The Path from Data to Actionable Information as a Driver for the Industrial Ecosystem

Author:
William Sobel
Co-Founder/Chief Strategy Officer
VIMANA
will.sobel@govimana.com

OVERVIEW

The foundation of the Industrial Internet of Things (IIoT) is the notion that abundant data will be the driver of new products and economies by providing objective realities from the production and use of industrial equipment and systems. There are several misconceptions about the nature of data and analytics and how to approach these problems to achieve actionable and measurable results. An example is the use of raw data and deep learning to create actionable insights. This has led to a great deal of disillusionment in the industry when implementing an IIoT strategy.

There is a general lack of understanding about how to characterize data and information and what is meant by semantics. The ultimate goal of any IIoT strategy is to provide business value. So in this article, we will look at the requirements from the perspective of the manufacturing business and ecosystem to understand the criteria that lead to actionable information and interoperability between industrial systems. We will provide an analysis of relevant industrial standards such as OPC/UA[1], STEP[2], EtherCat[3], SysML[4], and MTConnect[5] and differentiate between the syntactic and semantic standards in greater detail.

These core concepts are crucial to making the foundational IIoT technologies and architectures deliver on the promises and provide the fabric that will enable the new economies and business models. Never begin an IIoT project with technology, such as Artificial Intelligence (AI), as the driver: Start with a business objective and then determine the technology and data requirements that achieve measurable results and advance one's strategic goals. To illustrate the ideas, we will evaluate some discrete manufacturing use cases showing how one can deliver rapid business value integrating open standards from multiple industrial systems to create rich semantic context.

THE PATH FROM RAW DATA TO WISDOM

The first step is to understand the high-level taxonomy and the types of data that will be required to create actionable insights. When referring to data in the context of IIoT, one is usually referring to streaming data from sensors or control systems that are representing some characteristics about the real world. When one moves beyond IIoT sensor data, many other critical information models provide context and intent and are often overlooked.

[1] https://opcfoundation.org/

[2] https://www.iso.org/organization/9295.html

[3] https://www.ethercat.org/default.htm

[4] http://www.omgsysml.org/

[5] http://www.mtconnect.org/

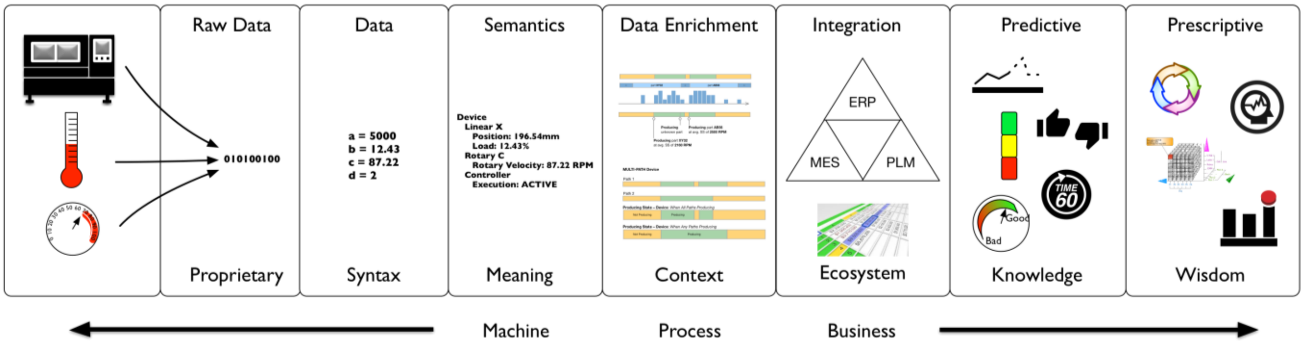

Figure 1: Data and Meaning

Without context and intent, one is often inferring the validity of the outcome. In highly complex systems, such as manufacturing processes, it is nearly impossible to provide valuable insights into the systems without context. This is often a key component to the success of any IIoT solution.

In Figure 1, we show the process of transforming data from a raw stream of un-interpreted bytes to prescriptive *wisdom*. The following sections discuss each of these steps in detail to provide a structured approach to achieving valuable insights from data. Many of the examples are manufacturing-related since that is our area of expertise.

Raw Data

Raw data is collected from the control systems and sensors to provide continuous streams of bytes from various sources. At this stage, it is imperative to create a consistent timestamp associated with each observation to enable sensor fusion during later stages of analysis. Sensor fusion is the ability to combine many disparate data sources to form a single stream of related events and assert causality between those events.

The data cannot be analyzed at this point since even the shape and structure is unknown. We can think of Linear A script, as pictured in Figure 2. If data represented language, we would be seeing the shapes of the letters, but not yet know how to interpret the marks.[6]

[6] https://en.wikipedia.org/wiki/Linear_A

There are standards that are used to collect raw data from manufacturing systems. These are often highly deterministic field bus technology such as EtherCat[7], Profibus[8] or Modbus[9]. The data in these standards have little to no syntax, so another layer is required to interpret the data and combine registers to understand the structure and types.

Figure 2: Linear A Script

Syntax

Syntax provides the data type–for example, integer, byte, floating point number, array or string – and the name – sometimes referred to as the tag or register. It is still unadvisable to analyze the data at this time since we have not provided meaning. To use the previous metaphor, we have now identified the letters and grouped them into words and identified parts of speech, but do not know what the words mean or the topic they are conveying.

Some standards provide a syntactic structure, one of the most common in the manufacturing space is OPC/UA [10]. It provides an abstract information model that allows for a common structure and syntax of the data with grouping and tagging. Syntactic transformation should be done at this stage to prevent having to provide some initial interpretation before it gains meaning.

The syntactic stage can sometimes be indiscernible from the following semantic stage if one combines the semantics into a single functional step, such as transferring from the raw data to OPC/UA with the MTConnect semantic model layered on top. There is still an intermediate syntax that must be created, but it may not be visible to the user of the data.

Semantics

Semantics creates the meaning and context of the data and turns it into information. There are many levels of context we will discuss, but the first is concerning to the "thing" or device we are collecting data about. Meaning requires that the specifics of the data be identified; for example, with temperature, it must be identified as a "Temperature," and the units must be given, such as "Centigrade." The logical device model must relate the piece of data to the logical component, such as the motor or amplifier, as well as the relation to the whole, the motor of the X linear axis (defined

[7] https://www.ethercat.org/

[8] https://www.profibus.com/

[9] http://www.modbus.org/

as the longest linear dimension perpendicular to the Z axis), that in turn rotates around the primary spindle of the machine.

When providing semantics, it is necessary to be specific enough that one can make sense of the data; this is where the metamodel comes in. Each piece of data is associated with a logical metamodel of the device or thing that describes the components, their relationships, constraints, and the data they can provide. This is what is meant by device context.

The complexity of the analytics will determine the complexity of the metamodels. With a complete digital surrogate or twin of the device, it is necessary to have a more complex metamodel that may refer back to the geometry of the parts of an assembly and various systems engineering models, given in standards such as SysML, that provide the first principles expectations of their behavior.

There are many ways to create semantics; these range from explicit – identifying the meaning of the data based on an understanding of the "thing" and its function; or implicate – using AI to perform feature recognition and classification of the data to determine the meaning. The selection of technology and methodology will depend on the nature of the data and if the data can be interpreted without complex statistical processes.

AI and learning models will be developed at the predictive stages of analysis with the deployed models at the semantic stage to classify the data earlier in the pipeline. This approach is a typical feedback mechanism since the full history, and the higher-level context is unknown at this stage, and to do so would impede the performance, function and utility of the systems because of the increased overhead.

Using standards for semantics is essential. One can sometimes make it to semantics with proprietary data, but if one does not use standardized semantic models at this stage, the value of the data will be limited to a single solution and most of the potential will be lost. Examples of semantic standards are MTConnect for manufacturing or CityGML [11] for smart cities. [12] Using standards will have a multiplicative effect on the value of the information since there is no way to predict the eventual use of the data and having an open and common meaning will protect the data collection investment.

With semantics, there is still little actionable insight since the data lacks the context of additional business systems and information sources. The next stage interprets the data within the context of the use of the equipment.

[11] https://www.citygml.org/

[12] R. Kaden *, T. H. Kolbe. 2013. "City-Wide Total Energy Demand Estimation of Buildings Using Semantic 3D City Models and Statistical Data." *ISPRS 8th 3DGeoInfo Conference & WG II/2 Workshop.* Istanbul, Turkey: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences.

DATA ENRICHMENT

This stage relates the semantics to the process and use of the equipment. This is where we introduce the intention of the processes, in discrete manufacturing this is done by providing the device constraints, process plans with expected parameters and expected performance. The process constraints allow the analytics to annotate the information stream by comparing the actuals with the expectations and then reporting deviations.

Value is emergent at this stage by using technology such as Complex Event Processing [13] (CEP) to recognize patterns. Since we know the meaning of the data, it is possible to place constraints on the data – for example, if the load exceeds a threshold when a tool is being used to cut a specific type of material, then create an event that indicates something may be going wrong. Enrichment can also make use of existing learning models. Once the semantics are present, it is much easier to build classification systems that provide more tangible value to the users using statistical analysis. Closed loop feedback can also be performed to alter or correct a process before damage or loss occurs.

Enrichment may also introduce additional information models; these are often static models that describe the expectations for the execution of a process and information relating to the localized process verification[14]. These additional information models allow the analytics at this early stage to gain a larger perspective and make judgments about the outcome and the operation of the equipment.

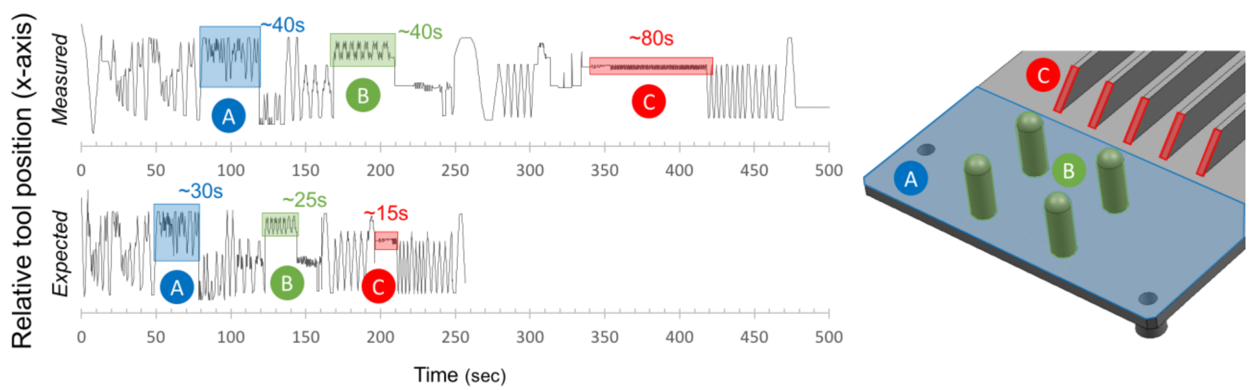

Figure 3: Comparison of simulated data for part build generated by Mastercam compared to actual machine data. Note: The X-position of each dataset has been translated for ease of comparison. The vertical scales are consistent with both datasets.

Figure 3 illustrates the engineering predictions regarding a manufacturing

[13] https://en.wikipedia.org/wiki/Complex_event_processing

[14] Brandl, Dennis. 2008. "T061_isa95-04.pdf." 05 19. https://apsom.org/docs/T061_isa95-04.pdf.

process compared to the actual execution.[15] As one can see, there is a significantly longer amount of time required to make the part than predicted, especially concerning the movement between angular fins (C). If this is anomalous behavior, the operation can be flagged as suspect and an analysis can be performed to determine why the deviation occurred. From the display, the engineering estimates are grossly optimistic.

One caveat is that at this stage the data is still point-in-time observations about the device and the analysis has a very limited amount of history, only enough to provide the running statistics that are used for categorization, signal processing and trend analysis, as well as comparisons to other static information models. The time horizon of enrichment is often minutes to hours, but long-term trend analysis and model creation are left to the predictive stage.

Integration and Ecosystem

The ecosystem integration connects the enriched and semantic information to the business systems, allowing for actions to be taken that have a larger scope than a piece of equipment and evaluate the impact on delivery and revenue. When integrated to the scheduling and resource management systems, jobs can be rescheduled to work around equipment failures or changes to process plans resulting from feedback from execution. Data enrichment is still device- and process-centric when the information is integrated into the business ecosystem, systemic changes can be made, repair tickets

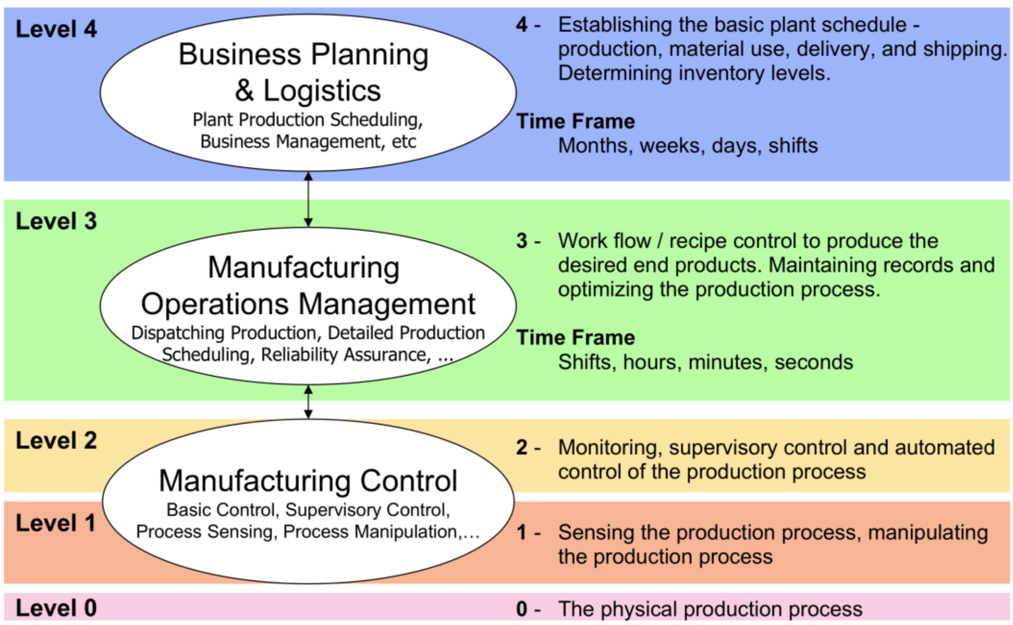

Figure 4: ISA-95 Levels

[15] William Bernstein, Thomas Hedberg, Allison Bernard Feeney. 2017. "Toward Knowledge Management for Smart Manufacturing." *Journal of Computing and Information Science in Engineering* 17 (3): 23

issued, engineers dispatched and processes relocated.

Standards that are useful for ecosystem integration include ISA-95 [16] or its implementation in XML by MESA, B2MML[17]. In Figure 4, ISA-95 presents a layering system that provides a logical separation of functionality for industrial manufacturing processes.[18] From a data perspective, the first four stages map to layers 0 through 2 and the ecosystem map to layers 3 and 4.

ISA-95 provides semantic information describing the requirements, resources, personnel and delivery of the job or order. When combined with IIoT data, ISA-95 enables dynamic feedback to verify that the intended process outcome matches the execution and enables increased stability and performance by informing design, engineering and planning.

Predictive

The previous stages provide information that is reactive to situations that have occurred but are not attempting to look into the future and predict outcomes or prevent problems before they occur. This stage begins to build the analytical models that will look into the future and extend the time horizon for problem avoidance.

Predictive analytics requires an understanding of the cause and effect related to the semantic and enriched data when combined with the business ecosystems to understand the impact and the outcomes of the processes. Predictive analytics also requires a statistically significant amount of history to correlate the execution with the expectations and interpret feedback from the operators who provide comments about the outcome. This determines the relationships and training sets to construct the statistical models for classification at the earlier stages with machine learning or deep learning.

Predictive analytics can also provide machine health-related events to remove machines from certain activities before they result in delays and loss of revenue. For predictive analytics to be effective, there must be adequate context to understand how the information relates to the equipment, process and business, as well as the intended results.

Predictive models are often used with simulations to create what is now being called digital twins or surrogates. The predictive models are commonly constructed using first principle engineering models (if standards are used, they are provided in SysML) to describe the expected behavior. A digital twin also represents a process or a product and a piece of equipment. IIoT data is used to refine the first principles models based on actual observations.

Predictive models can also be deployed in the enrichment stage local to the

[16] https://isa-95.com

[17] http://www.mesa.org/en/B2MML.asp

[18] Brandl, Dennis. 2008. "T061_isa95-04.pdf." 05 19. https://apsom.org/docs/T061_isa95-04.pdf.

equipment. For example, predictive vibration analytics can find a pattern for undesirable vibration when a machine is making a 20mm slot in steel with a 40mm endmill having three cutting items and rotating at 2500 RPM. The analytics will be continually refined as more data is collected and the model is improved. This update cycle allows the local systems to continue functioning and ensure safety even if they are not able to communicate with other parts of the ecosystem.

Prediction is often referred to as knowledge since one is building models that are capturing the causality relating to the objective truth. It has the potential of adding tremendous value to the manufacturing processes since it allows for the avoidance of loss and reduces unexpected process disruptions. With surrogate models and simulations, first principle models can be calibrated to the reality of the actual manufacturing execution and become more prescriptive.

Prescriptive

Following from predictive analytics, focusing on avoidance of problems before they occur, prescriptive analytics allows the system to avoid problems by predicting future outcomes and working around situations that are highly likely to cause problems or determining best practices. Examples of prescriptive analytics are technologies that prescribe optimal process parameters when using certain tools to cut a feature in a certain material, in this case, the information will inform the Computer Aided Manufacturing (CAM) engineers to better specify how tooling is used. One can also prescribe optimized material flows at the enterprise scale to increase on-time delivery and machine utilization. Maintenance strategies can be significantly improved by prescribing when repairs should occur based on the machine capabilities and the required activities in the job queue.

Prescriptive analytics avoid losses before they occur. By combining the IIoT information streams with the intent-based models of the product geometry and inspection plans, the causality of decisions and impact on outcomes can be better understood. The eventual goal is to get to a level of prescription where the outcomes can be forecast to the extent that on-demand scheduling can adapt to rapid changes in product requirements and new orders, down to individual parts.

As with predictive models, the prescriptive models will be created using large amounts of historical data. The models will be updated as they are refined and better predictions become available. The standards that are currently applicable to the prescriptive analytics are SysML for system engineering, STEP, specifically AP-242ed2[19] for solid model geometry and GD&T as well as QIF for quality reporting and statistics. Models like AP-238 or STEP-NC can also be used to provide the expected execution stage models to compare the engineering intent.

[19] http://www.ap242.org

Prescriptive analytics is often referred to as wisdom because they transition the analytical process from reactive to proactive and allow systems to make judgments based on historical evidence and learning. When prescriptive AI models are utilized at the enrichment stage of analysis, they can create self-aware, self-organizing equipment that can dynamically orchestrate to perform complex tasks without involving the ecosystem; the ecosystem, in this case, is providing high-level business requirements.

CASE STUDIES

OVERALL EQUIPMENT EFFECTIVENESS (OEE) – HOW TO MAKE IT A VALUABLE KPI USING TRUEOEE™

OEE is one of the most common key performance indicators (KPI) manufactures used to improve processes and equipment use. The Association for Manufacturing Technology (AMT), the trade association for the machine tool builders, set out to define how OEE was to be computed for their membership, specifying that OEE is to be used as a benchmarking and continuous improvement metric, not as a way to compare machines from different builders.

AMT published the standard methodology to calculate OEE for discrete manufacturing in the *Production Equipment Availability* report (now at edition 4) in 2011[20]. They define OEE as follows:

$$OEE = Overall\ Availability \times Performance\ Efficiency \times Quality \times 100 \qquad [1]$$

Where the terms are defined as follows:

$$Overall\ Availabilty = \frac{Production\ Time}{Scheduled\ Operating\ Time} \qquad [2]$$

$$Performance\ Efficiency = \frac{Planned\ Process\ Time}{Actual\ Process\ Time}\ or\ \frac{Measured\ Output}{Target\ Output} \qquad [3]$$

$$Quality = \frac{Good\ Parts}{Introduced\ Parts} \qquad [4]$$

[20] The Association for Manufacturing Technology. 2011. *Production Equipment Availability (Edition 4).* McLean, VA, https://goo.gl/hAqg7W

The OEE metric [1] is structured so that a one-hundred percent OEE is an impossible target that can never be achieved because it represents perfection. In a well-run discrete manufacturing enterprise, the correctly computed OEE is usually in the range of thirty to forty percent. In high volume low mix production, such as automotive parts, OEE has been measured as high as eighty percent. When a company reports an OEE metric over ninety percent, one should view that number as suspicious; when OEE is greater than one-hundred percent, the targets are invalid, and the number has no meaning and therefore is not actionable.

There is only one factor, *Overall Availability* [2], that has been consistently measured accurately and objectively. In the following section, we will discuss each factor and how to accurately compute OEE using IIoT data and the methodologies outlined in the previous section. This approach has yielded a much more valuable KPI, and that has been effectively used in-process improvement.

Overall Availability

The first factor is defined by slicing time into the following categories, as defined by AMT in Figure 5:

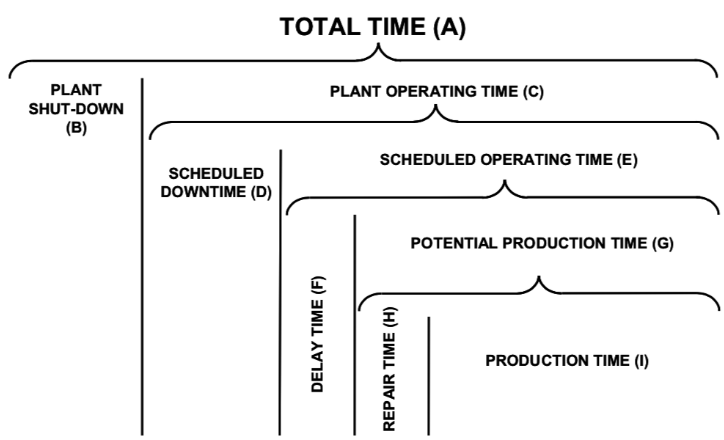

Figure 5: Chart of Equipment Availability Parameters

Production time can be further broken down into the following categories in Figure 6[21]:

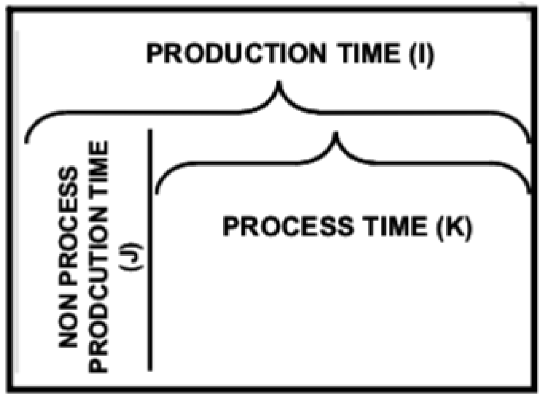

Figure 6: Production Time

To categorize time, one needs to understand the equipment's current operation states and when essential work is being done necessary to producing parts, even if it is ancillary to the production process. One should start by getting as much data from the controller as possible, use proprietary APIs or binary signals from PLC terminal blocks. The data must be translated into a timestamped stream of tagged values.

The next phase translates the data from the tag value pairs to the MTConnect standard by taking the tagged data and converting units and determining standardized machine states. After the semantic conversion, rules can be applied to multiple machine vendors and models. Sensor data can be analyzed to identify anomalous conditions and translate the conditions into MTConnect semantics using machine learning.

The initial categorization is done during the enrichment stage where the semantic data are matched with patterns that indicate production, repair, setup and non-productive. At the next stage, ecosystem integration with MES gives the plant schedule to determine if the machine is operating when it was scheduled to be operating; allowing one to discern *Plant Operating Time, Scheduled Operating Time* from *Potential Production Time* and compute *Delay Time* as well as *Lost Production time,* which is the *Production Time* minus the *Potential Production Time.*

QUALITY

The quality metric [3] is often ignored in discrete manufacturing since most manufacturing processes have multiple steps and inspection is often performed at the end. There are problems attributing the quality slip to the device and process step since there are many operations that create a single feature; it is often impossible. In most OEE systems, quality is reported at 100%, unless a capability exists at the machine to report scrapped parts or the operator identifies bad parts and enters the data manually.

Processes must be verified at each step for OEE to work properly. When we increase the part mix and variation, it is even more imperative that every step is verified. The value of in-process verification is much greater than getting a more accurate OEE metric: It is also the primary feedback mechanism to create the predictive and prescriptive AI models. Quality Information Framework (QIF) and MTConnect combined with AP-238 (STEP-NC) have demonstrated how this can be done using standards.

Performance Efficiency

Performance [4] is the most abused of the three factors. The numerator of the performance equation, the planned process time, is an engineering estimate that is often exaggerated to increase the OEE metric. For example, engineering may say the process takes 30 minutes, but the actual time to execute the process is 15 minutes. This will lead to a 2.0 factor for this metric. If the availability of the equipment is 60% and the performance is 200%, then the resulting OEE using these two metrics will be 120% since the quality factor is often 100%.

The correct way to compute performance is to baseline the process for a period and to determine the fastest time to execute under the best conditions. Measurement must also be performed on a continuous basis: It cannot be subject to a spot inspection since the results will not be realistic.

Using data from equipment, we have found the optimal process performance by historic data analysis. There is additional complexity when considering high part mix processes. The solution to high mix is to analyze the process down to each micro-planned step since each part is the aggregate of many smaller processes that are combined create an outcome.

By using AI, one can find equivalencies and analyze similar features using historical precedence. When combined, these can generate an optimal performance benchmark, for even a single, one-off part. The collection and classification of production time occur during enrichment stage, and the comparison to baseline will occur in the ecosystem integration where the current time accounting will be compared against the target using the benchmark created by combining the process plan and historical information in prescriptive analysis.

Towards Prescriptive Operational Effectiveness

The prior discussions began leading to the improvement of OEE to be a useful KPI and allow for correct attribution of quality, availability, and performance to each process step. By utilizing this metric and the additional data collected, optimizations can be made to the process while still meeting quality and schedule targets.

The methodology as described above will also allow for a more prescriptive approach to performance and quality by combining historical observations with predictions in a continual refinement process that can work across high part mix and variability. OEE done in this way can be used to prescribe process flow and manufacturing tasks to get optimal effectiveness from equipment.

GRINDING WHEEL ANALYTICS

We needed to determine why there was high variability in grinding wheel performance and life in centerless grinding as illustrated in Figure 7. Grinding wheels have a limited lifecycle and need to be resurfaced periodically, called dressing, to restore the cutting surfaces. The wheels eventually wear to the point they need to be replaced. Wheel changes were observed to be occurring between 150 and 1200 parts, where the process target was given at 200 parts. The larger runs did not necessarily create more bad parts.

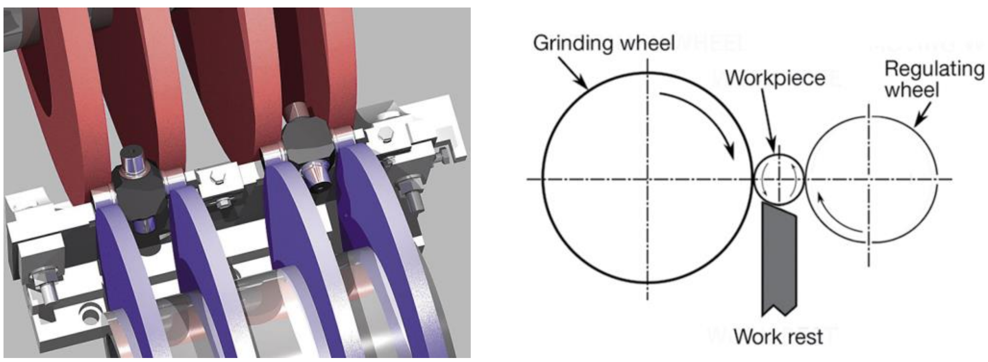

Figure 7: Centerless Grinding

The objective of the study was to analyze data from the grinders and determine the optimal wheel change and maintenance intervals and what the contributing factors were that led to the outcomes.

The project started off by analyzing load data collected from the machine-this was mapped from the spindle load sensor to the MTConnect standard. The initial data gathering is illustrated in Figure 8.

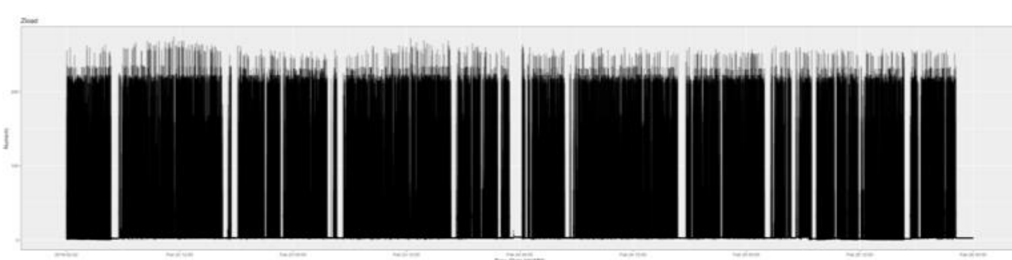

Figure 8: Load Sensor Data

The raw data, Figure 8, is almost unintelligible because of the high frequency fluctuations in the load over a large number of parts and machine cycles. The controller data is also translated into MTConnect and the machine states are used to identify the periods of time the machine is engaged in grinding a part. This is illustrated in Figure 9 where data are constrained to these periods (the colors only indicate a change of parts).

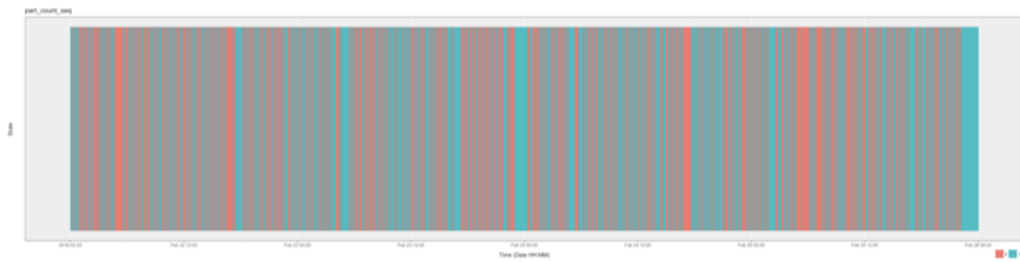

Figure 9: Individual Production Bands

In Figure 10, we compose the loads with the process periods and utilize some statistical analysis and signal processing during data enrichment, we are now able to recognize the load patterns and begin to identify periods when the loads are increasing in an orderly fashion (right-hand side) and in a highly variable way (left). The wheel changes are identified as bands, where each color change indicates a new wheel.

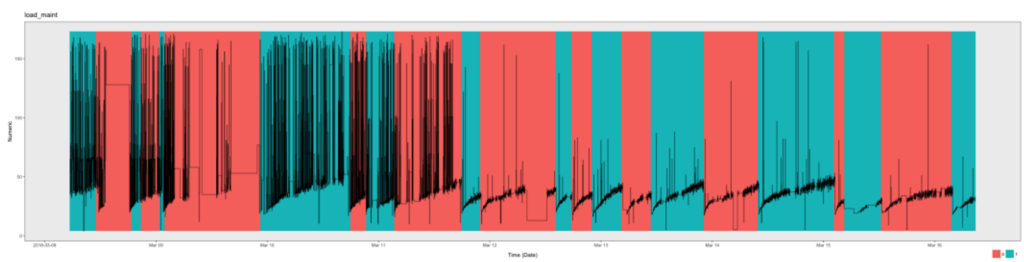

Figure 10: Loads Composed with Wheel Changes

The enrichment process will also identify the process parameters used as well as the dressing cycles to compute the frequency and duration against the process plan. When the process is not being performed correctly, the ecosystem integration will feedback the anomaly to the process planning and maintenance systems indicating something is wrong with the machine or the wheel.

Predictive

Predictive analytics can be deployed using a low latency feedback loop to stop or correct process parameters if the grinding wheels are not being used optimally. The possible causes are as follows:

- dressing cycles are not being done at the correct frequency,
- accommodation of material or wheel differences, or
- there is maintenance to be performed on the machine.

Tool management systems will also utilize the insights to correlate variations in the wheels to the lot and manufacturer. This takes the customer from reporting on what was happening in the manufacturing process to predictive analytics to identify potential problems.

These alerts created by defining models that can live at the enrichment stage of data analysis are created by analyzing historical data from multiple streams and joining it with requisitioning of material and wheels to the process and geometries being operated upon. The result is the ability to stop processes before a wheel or part is damaged.

Prescriptive

Prescriptive analytics allows us to take this one step further and knowing the wheel manufacturer, the machine, the wear on the machine and the material being ground: The system can determine the optimal process parameters to get maximum life and performance out of the equipment and tooling. This then becomes the operational recipe that is used for the execution of the process. The prescribed process can be verified with low latency feedback to ensure it is being executed correctly. Prescriptive models also allow us to build digital twins of the process and simulate the outcome to a greater level of accuracy.

Results

In production, our experience with this methodology has allowed the customer to gain between 10% and 52% savings based on prescriptive process parameters and verification of correct process execution. The savings are illustrated in Figure 11.

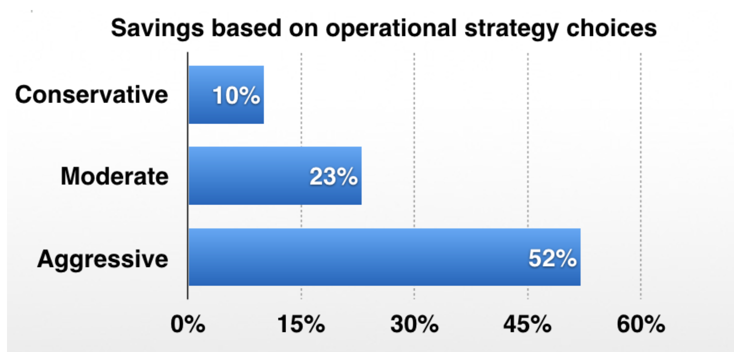

Figure 11: Grinding Process Improvement

The MTConnect standard was used in this project to collect the machine tool and load sensor data. The controller was a FANUC controller and the syntactic transformation was done first with an MTConnect adapter from FANUC's FOCUS2 protocol to the data as key/value pairs and then into the MTConnect semantic standard. The remaining stages were performed using proprietary technology for the statistical analysis (many open source technologies were used, such as R to find optimal solutions).

CONCLUSIONS

The process of taking data from a raw, proprietary format to prescriptive wisdom requires a set of transformations and analytics that adds meaning and context at every step. As with any good architecture, the process splits the responsibilities into multiple composable stages, as illustrated in *Figure 1: Data and Meaning*, where each stage adds capabilities and value to the business and helps achieve measurable outcomes.

In many implementations, some of these stages will be combined into a single step, but even when that is done, the intermediary transformations and analytics are hidden in a common component. We have found that in most cases, these stages of data analysis must occur and, when put into a framework, it is easier to reason on each step in the process separately and create a more flexible system.

➢ Return to [IIC Journal of Innovation landing page]() for more articles and past editions.