Business white paper

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DRIVING DIGITAL TRANSFORMATION IN THE MANUFACTURING INDUSTRY

Embedding edge IoT and AI in the digital factory

CONTENTS

INTRODUCTION

Internet of Things (IoT) and Artificial Intelligence (AI) are implemented in the manufacturing industry to drive digital transformation, as a result of Industrial Revolution 4.0. This white paper discusses the challenges in deploying IoT and AI, and describes how edge computing can overcome the adoption barriers by presenting an end-to-end digital transformation in the manufacturing industry.

EXECUTIVE SUMMARY

Charles Darwin once said: “It is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is the most adaptable to change”. This is especially true when it comes to the current rapidly changing world, marching into digital transformation to welcome Industrial Revolution 4.0. This fast-paced revolution, thanks to the Internet of Things, which speeds up the process even further with a total of an estimated 21 billion IoT-connected devices by the end of 2025.

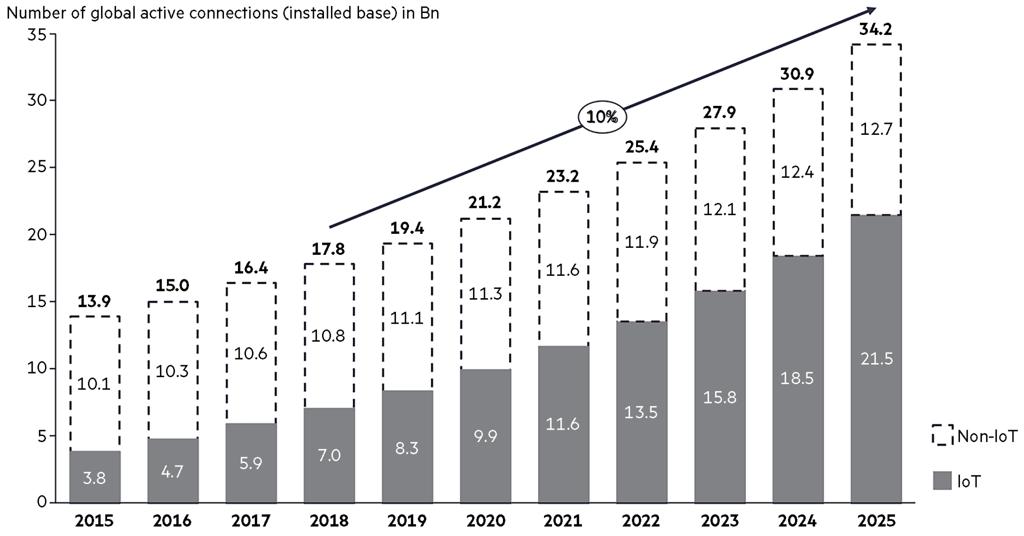

FIGURE 1. Total number of active device connections worldwide[1]

[1] iot-analytics.com/state-of-the-iot-update-q1-q2-2018-number-of-iot-devices-now-7b/

Global spending based on the adoption of Industrial Internet of Things (IIoT) is estimated at $645.9 billion in 2018 and is forecasted by International Data Corporation to reach $1.05 trillion in 2022, where the manufacturing industry is identified as the most to benefit from this technology adoption. With the advancement of AI and the rise of edge computing, this has now gradually redefined the overall IoT system architecture.

Technology adoption is transforming the manufacturing process to become intelligent and dynamic. Highly digitalized and connected environment where machines and equipment, such as automated robotic arm, automated guided vehicle (AGV), and the remote-controlled robot can automate the process and self-optimize. For example, Rolls Royce uses a camera carrying miniature robot to perform a visual inspection of the aircraft engine without dismantling the engine from the aircraft; Amazon deploys AGV in distribution centers to automate the package handling and logistics.

One of the major applications incorporating AI with IoT in the manufacturing industry is predictive maintenance, where it is expected by Deloitte to reduce maintenance costs by 40% in 2025.

On top of that, the International Society of Automation has estimated that worldwide manufacturers are affected by losing $647 billion each year to machine downtime. With the capabilities to predict asset downtime, asset availability is estimated by McKinsey to increase by 5–15%. Predictive maintenance enables manufacturers to reduce asset downtime and maintenance costs.

The cost could be further reduced through the implementation alongside other AI-enabled applications, such as automated visual quality inspection system, operating conditions prediction and adjustment, digital twin, and automated guided vehicle. Besides, a new stream of income is generated by unlocking a new business model when AI-enabled IoT technology is implemented to transform the supply chain, for example, when bundling product as a service. In this case, insights and demand trends of customers can be uncovered to provide supply chain transparency, to help businesses connect to customers.

With that being said, some IoT and AI applications require manufacturers to maintain local data storage to run a real-time process rather than depending on a centralized data center. While the latency of a small number of devices transmitting data across the network is feasible, bear in mind that as the potential use cases expand, the connected devices grow exponentially. It is estimated that the number of connected devices in a typical smart factory is 0.5 per square meter. Hence, this implies that the cost of bandwidth increases to a great extent, at the same time suffering from latency problems, with the increasing number of connected devices. Embedding edge computing into the IoT solution framework ensures that critical data is processed in real time, while less critical data is sent to central data storage infrastructure for processing.

CHALLENGES

Each technology introduced comes with its own set of challenges. An organization must be able to identify the set of barriers specific to their company, to tackle the challenges more efficiently so that businesses can reap the payoff on this technology investment.

Barriers to IoT adoption
One of the biggest challenges identified in deploying IoT is the connectivity issue, where uninterrupted consistent network connection between nodes is expected. Investing and maintaining such a network system which caters for hundreds of thousand devices is costly in terms of money and time.

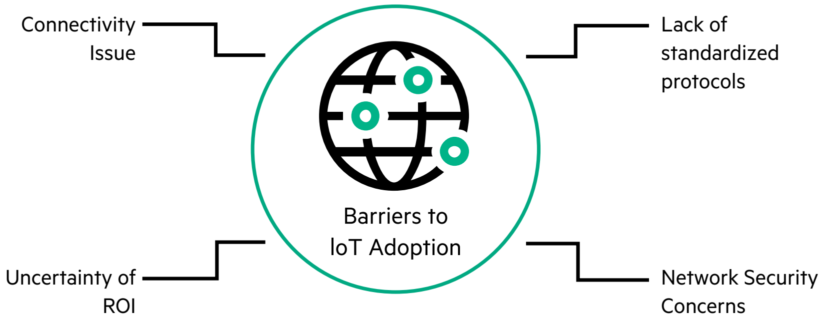

FIGURE 2. Barriers to IoT adoption

Another challenge which is common in halting companies from implementing IoT in their current operations is the compatibility of different IoT devices. This is due to the lack of standardized protocols; it is also a result of the diversities of the framework and operating systems among IoT devices. The barrier is set even higher when it comes to old Computer Numerical Control (CNC) machines, Programmable Logic Controller (PLC), Supervisory Control and Data Acquisition (SCADA) systems and other legacy systems. Some of these machines may not be equipped with sensors which are compatible with the current system and network to communicate with.

For the successful implementation of IoT, network security becomes the next concern. With the increasing number of devices connected to the network, the threat of security is heightened with more nodes being exposed.

Transmitting massive amount of data to a central location could also be a data security risk, which could be addressed by processing some important information at the edge. Overall, network security plans and data security policies have to be taken into account during the designing and building stages of IoT deployment architecture.

Business leaders are eager to invest in IoT due to the expectation and potential of IoT in achieving positive business outcomes. However, the uncertainty of return on investment (ROI), puts some leaders off due to the business decision risk, which might involve a large amount of investment and effort.

Barriers to AI adoption

To implement AI, a huge amount of data is unavoidable for fruitful outcomes. A large amount of data is made possible by sensors implemented for IoT. However, this does not guarantee the quality of this data. For AI applications, it is known that the quality of data is critical to obtain a valid result to avoid the **garbage in, garbage out** scenario. The poor quality of data could be categorized into poorly labelled data, inaccurate data, and incomplete data.

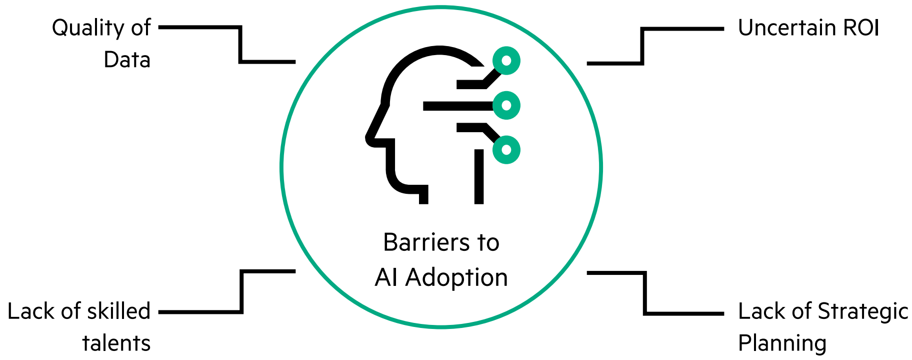

FIGURE 3. Barriers to AI adoption

When handling a large pool of data, 70% of time and energy is spent on preparing data to train machine learning algorithms. Intensive intervention is required to process and restructure before the data is put to good use in AI projects, which includes cleaning, standardizing, enhancing, sampling, and transforming the data.

With that intensive amount of data preparation work required, lack of skilled talents in managing this data becomes the next bottleneck.

The demand for these skills is on the rise, while the supply of individuals who are capable of handling the job is still insufficient. This means that talent recruitment for AI projects in the company requires a substantial investment.

As a consequence, the AI projects implementation budget with an uncertain return on investment often results in a lack of support from executive management. This has constraints the company to move forward with AI technology.

While businesses understand the advantages in which AI could potentially put on the table, it is often lack of strategic planning in identifying and addressing business objectives which are important to the company, as it causes failure to undermine the true value of AI. It is essential to understand the aspects of AI operations, from collecting data to extracting insights from this data. This is done to strategically prioritize the goals before time and money are invested.

IoT AND AI AT THE EDGE

While some companies are struggling to overcome the challenges in deploying these technologies, others have taken the stage to another level. Processing data at the edge for IoT and AI applications have been discovered to overcome the adoption barriers discussed to a certain extent. The demand for processing data and obtaining an immediate automated decision is becoming a necessity for some IoT and AI applications. By implementing edge computing, this has been made possible, and the latency issue can be avoided to obtain real-time responses. For instance, the breakdown of a critical machine could halt the operation on the factory floor, which could cost the factory a big sum of money even if it is only a few hours of downtime. It is reported that the cost of machine breakdown is between 4 to 15 times more than the maintenance cost of the machine itself.

With an increasing number of automated components involved in the factory floor, the latency for these automated components to process data is undesirable. By deploying edge computing in the infrastructure, this allows data to be processed locally, and the decision is returned in real time, delay in transmitting this data to make an informed decision in centralized data storage is eliminated.

Network connectivity which suffers from unstable availability can be mitigated with the deployment of edge devices. This allows data to be stored and processed locally and data insights to be derived in real time without disturbance from connectivity problems. Despite the benefits offered by edge devices, some data can still be processed on the cloud depending on the applications. By having this piece of information on which (data) to go where (edge or cloud), sustainable IoT architecture can be created to unlock the true value of technologies implemented effectively. With this strategic plan out, the cost to maintain data storage on a local or cloud server is cut down by not storing unnecessary data.

Edge computing ensures that sensitive data is kept within the local ecosystem by avoiding the threats that arise by utilizing the public cloud. It is arguable that keeping the data near to the source reduces security risk; AI could be implemented to detect anomalies at the edge to proactively reduce data security threats.

An edge strategy will help an organization toward:

- Faster time to value
- Up to 50% reduction in maintenance costs
- Accelerated deployment through validated solutions in a secure fashion
- Shortened time-to-insight ratio where data is generated, thereby reducing cost and risk

However, this is not achievable without implementing a strategic IoT and AI framework at the edge.

END-TO-END DIGITAL TRANSFORMATION SOLUTION

This section discusses the use case for digital transformation solutions at the edge in the manufacturing industry. The solution is divided into three stages, which are developing the network connectivity between various data sources, condition monitoring, and predictive maintenance. In the first stage, the integration of various data sources is investigated. During the second stage, data gathered from various sources is processed either in the cloud or at the edge for condition monitoring. At this stage, the application is designed and built to help effectively visualize the data in desirable form. Alerts are set to flag unusual conditions. This is taken to an advanced level of intelligence at the next stage, predictive analytics, which is to predict the anomalies before it happens.

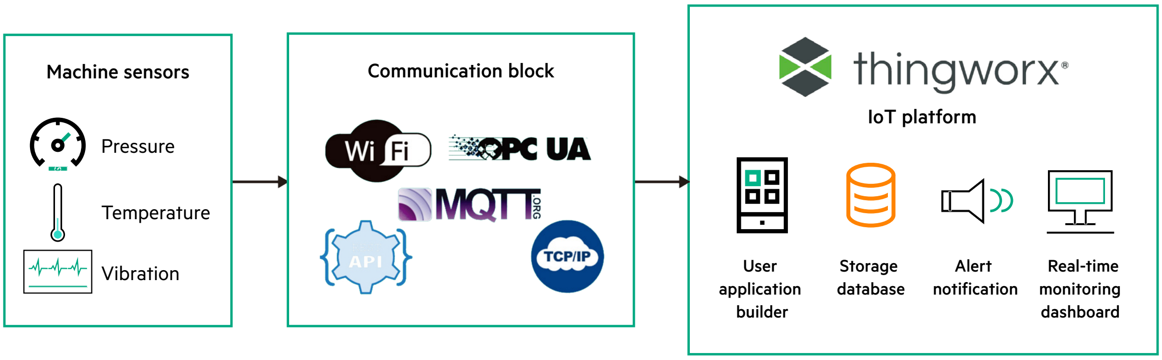

FIGURE 4. Digital transformation solution

Stage 1. Tapping the data

At this stage, data from various sources is extracted. Various sources of data from the existing enterprise systems, databases, sensors, SCADAs, PLCs, and machines is integrated into one ThingWorx IoT platform via the HPE Edgeline EL300. The IoT platform can be hosted on the cloud or on-premises HPE Apollo server. HPE Apollo is designed for high-performance computing (HPC) applications which include AI.

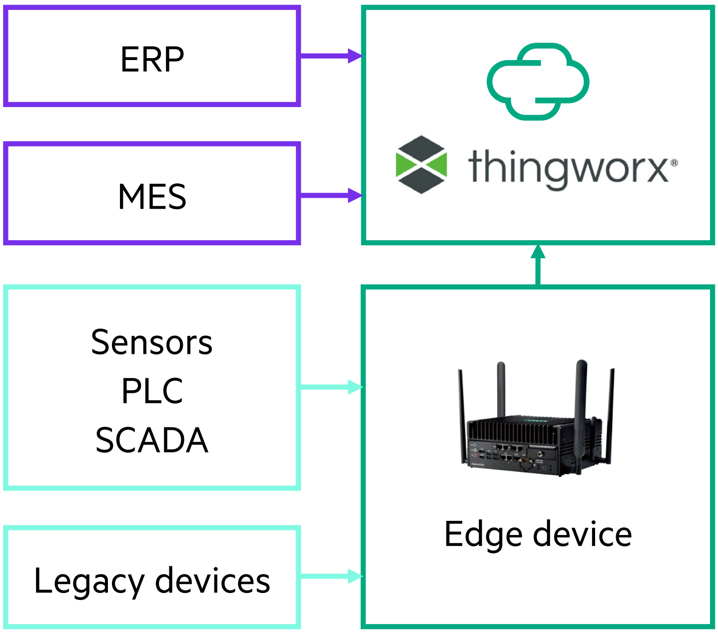

FIGURE 5. Extract data from various data sources

Stage 2. Condition monitoring and data analytics

Data is available for condition monitoring, thanks to IoT, before harnessing the information into achieving a higher level of orchestration and intelligence, which is predictive analytics. Condition monitoring presumes that machine health deteriorates with time and will eventually break down.

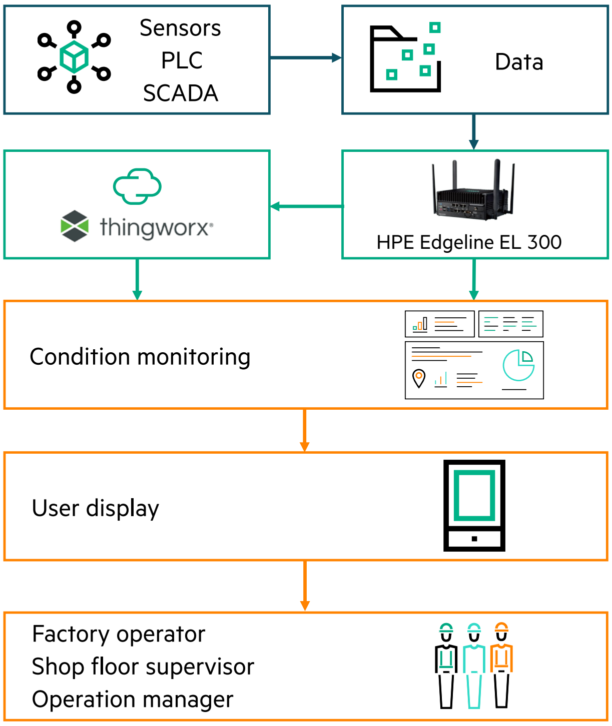

FIGURE 6. Condition monitoring and data analytics

Common machine faults are identified by monitoring equipment parameters such as motor vibration, engine temperature, and ambient conditions. From this data, it is possible to differentiate between wear on gear, lack of lubrication on the bearing, misalignment, electrical fault, and so on.

To ensure high reliability of the equipment and prevent unplanned downtime, monitoring the performance of the equipment takes a proactive role so that maintenance can be scheduled just right before the breakdown happens. Consequential damage which involves money, time, and effort could be avoided.

Data is analyzed, visualized, and presented to shop floor workers on a dashboard, in a mobile app, or an augmented reality (AR) application.

However, reporting and visualization are still far from prediction. To enable prediction, combined data set from various data sources are used to train the machine learning algorithms to identify abnormal patterns that may lead to equipment failure.

Stage 3. Predictive analytics

Predictive maintenance relies on the insights extracted from data gathered in continuous equipment condition monitoring. Machine condition parameters (temperature, vibration, pressure), operation parameters (speed, power) and environmental parameters (humidity) are within a normal threshold. However, combining these parameters and analyzing joint data set against the predictive model helps reveal that the combination of normal parameters, when taken separately can cause, for example, machine engine failure.

Combined parameters on equipment health (temperature, pressure, vibration, and so on), environmental conditions, and equipment operational settings are collected from sensors. This data is then combined with equipment operational settings, equipment history data in databases, service and maintenance data stored in ERP systems. The combined historical data set is fed into machine learning/deep learning algorithms on HPE Apollo 6500, so that the predictive model recognizes the combinations of equipment condition and ambient parameters data patterns of the healthy and faulty condition, by uncovering the causal correlations within the data set.

On the other hand, critical machine data is processed at the edge, and the decision is made on the spot. The trained predictive model is deployed on HPE Edgeline EL1000 for real-time prediction. Potential failures which are detected at real time will trigger a notification to alert the maintenance team while carrying out the corrective action through Programmable Logic Controllers (PLCs) via a feedback loop. This ensures that the process is uninterrupted by potential failures which are detected through predictive analytics.

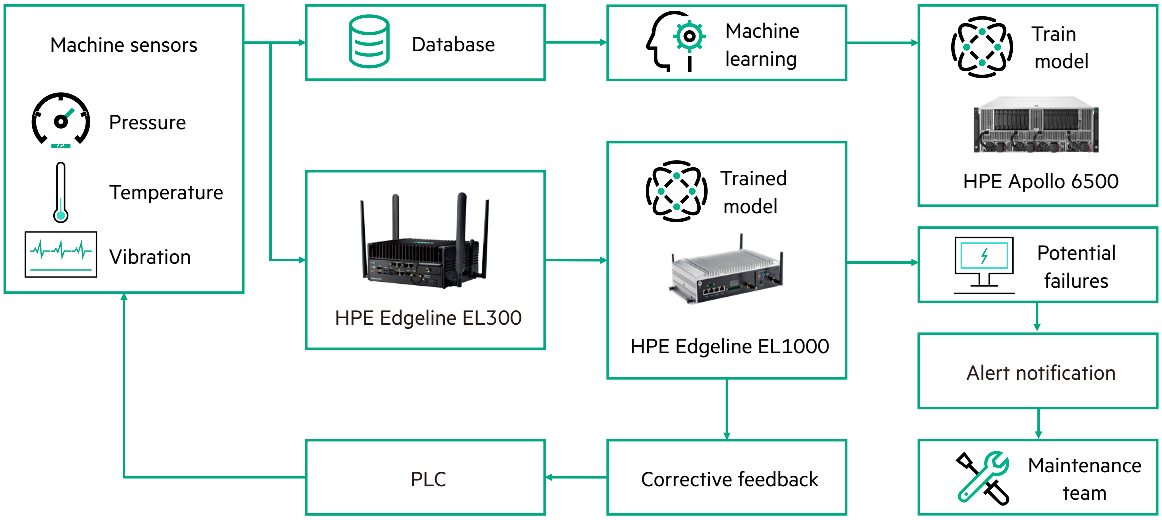

FIGURE 7. Predictive analytics

Performance overview of various machine learning models and deep learning model
In this use case, a critical machine is identified where the breakdown of this machine is costly in terms of time and money. Multiple types of failure are to be predicted. The data is time series machine data in the factory. Machine learning models selected to compare the performance are Support Vector Machine, Decision Tree, Random Forest, Neural Network.

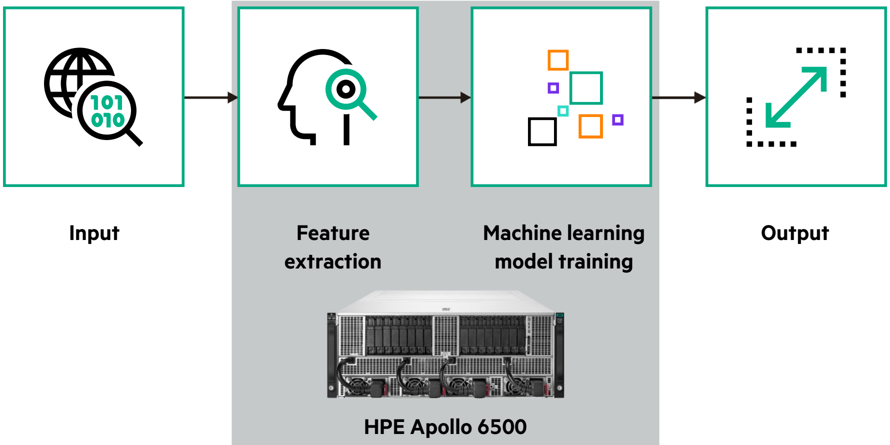

FIGURE 8. Machine learning standard steps

For the machine learning model, feature extraction on the time series data is done manually. Feature extraction is a process of creating new features which are able to summarize the information contained in the original data from the existing features. Characteristics feature from time-series data that can be extracted are min, max, average, percentile, or other mathematical derivations. The extracted data is then used to train a machine learning model while deep learning model, feature extraction is embedded within the repetition of convolutional layers and pooling layers. Hence manual feature extraction is not required to train deep learning model. Convolutional Neural Network (CNN) is one of the deep learning models and is selected to be used in this use case. Training of the deep learning models demands processing power which can be easily achieved by HPE Apollo 6500 Server. Eight GPUs per server for faster and economical deep learning model training to help ensure better efficiency.

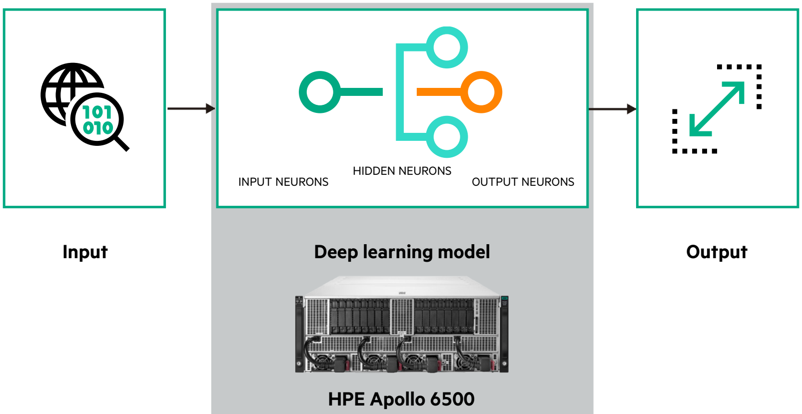

FIGURE 9. Deep learning standard steps

Feature extraction and prediction execution time for CNN takes only about 0.02 second. However, a deep learning model requires a huge amount of data to achieve better performance as compared to machine learning models. Despite that, in this use case, a fast prediction response with a reasonable prediction accuracy is attainable for CNN.

Although machine learning models can achieve better performance, there is a trade-off between execution time and prediction accuracy. As a result, CNN model is selected to be deployed due to the requirement on response time and good performance.

The trained model is deployed on HPE Edgeline EL1000 which facilitates the real-time prediction at the edge. The solution can be extended to other applications, such as remaining useful lifetime (RUL) prediction of equipment, fault level prediction, and anomaly detection.

Table 1 to 5 summarize the prediction performance for each of the machine learning and deep learning model.

TABLE 1. Support Vector Machine prediction performance

	Precision	Recall	F1-score	Support
HEALTHY	0.92	0.94	0.93	90
LACK OF LUBRICATION	1.00	0.99	0.99	90
BEARING DAMAGED	0.94	0.92	0.93	90
BEARING LOST	0.98	0.88	0.92	90
LACK OF LUBRICATION + BEARING DAMAGED	0.94	0.98	0.96	90
LACK OF LUBRICATION + BEARING LOST	0.94	1.00	0.97	90
MACHINE IDLE	1.00	1.00	1.00	90
AVERAGE/TOTAL	0.96	0.96	0.96	630

TABLE 2. Decision Tree prediction performance

	Precision	Recall	F1-score	Support
HEALTHY	0.91	0.89	0.90	90
LACK OF LUBRICATION	0.94	0.90	0.92	90
BEARING DAMAGED	0.79	0.84	0.82	90
BEARING LOST	0.83	0.64	0.73	90
LACK OF LUBRICATION + BEARING DAMAGED	0.84	0.97	0.90	90
LACK OF LUBRICATION + BEARING LOST	0.90	0.96	0.92	90
MACHINE IDLE	1.00	1.00	1.00	90
AVERAGE/TOTAL	0.89	0.89	0.88	630

TABLE 3. Random Forest prediction performance

	Precision	Recall	F1-score	Support
HEALTHY	0.91	0.98	0.94	90
LACK OF LUBRICATION	0.98	1.00	0.99	90
BEARING DAMAGED	0.98	0.88	0.92	90
BEARING LOST	0.99	0.89	0.94	90
LACK OF LUBRICATION + BEARING DAMAGED	0.91	0.99	0.95	90
LACK OF LUBRICATION + BEARING LOST	0.99	1.00	0.99	90
MACHINE IDLE	1.00	1.00	1.00	90
AVERAGE/TOTAL	0.96	0.96	0.96	630

TABLE 4. Neural Network prediction performance

	Precision	Recall	F1-score	Support
HEALTHY	0.94	0.90	0.92	90
LACK OF LUBRICATION	1.00	1.00	1.00	90
BEARING DAMAGED	0.89	0.94	0.92	90
BEARING LOST	0.95	0.86	0.90	90
LACK OF LUBRICATION + BEARING DAMAGED	0.93	0.94	0.94	90
LACK OF LUBRICATION + BEARING LOST	0.93	1.00	0.96	90
MACHINE IDLE	1.00	1.00	1.00	90
AVERAGE/TOTAL	0.95	0.95	0.95	630

TABLE 5. Convolutional Neural Network prediction performance

	Precision	Recall	F1-score	Support
HEALTHY	0.94	0.94	0.94	90
LACK OF LUBRICATION	0.98	0.99	0.98	90
BEARING DAMAGED	0.93	0.91	0.92	90
BEARING LOST	0.90	0.81	0.85	90
LACK OF LUBRICATION + BEARING DAMAGED	0.92	1.00	0.96	90
LACK OF LUBRICATION + BEARING LOST	0.89	0.91	0.90	90
MACHINE IDLE	1.00	1.00	1.00	90
AVERAGE/TOTAL	0.94	0.94	0.94	630

REFERENCE ARCHITECTURE

HPE and PTC have joined forces to help manufacturers deploy Industrial IoT and AR solutions at the edge, where data is generated and captured, while avoiding the costs, delay, and risks of sending data to the cloud or remote data center.

Since 2016, through the HPE Technology Partner Program, PTC and HPE have helped companies develop initial proof of concepts that have led to expanded factory rollouts of standard edge and bespoke hybrid architectures, enabling improved efficiencies in performance, cost, and productivity.

PTC and HPE's initial alliance, which converged operational (OT) and information technologies (IT) through PTC's ThingWorx Industrial IoT Solutions Platform and HPE Edgeline and HPE Pointnext Services solutions, has continued to evolve, most recently with the addition of PTC's Kepware industrial connectivity software and Vuforia Augmented Reality Products to the companies' joint offerings.

Enterprises that leverage the full joint-offering suite may achieve: accelerated deployment through validated solutions that address IT and OT components in a secure fashion; shortened time-to-insight ratio where data is generated, thereby reducing cost and risk; and condensed market readiness timelines through rapid innovation and accelerated expansion.

Over the decades, HPE has developed many IT and embedded electronics assets. Today, HPE is bringing these world-class competencies to the IoT edge, with the HPE Edgeline Systems family. In sum, the HPE Edgeline EL1000 and EL4000 create a new product category: "Converged IoT Systems". HPE is converging three crucial capabilities for efficient IoT solutions:

1. Deep compute (Stage 3)
2. Deep data capture and ingest (Stage 1)
3. Enterprise-class systems and device management

Combining these capabilities effectively converges Stage 1 and Stage 3 of the IoT solution architecture and blurs the line of the edge.

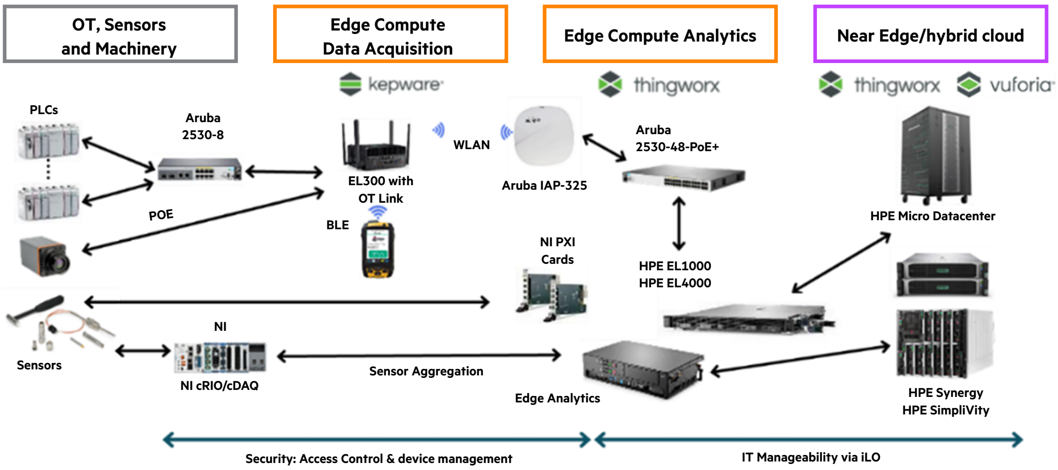

FIGURE 10. Reference architecture

PTC ThingWorx IoT platform

ThingWorx platform is a complete, end-to-end technology platform that enables industrial businesses to unlock the value of the Internet of Things (IoT). The ThingWorx platform includes complete modules of ThingWorx Foundation, ThingWorx Utilities, ThingWorx Industrial Connectivity, ThingWorx Analytics, and ThingWorx Studio.

ThingWorx combines the different components, such as, Studio, Utilities, Analytics, and Industrial Connectivity to provide a seamless approach. It is a leading platform in the industry today and offers the following capabilities:

- Application design: It boasts of ready-to-scale and high-quality tools that help in creating applications, interactive dashboards, workspaces, and mobile interfaces. The biggest advantage is that it requires minimal coding work.
- Connectivity: It offers the flexibility to put in place the connectivity strategy that minimizes integration and maximizes the market opportunity.
- Collaboration: It provides a platform that is accessible to both the developers as well as the analysts. This ensures that problems are solved much faster, and feedback from the ground is incorporated quickly.
- Security: ThingWorx puts special emphasis on creating secure solutions and ensures role-based access to all the stakeholders.

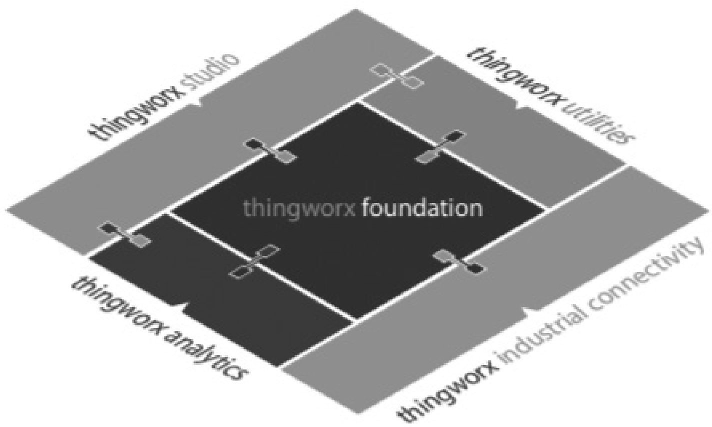

FIGURE 11. ThingWorx IoT platform

CONCLUSION

Before a decision is made on investing and implementing the technologies, here are some questions worth pondering upon:

- How to implement IoT, AI, and edge computing in the current framework?
- How to start right?
- Which business process would benefit most from a pilot implementation?
- Where to source talent? Whether to hire the talents within the organization or to outsource the projects or engage with the consultation team?
- What is the benchmark for a successful initiative?

All in all, successful IoT and AI implementation with a reasonable return on investment to unlock the true business value of these technologies requires a combination of domain knowledge (client), IoT hardware (HPE), software (ThingWorx), and expertise services (CAD-IT IoT Centre) to close the gap from paper to practice.

The digital transformation solution presented in this white paper can be extended to Digital Twin solution by creating a digital replica (twin) of the assets using the ANSYS Twin Builder. Please subscribe to our newsletter for updates on Digital Twin solution to bridge the digital and the physical world, in an upcoming white paper.

RESOURCES[2]

TABLE 6. Metrics definitions

Metrics	Definitions
Precision	Precision is the ability of a classifier not to label an instance positive that is actually negative. For each class it is defined as the ratio of true positives to the sum of true and false positives. Said another way, "for all instances classified positive, what percent was correct?"
Recall	Recall is the ability of a classifier to find all positive instances. For each class it is defined as the ratio of true positives to the sum of true positives and false negatives. Said another way, "for all instances that were actually positive, what percent was classified correctly?"
F1 score	The F1 score is a weighted harmonic mean of precision and recall such that the best score is 1.0 and the worst is 0.0. Generally speaking, F1 scores are lower than accuracy measures as they embed precision and recall into their computation. As a rule of thumb, the weighted average of F1 should be used to compare classifier models, not global accuracy.
Support	Support is the number of actual occurrences of the class in the specified data set. Imbalanced support in the training data may indicate structural weaknesses in the reported scores of the classifier and could indicate the need for stratified sampling or rebalancing. Support doesn't change between models but instead diagnoses the evaluation process.

[2] scikit-yb.org/en/latest/api/classifier/classification_report.html

About CAD-IT IoT Centre[3]

CAD-IT IoT Centre provides innovative enterprise digital transformation solution and services, including (but not limited to): sensor network, control system, edge computing, intelligent monitoring, artificial intelligence, visual inspection system, predictive maintenance, and AR based guided service instruction. By leveraging the experience and knowledge of its members, with the resources from its partners, CAD-IT IoT Centre has helped clients around the globe in achieving greater innovation, quality, and productivity.

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