The role of transactional data in prognostics and health management work processes

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ABSTRACT

Analytics supporting prognostics and health management (PHM) work processes traditionally leverage time-series data to monitor component states and predict fault progressions in order to positively impact performance related to safety, profitability and risk management. Developing analytical models for the purpose of monitoring is asset-specific and assumes that the data is captured and accessible. In practice, monitoring assets in real-time is reserved for highly critical assets, while all assets have transactional data stored in enterprise asset management (EAM) systems. This paper reviews methods for measuring transactional data quality and for measuring asset performance metrics and health indicators from historical maintenance records that can be used in PHM initiatives. Data from both transactional sources and from machine-measured sources should be used together to derive a complete picture of the maintenance strategies and actions in an industrial site.

1. INTRODUCTION

Asset Performance Management (APM) are work processes that are not only used to manage equipment performance but improve it. The end goal of all APM work processes are to satisfy business objectives of the organization, whether it be increasing profit through reduced spending or increased efficiency, demonstrating compliance, or improving quality of services or goods produced. Asset management involves factors which influence the trade-off between costs, opportunities, and risks against the desired performance of assets in order to optimally achieve an organization's objectives (ISO 55000, 2013). For an industrial organization, this could involve using information about an asset to improve asset availability, to manage risk, and to reduce downtime.

Prognostics and health management (PHM) is a family of APM work processes geared towards using asset information and technologies for diagnosis, prognosis and health management (Rajamani & Bird, 2016). Diagnostics is the process of determining the state of a component to perform its function, while prognostics refers to assessing the current conditions in order to determine performance life remaining in an asset or component. Prognostics methods answer questions related to estimation of the remaining useful life of a component and when a fault is expected to occur (Schwabacher & Goebel, 2007) (Coble & Hines, 2011). Prognostics and diagnostics can refer to individual components of a full health management system, which are work processes geared at making the informed and appropriate decisions about asset management based on the diagnosis and prognosis information, as well as also incorporating information such as available resources and operational demand (Rajamani & Bird, 2016). Health management work processes across a system may include monitoring and detecting changes in the system's performance, identifying the root cause of the change, assessing remaining useful life, initiating mitigating actions to prevent or minimize downtime, and/or minimizing factors affecting the life cycle costs of the system (Coble & Hines, 2009) (Saxena, Sankararaman, & Goebel, 2014).

Goals of prognostics and diagnostics powered health management systems are aligned with APM business goals – using asset information to maximize uptime, minimize maintenance and operating costs (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006) (Lee, Wu, Zhao, Ghaffari, Liao, & Siegel, 2014). Prognostic capabilities using existing monitoring systems, data, and information will enable improved system for assessing risk and can answer questions to help plan for maintenance such as determining whether to continue to operate as usual to the next maintenance opportunity, or to modify operations (Hines & Usynin, 2008).

The classic engineering model for the progression from when a potential failure becomes detectable to when it degrades to a functional failure (when an asset is unable to perform to specifications) is known as the P-F curve, describing the time elapsed between potential failure (P) and functional failure (F) (Gulati, 2009). Condition based maintenance (CBM) aims to evaluate the condition of an asset by continuous condition monitoring with the objective of detecting failures at the earliest possible time in order to allow scheduling for maintenance. While early warnings do avoid large expenditures from unplanned downtime and functional failures, they occur after the fault has already begun and are still a reactive process. Truly proactive processes predict and prevent failures from occurring, and prognostics is a maintenance strategy more focused in this area (Lee et al., 2014). In the P-F curve model, this corresponds to adopting a maintenance strategy that acts to extend the time period before a potential failure occurs (Casto, 2010).

An optimal maintenance strategy is one that minimizes the total maintenance expenditure while minimizing risks (Casto, 2010) (Whitt, 2009). An asset strategy itself is a maintenance plan in place aimed towards reducing risk to production through mitigating actions for known risks. In the context of health management, monitoring the health of an asset can be used not only for diagnosis and prognosis, but also to assess the efficiency and effectiveness of an existing strategy in place in order to make modifications.

Information about an asset can exist in many forms such as through engineering knowledge, data, or output from analytic models. In the past century, as sensor technology, analytic hardware and software have matured, the availability and forms of data providing information about an asset have increased. At the same time, technology capabilities have also increased, enabling platforms and architectures which expand the possibilities for integrated data-driven processes that use analytics to support decision logic. Data about an asset can be collected both automatically and manually, possibly involving different people such as maintenance technicians, inspectors, operators, or managers, can be automatically collected such as sensors, field devices, and can be stored in various places and collected in varieties of formats (Koronios, Lin & Gao, 2005).

Data collection and storage methods are typically designed for a specific original purpose, and using this data for PHM requires acquiring, normalizing, and characterizing the data. One approach for characterizing data is to think of asset data is in terms of information records, such as the registry of equipment and tags and engineering designs, and in terms of maintenance and operating information. Data from maintenance and operating activities can further generalized into categories depending on the form it takes and the manner in which the data was collected. We classify the data forms into two categories: transactional data and time-series data, and classify the collection manner into two categories: manual or machine. Transactions are collections of information exchanges describing events, and transactional data for assets may include work orders, work requests, financial records, and inventory management. Time-series are sequences of values obtained through periodic sampling of the data, and each data point is related to the next value sequentially in time. Both data forms can be measured manually or by installed equipment sensors for condition monitoring purposes.

Assets with installed sensors for condition monitoring are assets determined as both critical and with cost-benefits for continuous machine monitoring, making many time-series measurements such as vibration or infrared thermography readings only available for certain sub-populations of assets. Transactional data, such as work orders and failure records, are available in some form for all assets. Many maintenance events, from a major shutdown of a highly critical gas turbine to replacing a burned out light-bulb are captured in maintenance logs. Fusing information from transactional data with measurements from time-series data provides an opportunity for developing the most complete picture of the lifecycle of an asset and provides the opportunity for stronger methods for measuring and predicting field system performance (Meeker & Hong, 2014). Methods extracting the maintenance and operating history of an asset from any available data source may be used to fill in gaps in analysis such as providing data inputs for health monitoring for assets that may not have sensor data available, identifying redundant information in order to improve data accuracy for key measurements, and correlating failure patterns and maintenance actions with measured signals.

In order to extract the value from historical transactional data it is important to identify and measure the data quality problems, many of which are universal across plants. Data quality assessments not only verify completeness, consistency, and correct interpretations according to usage measures (ISO 14224, 2004), but also enable a measure of certainty for the desired analyses and can be used to gauge if the desired analysis is appropriate. The first step in any work process using data should be a data quality assessment, which can assess which data is good and usable for analysis, and which data needs improvements.

Once data quality is assessed and data with sufficient quality for the desired purpose has been identified, metrics, key performance indicators (KPI's) and analytics can be developed for health monitoring work processes. Transactional information can be used both as part of a health monitoring process itself and for evaluating metrics measuring and tracking the performance of a PHM initiative. Transactional data is available for all levels of assets, and the ultimate goal is to introduce a framework integrating transactional information with time series data. In this article, a discussion of transactional data, its quality, and its value to PHM work processes will be discussed.

The rest of this article will be organized as follows. Section 2 defines and summarizes different types of asset data available. Section 3 reviews data quality challenges and measuring data quality. Section 4 discusses value potential for utilizing transactional maintenance records in PHM work processes. Section 5 reviews performance measures and methods for justification for PHM and APM initiatives using all available data sources. Section 6 presents a case study illustrating the concepts. The paper ends with concluding discussions and suggests future research directions.

2. ASSET DATA MODEL

Asset information can be found in many isolated data sources, and we review available asset information in the context of how the data takes form and how it is collected. In our data model, we partition asset data into nameplate data containing information about assets themselves and maintenance and operating data. Maintenance and operations data is generated through the process of managing, operating, and implementing any process on an asset. We partition maintenance data into transactional data and time-series data, which describes how the data take form, and into human and machine data, which describes how the data is collected.

Nameplate data may include detailed records of assets (such as functional location, manufacturer, and installation date) and their tags, engineering information such as process designs, material specifications, expected useful life, design applications and operating parameters, piping and instrumentation diagrams (P&ID), vendor information such as recommended maintenance and specifications, and client data such as requirements and generic concepts (Milje, 2011).

A transaction is an event describing exchange or transfer of goods or actions and typical transactions could be financial (orders, invoices, payments), work (plans and activity records), and logistics (deliveries, storage records, etc.) (Wikipedia, 2017). From asset maintenance data, this includes maintenance records, results of preventative and planned maintenance findings, non-recurring work such as failures, backlogs of pending work, time keeping, work scheduling, and inventory and spares management. A major source of transactional data generation and storage is using a maintenance management system such as Enterprise Asset Management (EAM) or Central Computerized Maintenance Management Systems (CMMS) (Gulati, 2009). Capabilities of CMMS/EAM systems includes work task identification, planning, scheduling, and reporting. Databases from CMMS/EAM systems include records of maintenance and maintenance costs across asset fleets. Other sources of transactional data outside of the CMMS/EAM could be financial records detailing expenditures and production plans/ losses, production information, and inspections which detail human inspections of different assets to satisfy compliance and safety protocols.

Time-series data is a sequence of values obtained through successive measurements, and each value is related to the next value sequentially in time. Examples of time-series data are regular measurements in time for direct control on a process, and could include vibration, pressure, or temperature readings. While two successive points in a time-series are related by describing the same value measured at the next time point, two points of transactional data can be independent values or readings.

Data can be collected manually or automatically by a machine such as an instrument taking sensor readings. In general, transactional data generally has a human component to its generation, such as maintenance requests and inspections, but if a single sensor reading is studied point-wise as an event, it may be viewed as transactional. Time-series data generation may come from humans or machines, and how it is collected depends on the application and its requirements and technologies. A schematic of the data model, partitioned by different data types and collection methods, is shown in Figure 1. For each data-type partition, examples are provided.

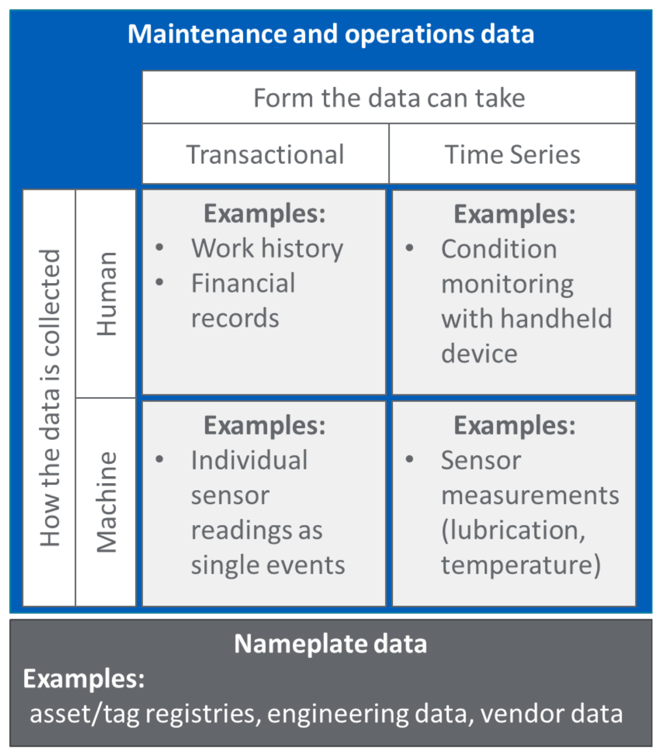

Figure 1. Asset maintenance data model. In our model, data that is generated and collected dynamically can be either transactional or time series. Data can also be generated manually, or directly from machine readings

Condition monitoring regularly measures asset condition through non-intrusive testing, inspections, and asset performance measures (Gulati, 2009). Regularly measured conditions of the asset (time series information related to the asset's condition) is collected either through manual inspections (visual inspections), spot readings (manual readings, route based with portable instruments), or online measured data from instrumentation, permanently installed.

Manually collected time-series data includes time-based inspections and spot readings. Spot readings are time-series data generated from using handheld devices to make measurements for condition monitoring technologies such as vibration monitoring or thickness measurements. Time series monitoring data with a human component involved in the generation are practical in scenarios where modes of degradation occur on a slower time scale such as weeks, months, or years such as some cases for monitoring pipe corrosion.

3. DATA QUALITY

3.1. Challenges in transactional data quality

Historical maintenance records are important for providing valuable insight in past maintenance on existing pieces of equipment (for example, deterioration mechanisms) and provide valuable asset information and material for reliability analyses. While the value potential from using transactional data is unbounded, the abundance of irregular and inaccurate data limits the analysis reliability engineers can conduct on data sets. Common data quality issues include missing information, and information that is not missing may be miscoded, may lack engineering information, or may be written against inappropriate systems. Other data quality issues are data isolation causing data islands (Koronios et al., 2005) (Meeker & Hong, 2014) (He, 2016) (Hodkiewicz & Ho, 2016) and that many standards for coding are subject to human interpretation.

Much emphasis in reliability is on failure mode identification, which may in practice be very difficult due to little or missing information about the failure mechanism or root cause (Sikorska, Hammond, & Kelly, 2007). Failure mode data analysis relies on consistent failure mode coding practices such as those standardized for the oil and gas industry in ISO 14224 (ISO 14224, 2004). Failure codes entered in CMMS/EAM systems take the form of structured fields for which values may be selected from a drop-down menu, but in practice, many of these structured fields may be incorrectly filled in or missing. Even more fundamental, the characterization of a failure event itself may be miscoded or missing. There is a lot of debate on how to define a failure, and as a result these fields may not be filled out.

CMMS/EAM data may lack important engineering information, because reporting was for financial purposes rather than answering engineering questions (Meeker & Hong, 2014). Data may also lack in the cases where the individuals executing the repair process are incentivized to get the equipment running as quickly as possible, leaving audit trails as incidental. An example is a compressor may have multiple valves, but the work order may fail to describe which valve was replaced. Another example is orders on instrumentation may be written against larger equipment. It may be difficult to locate records of when calibration was done for a sensor on a vessel when the order was written against the vessel and not the sensor. Work orders may also be assigned to the wrong piece of equipment or inappropriate system, or components removed or replaced may not even be assigned to the work order (Sikorska et al., 2007) (ISO 14224, 2004).

3.2. Measuring transactional data quality

All APM workflows (and hence, any PHM workflows) that use data to evaluate any quantity – whether it be a simple metric or a sophisticated model, should first begin with a data quality assessment. It is not desirable to use a performance measure that is easy to manipulate to make a user 'feel good' (Gulati, 2009) (Kumar, Galar, Parida, Stenström, & Berges, 2013), and poor data quality can erroneously alter many common metrics to look good such as leaving dates missing can improve the measured amount of downtime and not recording failures can improve measures of reliability.

After determining which data is sufficiently-good for analysis and which analyses are possible, you can analyze asset performance as far as it will allow, and start improving processes for the quality of the rest of the data (Naik, 2016). Improving data quality, once the data quality is measured, can be done by both changing the process in which the data is created and by improving the existing data.

Frameworks for assessing and improving data quality for asset performance applications such as evaluating metrics have been developed extensively (Hodkiewicz & Ho, 2016) (Hodkiewicz, Kelly, Sikorska, & Gouws, 2006) (Koronios, 2005) (Gulati et al., 2009). For developing any requirements, the first steps are to identify the business goals, identify the desired metrics, and to identify and summarize the available data. After this has been done, data measures can be put in place, and a measureable review process put into order. Then you can implement a plan for data quality improvement.

Frameworks for measuring data quality described in the literature are traditionally defined in terms of different attributes or aspects of data quality which are defined as data quality dimensions. There is no consistent or standard set of data quality dimensions, but there are many repeating and overlapping patterns which have been extensively reviewed and compared. Review articles of data quality assessment methods summarize typically 4-5 dimensions where completeness, accuracy/correctness and timeliness are the most common dimensions (Chen, Hailey, Wang, & Yu, 2014) (Lin, Gao, Koronios, & Chanana, 2007) (Weiskopf &

Weng, 2013) (Batini & Scannapieco, 2006) (Woodall, Gao, Parlikad, & Koronios, 2015). Completeness is the most straightforward data quality dimension measuring how much data is present and how much is missing. The other data quality dimensions address the question of, "of the data that is not missing, how good is it?"

3.3. Data quality for PHM

When executing a PHM work process, the available data may include both sensor readings and transactional information, so data quality assessment frameworks must also extend to time-series data. While challenges in transactional data quality largely stem from human error components, time series data collected from machine readings has its own set of challenges. Examples include faulty readings from sensors due to sensor failures, out-of-calibration, or distortion in the data collection and processing pipeline by faults in systems which compress data between collection and the consumer. Data collected by sensors may not always be accurate because sensor calibration and integrity checks may be overlooked by maintenance (Lin et al., 2007). Environmental conditions, ageing, and degradation may also affect the accuracy of sensor data (Smarsly & Law, 2014), and faulty sensors can cause false positive or false negative diagnoses in health monitoring processes. After any type of disruption (such as a repair or replacement on a critical asset), putting the sensor back on is often the last step and may result in periods of time where sensors remain offline.

In developing and executing a PHM work process that uses sensor data in conjunction with transactional data, the framework for data quality measures must be developed to involve data quality checks for both data types, and sufficiently-good data can be determined in this way. There is also the opportunity to employ data source agreement data quality methods by identifying possible redundancies in information between the two data source, and then use these methods to fill in missing data– such as fill in missing information from transactional data such as missing dates from time series readings. A schematic of this concept is shown in Figure 2. A specific example will be described in the case study.

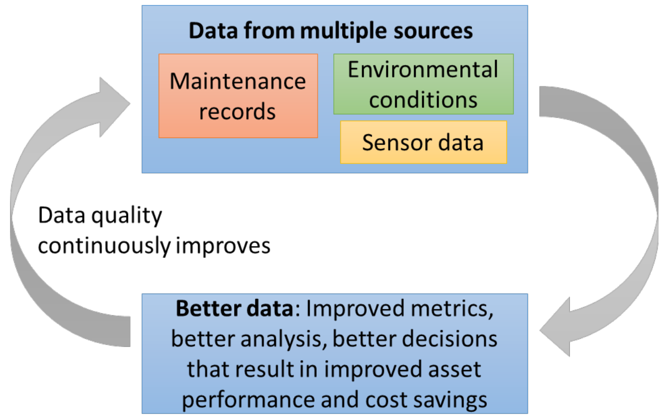

Figure 2. Fusing all available asset data can give the most complete measure on an asset, and identifying redundancies across different data sources can be used for improving data quality.

4. TRANSACTIONAL DATA IN A PHM WORK PROCESS

Transactional data is useful for identifying failure information necessary for root cause analysis, and for correlating failure event characterizations from a human perspective with observations measured by sensors and other monitoring devices. Knowledge mining past historical events can provide knowledge-based insights on failure modes and maintenance patterns across assets (Hodkiewicz & Ho, 2016).

Central to prognostic goals is estimation of remaining useful life of an asset, which depends on many factors including the time duration an asset survived before failure, operating conditions, and the different failure modes specific to an asset type. Traditional remaining useful life estimates are failure mode specific due to very different physical behaviors inherent in different failure modes (O'Connor & Kleyner, 2012) (Meeker & Escobar, 1998) (Abernethy, 2006).

Incorporating time-series data in remaining useful life models to provide more information about an asset's usage to generate more accurate estimates is a vast area of research in the field of prognostics with journals, societies and conferences dedicated to the topic. (Goebel, Daigle, Saxena, Sankararaman, Roychoudhury & Celaya, 2017) (Schwabacher, 2005) (Schwabacher & Goebel, 2007) (Hong & Meeker, 2013) (Coble & Hines, 2009) (Coble & Hines, 2011). There is a wealth of valuable information that could be extracted from the transactional data to generate effective and data-driven asset strategies for monitoring and managing a fleet of assets.

5. MEASURING BENEFITS OF A PHM INITIATIVE

The benefits and goals of a PHM initiative align with the benefits and goals for APM, and may be reviewed synonymously. Justification for a PHM or APM initiative are linked to measuring and evaluating processes and strategies. These evaluation measures quantify the value created by the process from the initiative, justify the investment for the initiative, make revisions on resource allocations, and align with compliance (Parida & Tretten, 2017) (Parida & Kumar, 2009) (Parida, Kumar, Galar, & Stenström, 2015). Strategic alignment with business goals may be cost oriented, but may also take operations, quality, and environmental/safety concerns into account.

Many standardized metrics and KPI's that have been developed to evaluate PHM performance are focused on assessing the performance and certainty for a prognostic method (Saxena, Celaya, Balaban, Goebel, Saha, Saha, & Schwabacher, 2008) (Saxena, Celaya, Saha, Saha, & Goebel, 2010) (Leao, Yoneyama, Rocha, & Fitzgibbon, 2008). Values from these metrics can be used in conjunction with transactional data (such as measures of cost or reliability performance) to model the effects of prognostic performance and PHM benefits. Metrics that measure the success of a PHM initiative can focus on either maintenance and reliability measures or business measures such as cost benefits depending on the business goals.

Transactional data is useful for building a business case and measuring the cost benefits and financial success of a PHM initiative. Benefits from any PHM initiative may include prevention of unplanned downtime, abilities to prevent accidents, reduced maintenance cost; all of which are non-monetary. While sensor data can be used to monitor an asset or components, financial success will be measured using information such as maintenance spending, production outputs, and failure frequency.

Challenges in building a business case include how to assign monetary value to these non-monetary benefits. Available data is transactional in nature and includes maintenance reports, inspection reports, surveys and service bulletins (Banks, Reichard, Crow, & Nickell, 2009) (Banks & Merenich, 2007). Different types of costs may be measured in a cost benefit analysis (CBA), such as direct costs, indirect costs, and costs at various points of the life cycle of an asset. Applications of CBA for PHM initiatives have been described in the literature (Feldman, Sandborn, & Jazouli, 2008) (Leao et al., 2008). CBA helps define requirements on various aspects that specify the cost-benefit equation and many studies have been developed for PHM systems (Saxena et al., 2010) (Sun, Zeng, Kang, & Pecht, 2012) (Esperon-Miguez, John & Jennions, 2012 (Kahlert, Giljohann & Klingauf, 2014) (Carter & Kennedy, 2016) (Scanff, Feldman, Ghelam, Sandborn, Glade & Foucher, 2007) (Ashby & Byer, 2002) (Kacprzynski, Roemer, & Hess, 2002).

5.1. Measuring performance efficiency

Maintenance performance metrics (MPM) are metrics that are used to measure the efficiency and effectiveness of maintenance strategies and frameworks (Parida & Kumar, 2009). There are many categories or pillars of metrics used in industry that have been extensively reviewed (Kumar et al., 2013) (Parida et al., 2015) and standardized definitions for best-practice have been established by the Society of Maintenance and Reliability Professionals (SMRP) (SMRP Best Practices, 2017).

There are three major factors that asset performance is based on: the operating environment, the maintenance plan, and reliability (Gulati, 2009). One possible approach for characterizing performance metrics is in terms of goals aligned with each of these factors and how different data supports these measures. The operating environment refers to performance efficiency of the overall asset system or process, and considers both the physical operating conditions and the skill of the operator. Gulati (2009) cites the result of several studies which suggest that 40% or more of failures are due to operator errors. The maintenance plan refers to the strategy for maintaining the asset, and the inherent reliability refers to the design. These three factors are all linked together for optimal asset performance, so overlap between measures and different information from the different data types to evaluate these measures may occur. We focus in detail on measures of performance related to the operating environment.

The major APM/PHM goal for performance efficiency is coordination between operations and maintenances to achieve business goals of optimal performance such as eliminating breakdowns, and ensuring safety and high quality product. Performance efficiency is the measure between the actual output compared to the expected or planned output, and metrics to evaluate efficiency measure the gap between the ideal and actual performance. The main measure for performance efficiency is Overall Equipment Effectiveness (OEE), and is measured based on availability, performance, and quality (Gulati, 2009) (Muchiri & Pintelon, 2008). Availability is the ratio of actual operating time to the scheduled time, and is related to utilization, which is the ratio of actual operating time to the total time elapsed. Performance is measured as the ratio of actual production to availability, which is penalized by slow-downs (such as a pump not pumping to capacity). Quality is the ratio of sellable production output to actual production output (penalized by defects for instance).

While the metric definitions that are input to OEE evaluation are theoretically sound, in practice, accurate evaluation requires available and clean data. Calculations of availability require both the equipment runtime and the scheduled runtime, which may not be straightforward information to obtain or extract from the data. Transactional data in the forms of work orders in a CMMS/EAM contains maintenance start and completion dates which may be used to estimate the downtime. However, these dates may not indicate the true start and finish dates due to delays in data entry or may be missing. Process historians measure cumulative equipment runtime, but utilization estimates from historians may be missing qualitative features such as if a stop time was planned or unscheduled. Further, while historian estimates may be precise, they typically will not be available for all assets, which is needed to provide a complete picture of the entire operations process. The ideal picture is to design and develop methods that fuse all available asset data to provide the most accurate measures across an entire fleet or production process, and estimating availability and downtime are discussed in more details in the case study below.

6. CASE STUDY

Using transactional data from the CMMS/EAM systems in combination with other sources of data can allow companies to create a virtuous data improvement cycle. In this case study, we walk through an example of how identifying redundant information from different types of data on the same asset can be used to extract more information about that asset. As discussed above, a common data quality issue in CMMS/EAM data is due to open and close dates on work orders frequently left missing or not accurate. While data providing exact time windows for when an asset is running may be extracted from a process historian, process historian data may not be measured for all assets in a process, only highly critical assets. For those assets, knowledge in which equipment stops are scheduled and which are unscheduled may not be readily available from the time series readings. For those assets which have available data from both sources, there is potential to compare information for data improvement knowledge which can be used to clean up work history data for all assets, as well as develop a more complete picture of those assets refining asset utilization to scheduled and unscheduled downtime.

Our example is based on information about a rotating asset in an industrial application. To protect sensitive proprietary information, we present either abstractions of the actual measurements or simulate data based on the actual observations made on the data. We abstract the time-series measurements recorded in the historian of gross load in terms of if the asset is running (100%) or down (0%).

For this case study, we compare complementary information from the work history records and the process historian over approximately a 2 year period of time. We assume that the asset is scheduled to run 24 hours a day, 7 days a week. Under this assumption, the availability measured from the work history records should match the utilization measured by the process historian. We compare estimates of availability and downtime measured over this time span in Table 1 for the same asset calculated from the work history records and from the sensor data. Mechanical downtime is calculated as the average total downtime per month, and the mean idle as the average total idle time per month.

Table 1. Comparison of maintenance metrics for a gas turbine over 29 months from work history data alone (left) and time series data alone (right).

Transactional Data		**Time series Data**	
Availability (%)	91%	**Utilization (%)**	88%
Unavailability (%)	9%	**Idle (%)**	12%
Mechanical Downtime	2.9 days	**Mean Idle**	3.7 days
Mean time to repair (MTTR)	2.0 days		

In general for this asset, the metrics compare favorably, but investigation of the differences provides interesting observations. The metric mean time to repair (MTTR) measures the average length of time from when a corrective work order is written to when the work to repair an asset begins. This metric may be estimated from the transactional data but impossible from the process historian data, and is valuable as an input parameter for planning models as well as a performance measure.

We next compare the two sources of information (historian measurements of runtime and work orders (WO)) over time to identify similarities and differences between work order events and asset stops. We show a sample of a 100 day interval to interpret these scenarios with respect to the observed data in Figure 3. A sample of the corresponding work order events are in Table 2.

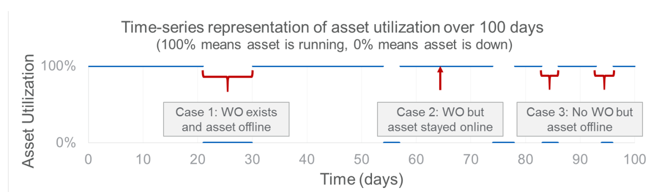

Figure 2. Time-series information about an asset's runtime over 100 days. A value of 100% means the asset is online at this time and a value of 0% means that the asset was offline. The corresponding work orders (WO) during this time are found in Table 2, and the cases are summarized in Table 3.

When comparing the actual data between the two sources (historian and WOs), we identified two perspectives for comparing the data. The first view is by comparing the occurrence (or non-occurrence) of a work order with the equipment's online/offline status, and the second by comparing the actual data between the two data sources in the case a work order exists. For the first scenario, there are four possible combinations between on/off and exists or not, which we summarize in Table 3.

Table 2. Sample work history events for the asset during a 100 day window. Cases 1-4 are defined in Table 3.

Observed case	**Event short descriptions**	**Event Type**	**Event start day**	**Maint. complete day**
Case 1	Place exhaust thermocouple wire into the piping	Repair	21	23
Case 1	Annual visual inspection	PM	22	22
Case 1	Disassembly and assembly of bearing instrumentation	Repair	22	29
Case 2	Replacement of extension cable	Repair	61	71
Case 3	A repair on day 100 (there were stops around days 85 and 95 not accounted for in work history)	Repair	100	

Table 3. Different possible data quality scenarios from combinations of equipment online/offline and a work history record existing or not.

	Work order exists	**Work order does not exist**
Equipment Offline	**Case 1**: Equipment is offline and there is a work order • There is data from both data sources supporting a maintenance event • Compare estimates of availability and downtime for further data quality checks	**Case 3**: Equipment is offline and there is no work order • Is it idle or unscheduled downtime? • If Downtime: Possible data quality problem • If Idle: Not necessarily a data quality problem
Equipment Online	**Case 2**: Equipment is online and there is a work order • Work possibly performed while machine is Online • Downtime estimate from time-series data is zero; compare against work order	**Case 4**: Equipment is online and there is no work order • Normal Operation

Cases 1 and 2 describe where there is a work order written, but are differentiated by the asset's online/offline status. Case 1 is when the equipment goes offline, and in this scenario, we can compare the downtime measurements between the time-series and the work order. In the example (Figure 3), it appears a scheduled shutdown occurred and other maintenance activities were conducted at the same time. This shutdown was probably scheduled, and availability estimates (as well as the continuous scheduled running assumption) could be modified to account for this and improve metric accuracy. Case 2 covers when there is a work order, but the equipment is running. We observe in this example that an extension cable was replaced, which may not merit downtime. Case 3 describes when a work order was not written, but the asset goes offline. In this example there were stops around days 85 and 95 not accounted for in the work history. This should be investigated as a possible data quality problem. Case 4 is the case of normal operation.

To further investigate cases 1 and 2 where a work order was written, we can compare estimates of downtime between the work order estimate and the historian. We calculate the ratio between the estimates historian downtime and the work order downtime and plot the ratio for each work history item in Figure 4. A value of 0 signifies case 2 (equipment stayed online), and a value greater than 0 represents case 1. Different regions which describe different types of relationships between downtime estimates from the different data sources are highlighted. The green region identifies repair events where the two downtimes are congruent, while the red and yellow regions identify events where the CMMS/EAM data needs to be rechecked for accuracy.

The potential to use these sources of data together as data quality measures exists. In this case study, 22% of work orders had a ratio approximately 0, while 64% had consistent downtime estimates. These measures could be used to measure and track data quality improvements. Using transactional data from the CMMS/EAM in conjunction with sensor data as inputs to help automate this process will improve data quality, which in turn will improve metric accuracy.

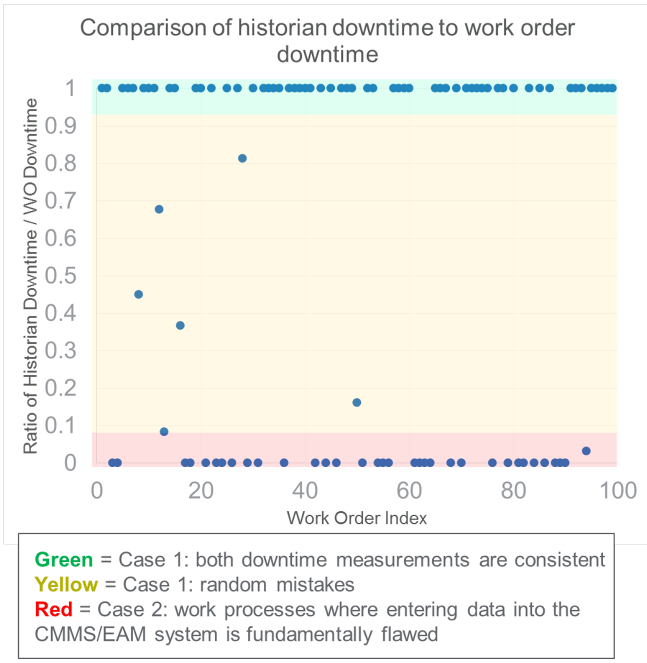

Figure 3. Comparison of downtime estimates for work history between the maintenance record data and the downtime measured from the process historian.

7. CONCLUSION

Transactional data provides a rich source of information about an asset to enrich, scale, and evaluate a PHM work process. Transactional data is generated through many forms, but generally has a human component to its generation which means that there is both a wealth of knowledge within transaction records but also introduces errors and inconsistencies in the generation process. While historical transactional data may be available in wealth, there are many data quality challenges to face to enable meaningful analytics. However, identifying which data is sufficiently-good is enough to take advantage of evaluating data-driven metrics and analytics, while executing data cleanup initiatives will help to get you there. Using all information sources about an asset can further enrich the information about an asset and its lifecycle, which can improve the potential of prognostic and diagnostic models for executing effective health monitoring systems, improve data quality, and measure the outcomes.

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