Outcomes, Insights and Best Practices from IIC Testbeds: Smart Factory Machine Learning for Predictive Maintenance Testbed

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To extend the usefulness of the published testbeds in the Testbed Program of the Industrial Internet Consortium (IIC), the Testbed Working Group has developed an initiative to interview the contributors of selected testbeds to showcase more insights about the testbed, including the lessons learned through the testbed development process. This initiative enables the IIC to share more insights and inspire more members to engage in the Testbed Program.

This article highlights the Smart Factory Machine Learning for Predictive Maintenance Testbed. The information and insights described in the following article were captured through an interview conducted by Mr. Howard Kradjel, Vice President of Industry Programs at IIC, with Dr. Javier Díaz, Chief Technology Officer of Aingura IIoT. Javier is an active member in the IIC where he serves as a co-lead of the Smart Factory Machine Learning Testbed and is a key contributor to the Testbed Working Group.

Smart Factory Machine Learning for Predictive Maintenance Testbed – From Concept to Reality

Founded in 2017, the Smart Factory Machine Learning for Predictive Maintenance Testbed seeks to test algorithms and architecture solutions in the form of technologies: communication protocols, cloud platforms, cybersecurity, etc. to achieve predictive maintenance. Many existing machine learning technologies can be applied to predictive maintenance, but most are not fully developed to optimize the accuracy or performance of those elements in order to retrieve actionable insights. Many are able to detect a failure, but they do not have the ability to perform the specific activity in real, industrial environments. The testbed's goal is to develop algorithms and test them in IIoT architectures and real industrial environments.

Some experimentations lead to the development of dynamic algorithms—machine learning algorithms that are not necessarily well expressed in state-of-the-art industrial environments but that guarantee the quality of the data coming from the industrial environments (i.e., in terms of noise reduction) in order to get the right quality of data to perform the advanced analytics. The transportation of data from one place to another, the storage of that data and the implementation of these new machine learning algorithms must contribute to forming actionable insights for the end user. The actionable insights depend on the question or problem the end users are trying to solve. Related to predictive maintenance, the questions are related to the degradation level of a specific part of the machine, cell or line that could fail stopping the production, i.e., increasing downtime or long mean time between failures (MTBF), etc. Therefore, the output of the algorithms or the machine learning system is to tell the end user the remaining useful life (RUL) of that particular element. For example, a first use case in the testbed is working to predict the RUL of the frontal ball-bearing of a spindle head. Specifically, the actionable insights given to the end user is the % of RUL, where the end user can support their decisions to change it during the next maintenance stop. Usually, the result or output of machine learning algorithms is quite complex and requires a lot of experience to properly interpret the results—arguably no other field of experimentation requires the feat of knowledge that the end user needs for machine learning algorithms. It is also important to consider that the actionable insight given to a machine operator would not be the same as the insight given to the line manager of a production facility.

The Smart Factory Machine Learning Testbed is currently working on various use cases, one of which involves the spindle head of a Computer Numeric Control (CNC) machine tool used to manufacture crankshafts for the automotive industry. The spindle head is the most difficult part for which to predict the failure of internal elements. Other use cases of the testbed are related to failure points such as ball bearings and ball screws, where behaviors and patterns in energy consumption are used to support the decision making. The energy data can be fused with other types of data coming from the machine to solve specific problems. Different use cases will be addressed in the near future as the next phase of the testbed addresses problems with surface heat treatment. The testbed will need to detect and analyze particular failures of a critical element in a laser heat treatment process.

Many unique technologies have been utilized in the testbed's use cases. In terms of hardware, the testbed is working with Xilinx's UltraScale™ MPSoC Architecture to pull sensor readings from different places, which is a form of sensor fusion. Taking advantage of this element's Field Programmable Gate Arrays (FPGAs) helps to accelerate the machine learning algorithms and is another technology the testbed aims to develop further. The hardware being used acts as a platform in which the new predictive maintenance technology can be deployed. Regarding software, the testbed works with different protocol technologies related to industrial parts. It also incorporates Industrial Internet of Things (IIoT) technologies which help transport the data. OPC Unified Architecture (UA) is one example of this IIoT utilization. The Data-Distribution Service for Real-Time Systems (DDS) standard, as implemented in DDS-Secure from RTI, is another example included in the testing.

The Smart Factory Machine Learning Testbed is deployed over highly sensorized machines which are nearly autonomous. There is a sufficient amount of data coming from different sensors already in place. For state-of-the-art industrial machines, the acquisition of the energy consumption is done at a relatively low frequency, around three kilohertz. The testbed is deploying a new sensor to measure energy. In one platform, the sensor might measure eight kilohertz to 32 kilohertz. In this unique case, the testbed must detect the small deviations or sparks that occur during processing and analyze the output pattern to understand whether something is changing to affect the energy consumption of the production element.

The testbed is deployed in three locations. The first is in the Aingura IIoT labs in Spain, and the second is in the manufacturing facilities of the CNC machine tool manufacturer—Aingura's parent company, Etxe-Tar. The machines here are able to produce 1,000 crankshafts per day. Before going to the end customer, the machine must undergo a pre-series of work pieces where the technology is deployed and tested while the machine is producing crankshafts. The cycle time and output is near real-time production but in a controlled environment. The third deployment of the testbed is in a well-known automotive OEM's production facility.

Several deliverables are planned for the Smart Factory Machine Learning Testbed. The most significant ones involve the new algorithms developed by the testbed. The testbed aims to give feedback to different technical sessions and IIC documents based on the testbed's various deployments. It also hopes to be able to guarantee the performance of the predictive maintenance technologies and determine what is needed to deploy these technologies into real industrial environments.

Testbed Planning

The IIC ecosystem played a major role in building the testbed and providing the needed resources. Every partner within the testbed specializes in a different real need used in testbed deployment, whether it is cybersecurity, connectivity or cloud integrations. The testbed started with a product from Xilinx used to incorporate the computing capabilities necessary for deployment in the real industrial environment, and now the testbed works with one of Xilinx's latest technologies. Technologies from iVeia and other vendors of technology make up the testbed's hardware system.

To choose partners, testbed leads Aingura and Xilinx combined their experience and perspectives to understand the needs for deploying the new technology, whether those needs were in hardware, software, connectivity or different platforms in the cloud. The testbed team is built on the needs of its architecture and continually improves as needs become clear. Utilizing the IIC ecosystem to find partners able to solve new problems is crucial for building the architecture within the testbed.

IIC Interactions

The IIC Industrial Internet Reference Architecture (IIRA) is referred to for nearly all aspects of the testbed and helps in understanding which partners may be useful to build the complete architecture of the testbed. In addition to following the guidelines set by the IIRA, the testbed aims to give feedback to the document, most likely in terms of improving deployment.

With two cybersecurity companies involved in the testbed, the IIC Industrial Internet Security Framework (IISF) also comes into play. The two companies combine their points of view in conjunction with the IISF to work toward effective security practices in testbed implementation. These efforts are crucial in terms of maintaining connectivity and avoiding losing data, and the testbed team especially considers those risks stressed by the IIC Security Working Group. The testbed hopes to give feedback to the

IISF from the cybersecurity point of view.

Time Sensitive Network (TSN) standards, as related to the IIC TSN Testbed, play a role in the implementation of the Smart Factory Machine Learning Testbed. Between decision-making, processing and pre-processing, there is communication—the transportation of data from one place to another. The deterministic approach of TSN increases the security of the data during communication, helping to avoid the loss of that data. In the Smart Factory Machine Learning Testbed, the gathered data needs to feed into the machine learning algorithm—TSN protects the data during this communication.

Testbed Results

The testbed's first deliverable was published in the *IEEE Internet of Things Journal* in May 2018, covering the results of one of the testbed's first dynamic machine learning algorithms which works with the data stream coming from a machine. At this time, the testbed team is working on a new article for the *Engineering Applications of Artificial Intelligence* which is aimed to be published by early 2020. This paper discusses machine learning algorithms oriented to predictive maintenance. Next, the testbed team was granted a U.S. patent for their architecture that increases computing power by connecting several aspects of Aingura's hardware platform to deploy the testbed's solutions. The hardware integration gives more computing power at the edge and allows for more complex machine learning algorithms to be deployed in real industrial environments. Finally, the testbed team published a book, *Industrial Applications of Machine Learning*, in late 2018 which features two chapters that discuss the testbed's results in the Aingura lab.

The deployment of the testbed's technologies in the controlled lab environment is fairly straightforward, but deploying in the real industrial environment involves several challenges. In a real production facility, the window of time available to deploy the technology is drastically limited due to the production schedule of the facility. As a machine is producing, it cannot be stopped or tampered with for the sake of running tests. When that short window of time opens, the system is connected and deployed, but to check if it is working properly may take several months and is thus not feasible. This differs from deploying a brownfield system which can be deployed in existing production lines. In a scenario where production machines are built in the Aingura lab and sent to the end user with the technology already installed, proper validation tests can be implemented. However, it is not common that a machine is installed in a new production line—so the opportunities to deploy the testbed's technology are limited.

To bypass this challenge, Aingura's parent company Etxe-Tar, which has developed strong relationships with OEMs for the last 20 years, is able to provide a channel for the testbed's technology to find its way into production facilities. Without a strong relationship with an end customer's production department, this is far more difficult. The testbed team seeks to find other ways to implement the testbed in real production environments, and some customer engagements are currently being explored.

An important issue is that, currently, there are many "expert systems" in production; however, those systems have problems with large false positive rates. In the testbed team's experience, almost all expert systems of the type in focus experience shutdowns. In a facility such as the OEM testing this testbed solution, downtime costs USD 50,000 per hour, with unexpected failures potentially taking 40 hours to address. In this case, the testbed team's approach is to test specific algorithms that take into account the dynamics of industrial systems, where degradation occurs and normal limits are understood (such as our cars where, five years later, they are not as new but work perfectly). These dynamic algorithms are also mathematically supported, where the designer (data scientist) is able to understand what the algorithm is doing internally (not black-box algorithms such as neural networks, deep learning, etc.). All these efforts help the predictive analytics to minimize the false positives rate and save significant costs."

One key takeaway learned by the testbed team is that something is not *finished* when only tested at a home facility. The team may design the best machine-learning algorithms, best IoT hardware and best architecture, but many changes take place when going from a lab to a real industrial environment. If not tested during real production, there will be many false-positives. For other testbeds and companies considering an IIoT implementation, the testbed team strongly suggests conducting tests in real environments rather than limiting results to a proof-of-concept or applications in a controlled environment.

EXPERIENCE

Aingura IIoT has derived business value through the Smart Factory Machine Learning Testbed by connecting with high-quality vendors of specific technologies Aingura needs to develop products. Finding vendors with high-quality products to fulfill specific technology needs is very difficult, but the IIC ecosystem facilitates connections which would otherwise be unlikely to form outside the IIC. Not only has this helped Aingura create new customers, but the testbed itself has benefitted—for example, accessing a testbed partner's products for use in its hardware platform. In addition, the testbed can act as a marketing tool for partners to showcase their products in real applications.

The partnerships within the testbed expedited certain processes necessary to build the testbed. The relationship with iVeia and Xilinx, for example, enabled record-time building of the new hardware platform with the latest technology from each company. Such a complex platform was expected to take two or three years to create, but the relationships shortened this process to only six months.

CLOSING

The most significant surprise throughout the testbed's journey has been the relationships formed between partners. In particular, it was unexpected how open to collaboration each partner was and how an open communication protocol was established. When examining the testbed's progress, much can be attributed to the effectiveness of these relationships.

The testbed team views the creation of a testbed as a very complex process, from starting with a unique, compelling proposal to implementing new technological applications in real environments. Throughout the dedication and diligence necessary to build the testbed, the team recognizes that the experience and results have been well worth the effort.

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