environment returns a reward and a new state in response to the action. With the new state, the agent takes and executes another action, the environment returns a reward and new state and this procedure continues iteratively. RL algorithms are designed to train an agent through this interaction with the environment, and the goal is maximizing the summation of rewards.

RL has received much attention due to its successes in computer games and robotic applications. Besides simple RL applications, there are still few real-world applications of RL to increase efficiency. We studied and did some research to extend an RL algorithm for controlling the heating, ventilation and air conditioning (HVAC) systems. HVAC includes all the components that are supposed to maintain a certain comfort level in the building.

Buildings consume 30 to 40% of all consumed energy in the world, so any improvement could result in huge savings in energy consumption and carbon dioxide release. Advances in new technologies in recent years have improved the efficiency of most components in the HVAC systems. Nevertheless, there are still several directions to reduce the energy consumption by controlling different decisions on these systems.

We considered a multizone HVAC system and selected the amount of air flow as the main control decision. Using the obtained data from an SAS building in Cary, N.C., we trained an environment and used it to train an RL algorithm when there are 10 zones in the system with a set-point of 72 with ±3 allowance.

The figure below shows the results of 50 cases with different initial temperatures. The upper figure is the temperature and the lower figure is taken actions over 150 minutes in which every three minutes a decision is taken. We compared this result to the commonly-used rule-based algorithm (in which the system is turned on/off at 69/75), and RL obtained 47% improvement on combination of obtained comfort and energy consumption.

Hyperparameter tuning for deep learning

For all deep learning methods, hyperparameter tuning is an important step. Hyperparameter settings are often dependent on the domain knowledge of the application. Research into the specific application can yield a set of parameter settings to be tested. In some cases, a set of parameter settings has been established as best practices. In other cases, research is needed to determine the best settings.

A feature in software for visual data mining and machine learning is hyperparameter autotune. This feature will take a range of potential parameter settings and perform an optimal search for the best performing settings. This will greatly help cases where research is needed on the parameter settings.

Machine vision and digital twins

Computer vision or machine vision is a powerful tool that has caught the attention of many with its ability to recognize faces and objects within a scene. For digital twins, it can add important information about the quality of the things being monitored. A task that requires visual inspection could be enhanced with an AR interface to a digital twin. For example, computer vision can detect defects by comparing thousands of images for anomalies that may not be as detectable by a human. Moreover, specialized cameras, such as infrared, allow for even further analyses by combining multiple streams of information. A process for implementing a computer vision model is as follows.

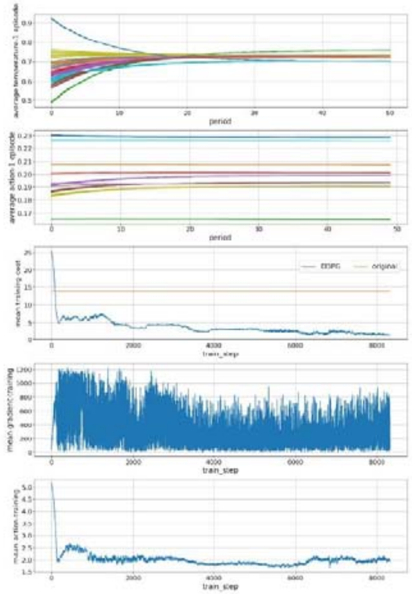


Figure 7: *The average temperature and average action of the reinforcement learning (RL) algorithm are shown. A feature in SAS Visual Data Mining and Machine Learning is hyperparameter autotune, which takes a range of potential parameter settings and performs an optimal search for the best performing settings. Courtesy: SAS and IIC*

If possible, fix the camera to a stable mount point so that all images will be taken from the same angle and with the same proportions. This simplifies the model training compared to general object recognition models, which must capture objects from many angles. The fixed camera location also simplifies the process of determining the location of defects on the piece.

Create a digital twin with machine vision

Another option is creating a model that finds easily identified features on the piece. For a power substation, it's possible to have general instructions on how to point the camera at a transformer in the substation. An object recognition model could identify the bushings on the top of the transformer. This would provide reference points to scale the images with images captured at similar angles, similar to how facial recognition models determine various key points on a face.

Resulting images can create a classification model using convolutional neural networks (CNN). Depending on how well-labeled the data is, models can be of various complexity.

With a collection of mostly good images, a binary classification model can be created that identifies images with a high likelihood of known good or suspected anomaly images. The power transformer is an example of this.

By having images labeled with known defect types, it is possible to create a more complex classification model that identifies the various defects. The discrete parts are an example of this. There might be previous images labeled with an incorrect bearing insertion and other images labeled with incorrect part milling.

With good location identification, it's also possible to break down the images and find the portions of the image with defects. The semiconductor wafer is an example here. Expected yield can be quantified based on the proportion of the wafer with defects.

After the model is trained, determine the inferred latency and test new images being captured and if there's a need to stream image-by-image and get immediate results. It might also be possible to capture a batch of images and process in batch. Also determine if the inferencing can be done in the cloud or server or if an edge gateway is needed.

Digital twin applications for smart facilities

Smart facilities offer a perfect example of how a digital twin can offer features that cannot be accomplished in the physical world. Although buildings are becoming smarter and smarter, walls cannot yet turn transparent on command. If a building administrator wants to look through walls, AR and digital twins provide this. In this case, the information pipeline goes through the following steps.

Raw data gathering for a digital twin

An air-handler can have hundreds of sensors monitoring things like duct pressure, valve-positions, outside air temperature and power draw. Traditionally, these systems are left alone until they break down or need maintenance; however, that approach does not consider how efficiently the system is running and offers little insight into problems or places for improvements. The data streams generated from the sensors can improve maintenance. Other sources of raw data include thermometers, motion detectors and signal monitors for Wi-Fi and other wireless networking.

Digital twin models: AI, analytical models

Models can be trained to twin the system and alert administrators when the digital model does not match the physical performance. This approach minimizes downtime and helps pinpoint issues. The end user does not need to know all the math behind the model, but the twin can be crucial to separating important information from the noise. For example, the model can detect when the power draw of the air-handler is more than expected given the outside weather.

Always aware building management via digital twin, AR

With the raw data processed into intelligence, many options are possible for rendering the digital twin output. Most importantly, the physical and digital realities can be combined for a facility manager so they are situationally aware. When AR headsets are used, the digital twin can be merged into the physicality of the facility as a manager moves around the facility. Just as managers can take note of physical flaws and issues, they can use AR to see into walls, make invisible Wi-Fi coverage visible and see temperature differences throughout the facility.

> **"Most importantly, the physical and digital realities can be combined for a facility manager so they are situationally aware. "**

While an alert-driven approach based on defined thresholds would remain important, a situationally aware approach lessens the chances alerts would be surprising to a manager. Also, a manager can use intuition and judgement to prioritize issues that may fall in blind spots of defined rules.

A situationally-aware approach is possible due to the advent of lightweight AR headsets with strong battery life. Without modern AR headsets, the digital reality of the facility is only visible at a desktop or perhaps on a tablet; but even with mobile use of a tablet, the manager would still have to operate the computing device as they move about. This approach is not heads-up and hands free. With an AR headset, the digital output is ambient as the manager moves about.

Since a digital twin of a facility can produce a lot of output, it is likely it could produce many visual representations in the same physical space. A digital twin AR application that attempts to render all possible information for that space would not be usable. An AI agent can select the most pertinent digital twin output based on several criteria such as the manager's role, newness of information, situational urgency and the manager's history of interest.

Digital twin, IoT, AI, AR and other user interfaces

When properly architected and integrated under the intelligent realities umbrella, IoT, AI and UI technologies can open new possibilities, and digital twin provides a usable representation to consume the massive amounts of information inherent in such an architecture. Various UI options are available for interacting with digital twins. AR and VR are included, but more traditional options like tablets and desktop computers also should be considered. Michael Thomas is senior systems architect; Brad Klenz is distinguished systems architect; and Prairie Rose Goodwin is senior product developer with SAS Institute, an Industrial Internet Consortium (IIC) member. IIC is a Control Engineering content partner. Edited by Mark T. Hoske, content manager, Control Engineering, CFE Media, mhoske@cfemedia.com.

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Improving automation safety with self-taught industrial machines, robots

Future automation safety will involve machines that learn. Artificial intelligence (AI) and machine learning (ML) advances can prompt robots and other industrial machinery to learn from a massive pool of safety-related data to make today's manufacturing applications safer than they've ever been.

The primary focus of industrial safety measures used to involve isolating the machines from personnel as much as possible. Nowadays, technological advancements in automation equipment have made it possible for machines — particularly collaborative robots — to work with human operators in close quarters. These technologies have features like rounded edges and force-feedback sensors to reduce the likelihood of an injury upon contact with an operator.

In addition to these developments, automation systems are in the process of transitioning from fixed to autonomous mobility. One manufacturing solution poised to transform manufacturing involves connecting a collaborative robotic arm to a self-navigating mobile base. For control design engineers to employ risk reduction measures for innovations like this, they need to understand the requirements of the technology, its potential hazards, and the ways operators will be working with it.

As systems get more complex, it becomes ever more challenging for manufacturers to analyze all the data applicable to a risk reduction plan. The amount of information can be overwhelming, and the mechanisms available to govern the decision-making process are limited. Artificial intelligence (AI) can help overcome these limits by providing multiple options the automation designer may not have considered, and this quality combined with its sheer number-crunching power makes it an essential component of today's automation systems.

Determining the safety requirements of near-future technology

The standard IEC 62061, which deals with safety-related electrical, electronic and programmable electronic control systems, defines functional safety as:

"Part of the safety of the machine and the machine control system which depends on the correct functioning of the SRECS (safety-related electrical control system), other technology safety-related systems and external risk reduction failures."

Autonomous mobile robots can self-navigate throughout a facility using onboard mapping software. Courtesy: Omron Automation Americas

This definition makes more sense when re-framed as a goal, which is to design a system that, in the event of a failure, will fail in a predictable manner. The manufacturing industry has become proficient with hardware solutions. Safety standards provide manufacturers, integrators, and end users with a best-practice methodology to achieve

> **"The main challenge of ensuring the safety of near-future technologies is not a lack of applicable information, but rather an overabundance of it. "**

tolerable risk levels for these solutions. We can also draw upon these standards to help determine the safety requirements for developing technologies.

At present, there are no safety standards specifically for an industrial robot integrated with a mobile platform. Nonetheless, we can gather relevant information from existing safety standards, such as ANSI B11.0 or ISO 12100 for risk assessments, ANSI RIA R15.06 or ISO 10218-2 for industrial robotic systems, ANSI/RIA R15.606 or ISO 15066 for collaborative robots, ANSI/IT SDF B56.5 or EN 1525 (to be replaced by ISO 3691-4) for industrial trucks, and ISO 13849-1 for failure prediction and validation. Sources of hazards and recommended risk reduction measures should be available in vendor manuals.

After determining the applicable standards, the engineer needs to evaluate and design for things that influence the space, such as workflow, obstacles, accessibility, misuse and training. Technology also plays a role, as feedback error can cause measurement noise that affects position tracking, and compliance in the joints can have inherently nondeterministic behaviors. The engineers also should consider ways in which the system absorbs energy, the methods used to limit forces, and the use of safety functions.

Where artificial intelligence comes into play

The main challenge of ensuring the safety of near-future technologies is not a lack of applicable information, but rather an overabundance of it. When there are too many variables, the major limitations of developing binary rules to represent past experiences become more apparent. As technology advances while the development of standards lags, designers are often left with making future predictions. This causes them to overestimate or underestimate the necessary safety functions.

Manufacturers can deal with this information more effectively if they expand their toolset supporting the data-crunching and decision-making processes. In particular, they can find a welcome solution in the form of AI and machine learning (ML) algorithms. An AI system could recommend new system-specific guidelines based on case studies and research data as these become available.

ML brings hidden correlations to light by analyzing large amounts of data to discover underlying patterns and trends that aren't readily visible using traditional statistical tools. Humans can find abstract models from these correlations and perform experiments to determine how well the models work. Designers and engineers can rely on a smart system to guide them through a design, making sure to incorporate the best approaches and stay as close as possible to the desired solution.

AI is important for eliminating biases that could hamper decision-making. Since memory is a large part of how the brain makes decisions, experts' perceptions of past experiences can create biases that affect how they deal with new situations. An expert also could either fail to recognize that crucial information is missing or make the mistake of starting with an endpoint solution at the beginning of the decision-making process. ML algorithms reduce biases because they find patterns in the current and actual data that help solve a particular problem as part of the process, using either a supervised training set or an unsupervised starting point.

From hardware-driven safety systems to software-based solutions that use AI

Since the majority of today's safety systems are separated from rest of the system, they have a reactive response to hazardous occurrences. The levels and types of risk change when the system changes or wears down, or if it includes mobile technologies such as self-navigating robots. For example, drift may occur on a robot as it heats up and the bearings wear down; changing an end-effector can alter a robot's potential for harm. Other changes may occur from variations in the characteristics of incoming materials or the effects of ambient conditions such as temperature and vibration.

The factory of the future utilizes artificial intelligence in combination with mobile manipulators to boost quality, flexibility, efficiency and traceability. Courtesy: Omron Automation Americas

As automation transitions from hardware to solid-state and software-driven systems, data scientists and programmers are using AI models to determine what is possible while subject matter experts determine what is usable. An example of a practical AI application is one that tracks and analyzes everything within the manufacturing process to find possible issues before they emerge. It also could monitor the ambient conditions to analyze their impact on a machine's functionality, and then use the discovered correlations to make predictions for the future and optimize the process of scheduling repairs.

AI-monitored predictive maintenance is essential for reducing the likelihood of hazardous events and improving the decision-making process in case such events occur. Unexpected equipment shutdowns can create stressful situations in which people make quick, error-prone decisions based on gut reactions rather than rational decision-making skills. By continuously monitoring the system to detect changes that might be indicative of a problem, the ML algorithms gives human operators a heads-up that something's wrong, and the advance notice will make it easier for the operators to make controlled decisions.

This is important given the current transition of manufacturing from a static enterprise to a largely mobile one. Robots were once designed to perform the same task for well over a decade. With today's demand for production lines that are flexible and adaptable, robots stay on the same task for two years or less. Some will be attached to mobile bases that zip across the factory floor of their own accord. This means the safety system needs to be updated much more frequently, and the number of variables to consider is exponentially larger than before. Only ML can successfully deal with all these variables.

Artificial intelligence also can help make robots and other equipment more ergonomic – a safety concern in its own right. Robots are designed to function with a person regardless of height, while the human is often the entity responsible for any necessary adaptation. Built-in ML algorithms ideally allow the robot itself to learn how best to work with its operator to provide maximum comfort. Based on cues taken from the operator, the robot could discover whether it's been paired with a right-handed or left-handed person, or if the operator has some sort of physical disability.

Data-driven challenges

The driving force behind the introduction of AI into industrial equipment is the sheer plethora of safety-related information in today's manufacturing facilities. There's so much data out there even experienced workers are having trouble learning and retaining it all — not to mention the junior employees who are just stepping into their first manufacturing job. By getting the machines to learn for themselves, companies can take advantage of a powerful risk-reduction tool that will offer both short-term and long-term data on safety requirements in a changing environment.

Everything being applied in safety solutions today is based on things engineers, operators and manufacturers have learned from the past. In that sense, AI isn't all that different. Neither humans nor algorithms start off knowing anything about industrial safety — we must all make connections using bits and pieces from past experiences that we can apply to new situations. We learn what works and what doesn't work, and we use this knowledge to make future decisions. AI works the same way.

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