Making Factories Smarter

Through Machine Learning

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1. INTRODUCTION

With the advent of the 4th Industrial Revolution, referred to as Industrie 4.0 (I4.0) and the Industrial Internet of Things (IIoT), machines and systems have become more intelligent and more connected. This connectivity has enabled data from the operational domain, the Operational Technology (OT), to become more accessible to the information technology (IT) domain.

The continual growth of machine intelligence and proliferation of sensors generating non-stop data has created a tremendous body of information. While data may have been acquired before, with some degree of analysis performed, the data was not being analyzed and understood to the extent possible today, especially in terms of real time analytics and related command and control.

This wealth of actionable information provides the key to unlocking higher efficiency and increasing reliability of these machines and systems through predictive, connected and precise operation. To remain competitive, companies are looking to evolve their analytics approaches and decipher the true meaning in the data. This data provides insight into their system operations enabling reduction in overall operating and maintenance costs.

One particular means to accomplish this reduction in costs is to maximize assets by minimizing downtime. Using sophisticated data analytics, combining the wealth of sensor data and other asset-related lifecycle parameters, companies are shifting their focus on "Preventative" maintenance with greater emphasis on "Predictive" maintenance. Using this approach, companies can begin to keep their assets operating more efficiently, more reliably, with longer periods of uptime, without taking their assets offline, avoiding costly downtime for regularly scheduled maintenance. By increasing uptime, with the ambitious goal of no unscheduled downtime, companies can keep their assets operational until the data analytics indicate a specific asset or part of an asset is approaching need for maintenance, thereby avoiding potential costly unplanned system failure.

This article highlights a specific company that is not only aware of the value of the IIoT but is truly recognizing value from unlocking the meaning of the data. The predictive maintenance presented in this article is representative of actions being taken as a result of IIoT and I4.0. To become more competitive by leveraging the convergence of the IT and the OT in a secure, safe and connected manner, smart factories see this as one of the key ways to increase productivity and operate more efficiently through higher availability and increased machine and asset utilization.

2.   BACKGROUND

Plethora IIoT [1] , part of the ETXE-TAR Group, a federation of closely coupled industrial manufacturing companies, through use of machine learning is utilizing predictive maintenance to minimize downtime and maximize the operation of their sophisticated Computer Numeric Control (CNC) machines. These machines are used to build automobile powertrain parts, like crankshafts, camshafts and connecting rods, with highly precise requirements executed over an extremely short cycle time. A key advantage that Plethora utilizes is monitoring key parameters to effectively learn the system behavior to predict failures before they occur. With the support of ETXE-TAR and Ikergune, the research and development company for the ETXE-TAR Group and other ecosystem partners, Plethora IIoT has developed a system called Oberon. This system covers the needs from data gathering independently from the domain to visualization, giving important information in terms of machine behavior (useful for machine or system builder) and process behavior (useful for machine/system user).

One of the key elements of the Oberon system is the intelligent gateway, designed and manufactured by System-on-Chip Engineering (SoC-e)[2]. The gateway utilizes the Xilinx Zynq SOC, combining both ARM processing and Programmable logic fabric in a highly integrated and reconfigurable System-on-Chip (SoC) device to perform real time acquisition, sensor fusion, filtering, pattern detection and analysis of the data extracted. The gateway is intelligent in the way that it combines smart networking, flexible hardware-software computation and high speed data acquisition systems. This system is able to provide "Plug & Work" operation through time-sensitive, redundant protocols for Ethernet (High Availability-Seamless Redundancy / Parallel Redundancy Protocol - HSR/PRP). These protocols ensure zero loss of data in the event of network failure or hot plug-in due to plant layout changes. From the security and cyber-security point-of-view, the intelligent gateway ensures a multi- layered security approach. Strong security means are applied at the device, system, network and application levels. This approach, based on *cybersecurity by design* is a key element in the emerging connected industrial environment. Learnings from the Industrial Internet Consortium's (IIC) Industrial Internet Security Framework (IISF) document are directly applied, as this is the same gateway found at the heart of the IIC Security Claims Evaluation Testbed. Details of the intelligent gateway functionality and capabilities applied to the Smart Factory are described in "Intelligent Gateways Make the Factory Smarter."

In terms of acquisition, sensor fusion, pre-processing and processing software developed by Ikergune, the main objective is to gather data coming from sensors with the required sampling rate, independently from the variable. Therefore, it can sample each variable with smart criterions: For example, temperature may not be measured with the same frequency of vibration

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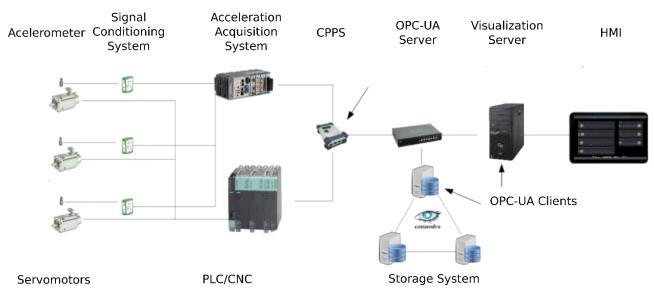[1] SPRI, *Basque Industrie 4.0*, 29 Nov 2016. [En línea]. Available:https://goo.gl/jrzFlF
[2] System-On-Chip engineering – SOC-e CPPS 40 Intelligent Gateway.

because the data memory size required would need to be exceedingly large - impractical and unnecessary.

The other capability provided by the software is the ability to read complex sensors and perform pre-processing in terms of data reduction: For example, vibration is sampled at least two times the vibration frequency. In this case, a fast Fourier transform is performed and only the frequency of interest is stored. This is an area where there is high opportunity for more efficient processing – effectively using machine learning for pre-processing and feature selection.

Next, data acquired from different sources needs to be joined to assure completeness of database and avoid empty data spaces (Not a Number -NaN)[3]. This Sensor fusion is performed using different multivariate techniques in real time.

From this point, as shown in Figure 1, data is processed and then served to a superior process, which can be a machine learning algorithm, visualization and/or storage. The data is sent using OPC Unified Architecture (OPC-UA) or other protocols depending on the needs. For example, if data is needed for real time visualization below 45ms, OPC-UA protocol is used.

Figure 1: The elements and the connectivity being utilized to develop and provide updates to the production system.

Based on historical data acquired during typical operation, machine learning algorithms, both unsupervised and supervised, utilize this and other real-time operational data to identify and effectively learn system behavior patterns during the machining process. The data is analyzed in

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[3] R. C. LUO, C.-C. YIH y K. L. SU, «Multisensor fusion and integration: approaches, applications, and future research directions.,» *IEEE Sensors journal,* vol. 2, nº 2, 2002

real time on the intelligent gateway and compared to trained data to identify anomalous operation and predict degradation down to the component level, prior to system failure.

3. MACHINE MONITORING WITHOUT PREDICTIVE MAINTENANCE

Operational failure of the CNC machines' spindles can result in hundreds of thousands of dollars of damages[4]. When spindle internal bearings fail, they effectively create a chain reaction that can destroy any linked device in close proximity due to stored energy. One such occurrence can shut down the production line for weeks, depending on the severity and spare parts availability. Total impact in terms of cost for a failure of this nature must include cost of materials and labor needed to replace the damaged parts and costs incurred due to system downtime, idling an entire production line and costs associated to delay of the assembly of vehicles waiting for the powertrains. Accounting for all related aspects including the idled workforce, total cost impact can easily reach millions of dollars per week.

For example, a major manufacturer installed a monitoring system where data was being captured but never analyzed. During a post mortem of a CNC spindle failure, closer analysis of the data revealed telltale signs indicating the system functionality was outside of its normal operating range. Specifically, key vibration data acquired days prior to the failure, as shown in Figure 3, had a first peak, where failure initiated. At this first peak the only damaged part was a ball-bearing inside the component. Four days later, parts inside the bearing started to damage other nearby parts creating a catastrophic failure, where a 1.4g peak has been registered. At the first peak, the damage cost 25,000€ (Euro). At the second peak, the damage cost was 250,000€.
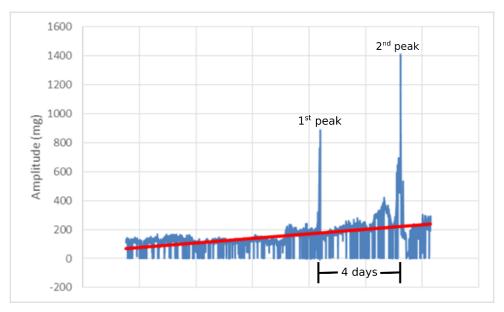
Figure 2: Data leading up to a CNC spindle failure with spikes reflecting anomalous behavior

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[4] X. W. B. A. S. D. &. L. J. Jin, «Present Status and Future Growth of Advanced Maintenance Technology and Strategy in US Manufacturing,» *International journal of prognostics and health management,* vol. 7, 2016

This failure happened to a production line with a turnover capability of 30 M€ per day with 50 operators directly working on the line per shift. When the failure occurred, the complete line had to be stopped during 3 shifts until the repair was completed. However, these failures may last for at least 30 shifts and the repair time is directly related to the availability of spare parts. In this case, the workforce cost and the lost turnover should be added to the complete cost.

It is important to state that a machine learning-based monitoring system could detect the first failure peak, giving enough time to stop the line in a controlled manner. A production and workforce could then be reassigned to reduce the failure impact over production line productivity. In this case, a relatively simple machine learning algorithm is able to detect these types of anomalies within a variable, effectively warning about the problem when a first peak is detected or before.
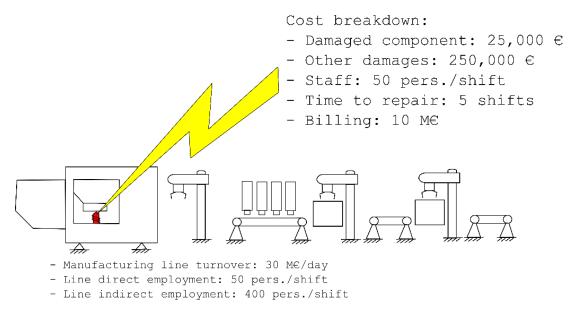
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Cost breakdown:
- Damaged component: 25,000 €
- Other damages: 250,000 €
- Staff: 50 pers./shift
- Time to repair: 5 shifts
- Billing: 10 M€
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- Manufacturing line turnover: 30 M€/day
- Line direct employment: 50 pers./shift
- Line indirect employment: 400 pers./shift
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Figure 3: Summary of costs for damages due to bearing malfunction

4.   MACHINE LEARNING FOR PREDICTIVE MAINTENANCE

Fast forward a few years to a new system where machine learning is being used to analyze the data to predict potential system failure[5]. First an understanding of the machine learning approach is needed to gain full appreciation of the scope of the predictive analytics performed to predict when the component/system may fail and even more importantly why the failure may occur. This, in turn, allows system optimizations that can extend the lifetime of the asset and the overall system.

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[5] D. GOYAL y B. S. PABLA, «Condition based maintenance of machine tools—A review,» *CIRP Journal of Manufacturing Science and Technology,* vol. 10, pp. 24-35, 2015
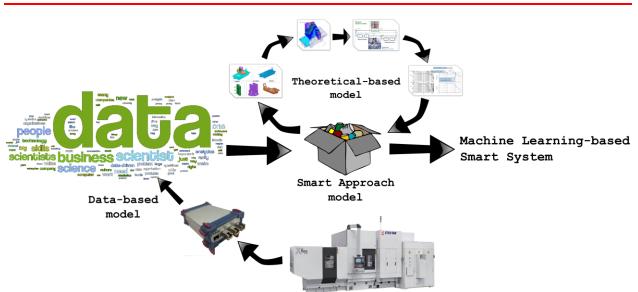
In terms of machine learning methodology, it is important to find the relevant variables to answer specific questions. This way, noise, overfitting and bandwidth usage is reduced. This technique is called "feature subset selection."

After the questions are selected, there are mainly two types of algorithms that should be selected, depending on the stage or the answer required. These algorithms are unsupervised and supervised learning[6]. When it is not clear which type of information is going to be found, unsupervised learning (mainly clustering techniques) are used. This step is called knowledge discovery, where measuring techniques applied to data are used to group into different clusters or partitions. Those measuring techniques might be based on distances, densities, probability distributions, etc. The usage of each type of measurement depends on dataset complexity and size.

However, if you want to answer a specific question and you have examples to train the system with known results from those examples, supervised learning is used. By example, knowing that the tool tip behaves at certain values of temperature but not all of the values are known, one would use supervised learning to determine the unknown values. Here, a machine learning system is trained using the examples and then is tested with new examples.

To build the complete system, the workflow with data reduction, described in Figure 4, would be used. The data is taken from the manufacturing system and sent to a machine learning algorithm that uses the new data and other information, such as mathematical models (Finite Element Method (FEM) results, behavior equations, etc.), to produce the predictive system. While data is travelling within this process, a summarization is performed, helping to only move data that is needed to solve the asked question. This helps to reduce the bandwidth utilization and increase the response speed. This type of data is called Smart Data: For example, reduce the system's 50K variables to select the most important variables – the "smart" metadata that addresses the key criteria is determined and communicated vs. flooding the network with non-critical data.

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[6] O. CHAPELLE, B. SCHOLKOPF y A. ZIEN, Semi-Supervised Learning, Cambridge, Massachusettes: The MIT Press, 2006

Figure 4: Reducing the Big Data to Critical Metadata to Get to the Smart Data

One example of an application is when the tool tip is monitored for process deviations. Note, there are many types of process deviations possible depending on the nature of the product line operation and the required cycle time – there are many types of tools: A typical CNC machine has multiple tools with many different types of tool tips (laser, milling, drilling, grinding, tapping, etc.).

Temperature fluctuations cause most common deviations. In these cases, variables like position and temperature in different points has to be measured. If 14 measuring points are selected (mainly different temperatures and tool tip position), using a sample rate of 5 minutes can give enough data to produce 11.2 KB/day (4 MB/year). This data with a supervised learning algorithm can increase the machine availability by 20%, which is nearly 3 hours/day.

Another example is the operation behavior of servomotors. In this case, variables like torque, power, temperature, vibration and angular speed can be measured. The number of variables could be up to 15,000. However, using feature subset selection, the reduction could leave only 50 variables and 1 TB/year. Figure 5 shows the results of using Unsupervised Learning to identify patterns relative to Power Consumption, Torque and other variables generating a "fingerprint" of the servo drive, where servomotor behavior is represented in the X-axis.
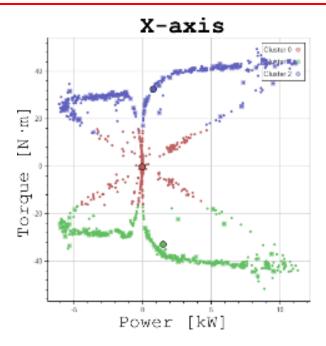
Figure 5: Clustering results for Torque vs. Power Consumption in X-axis

The distinctive Butterfly pattern, shown in Figure 5, represents a complete cycle of the servo motor axis. Clustering of data is shown with the blue data points related to acceleration, direction and peak power in given cycles – acceleration and deceleration – symmetric – around the 0 power. Green data plotted is similar to Blue but at different positions. Whereas the data plotted in Red reflects when the drive was stopped but where power and torque was still consumed to avoid movement while held in position. The data plot using the clustering technique produces a graphical representation that identifies the three states of the servo axis – acceleration, deceleration and the idle state to hold the position.
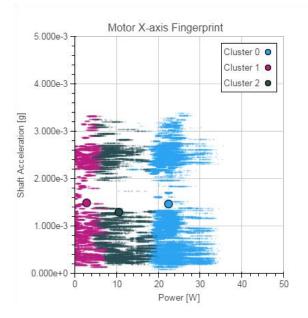

Figure 6: Clustering results for Shaft Acceleration vs. Power in X-axis

Another point of view can be seen in Figure 6, where the acceleration level related to the shaft is plotted against servomotor power. In this case, the clustering technique distinguishes between idle, acceleration and deceleration and maximum power in terms of acceleration levels. The acceleration level is independent from the power consumption. However, power levels can be distinguished more clearly than in the data shown in Figure 5. Therefore, from the point of view of predictive maintenance, it is expected that a servomotor should maintain this fingerprint acceleration level at all power consumption levels. Since the acceleration is related to the shaft angular speed, a malfunction of the servomotor could be detected when anomalies are outside the clusters: for example, anomalous vibration levels at a given acceleration state.

5.   SUMMARY

This system represents the convergence of the OT and the IT. Through this convergence and advances in sensor fusion, edge and cloud computing, machine learning is seeing adoption in many ways and is now playing a central role in smart Factory predictive analytics. This article provides an example where both unsupervised and supervised machine learning are used in predictive maintenance:

- Unsupervised Learning: as a first step to detect or find new information within data and for machine monitoring.
- Supervised Learning: to answer specific questions regarding the spindle and overall machine behavior providing a 20% increase in improved asset availability, estimated at an additional three hours per day of use.

Maximizing system operation and lifetime provides valuable advantages to further advance the intelligence of manufacturing facilities. Specific areas directly related to Predictive Maintenance include:

- Machine knowledge discovery
- Transparency to the machine and process behavior
- Increased understanding of system weaknesses
- Ability to tune the operation to increase asset utilization
- Optimizing the system for maximum productivity
- Preventing Unplanned Downtime; detect anomalous operation; predict in advance of failure
- Extending asset and system life

6.   FUTURE OUTLOOK: SMART FACTORY OPERATION: FROM PREVENTATIVE TO PREDICTIVE TO PRESCRIPTIVE

The path to intelligence is through "listening" to and "learning" what the data is saying. Gaining actionable insight is only valuable when acted upon in a meaningful way that provides value. Today a human operator is involved in many areas for preventative and predictive maintenance.

Looking to the near future, not only will the Smart Factory (and other IIoT related "things") track and identify issues prior to failure, but also without human involvement (Figure 7). Already in various stages of development, we will see products and systems taking action on their own, self-optimizing – a more prescriptive approach leading to the future of real machine time self-optimization through Machine Learning at the Edge.
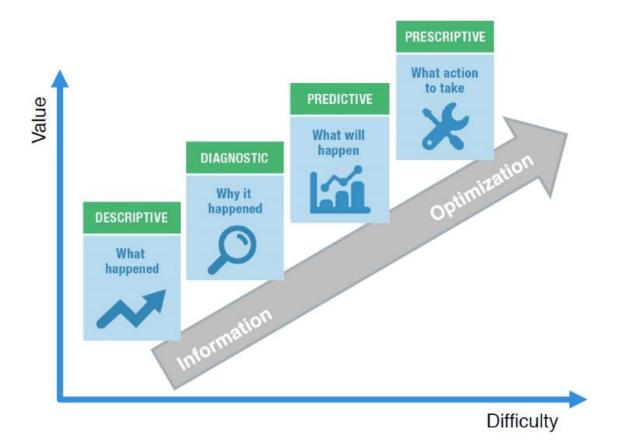

Figure 7: Evolution of Information Optimization (Image Source: Automation World webinar)

This approach, of self-optimizing and self-prognostics is already under investigation. As recognized today, Machine Learning is rapidly evolving and will continue to increase in adoption in new and innovative ways, taking a pivotal role in further enhancing the intelligence of the factory.

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