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UN-BUZZ-WORDING THE DIGITAL TWIN: A PRACTICAL GUIDE AND EXAMPLES FOR POWER PLANT OPERATORS

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ABSTRACT

Over the last 5-10 years, "Digital Twin" has become a ubiquitous term used to market a wide variety of seemingly unrelated products. This has caused confusion of products and services being marketed using this term. This use also leads to missed expectations between the solution provider and the customer. This paper will use experiences from the authors and end users to provide a guide which describes: what are the different flavors of 'digital twins'? What should a true 'digital twin' be able to do with respect to power plant operations? How do "twins" make use (or repackage) existing technologies to make them more practical for the power plant operator? Examples related to power plant performance estimations using a twin are also provided.

Keywords: Digital Twin, Gas Turbines, Analytics

INTRODUCTION

A Digital twin–a virtual model of a process, product, or service–is a promising technology for understanding smart manufacturing and industry. The blending of the physical and virtual worlds allows data analysis and system monitoring to identify problems beforehand, prevent downtime, and investigate the impact of potential hardware or software changes by simulations (Marr, 2017). In theory, a digital twin also allows companies to have a complete digital trajectory throughout the lifecycle of an asset, ranging from design and development to maintenance and service phases. Through gathering physical and virtual data of an asset at each phase, a digital twin collectively analyzes data points to identify failures by detecting precursors earlier and predict outcomes of the process through analytical algorithms. In addition to component health applications, a digital twin can also serve as a highly accurate operator training simulator (Brosinsky et.al., 2018) or to improve control performance when linked to cyber-physical systems (Bevilacqua et.al., 2020). Such opportunities increase reliability and flexibility, improve quality, save maintenance costs, and provide a tool for more consistent operation.

Further applications of the digital twin include pre-processing of measured performance data to better quantify shifts in gas turbine performance and operation. This is done through the creation of 'virtual' or 'soft' sensors. Soft sensors are predictive models based on the large amounts of data being measured and stored in the process industry (Kadlec and Abrys, 2009). These are often more direct indicators of unit health than the direct performance measurements typically recorded. Virtual sensors are used to calculate health parameters which can be tracked and trended in advanced pattern recognition (APR) software, PI AF, or any other monitoring framework.

In addition to monitoring, a digital twin can also be a 3D representation of the product derived from a detailed CAD model or image rendering. To avoid misinterpreted uses of digital twin for a process, product, or service in power industry, both plant operators and other end users should first understand the correct concepts and variants of the digital twin, and its typical applications in industry. This paper provides a survey of different digital twin definitions based on an asset's lifecycle: before and after production of an asset and data structural types: analytical, process, and visual information.

The use cases in this paper revolve around issues with aging gas turbines (GT) with multiple overhauls, including cases where advanced hardware for increased output had been installed. It has been found that many of these GTs, especially those configured as simple cycle units, have been de-rated due to elevated combustion dynamics, lean blowout (LBO), and/or lack of emission compliance. The potential application cases for a digital twin are multi-faceted as it can be applied to a wide range of diagnostics, prognostic, and 'what-if' problems. Examples include using the digital twin to identify causes of post-outage emissions and performance issues, expected impact of degradation and fault conditions, simulating improvements to operation through part repair and upgrades, and eventually estimating component remaining useful life (RUL). In all these cases, there must be an interface that uses the predictive analytic capabilities of the digital twin with the physical plant.

A list of abbreviations and acronyms used throughout the paper is summarized in the following Table 1.

Table 1. List of Acronyms and Abbreviations

AI	Artificial Intelligence
APR	Advanced Pattern Recognition
CPS	Cyber Physical System
DFDD	Digital-twin-assisted Fault Diagnosis method using Deep transfer learning
DNN	Deep Neural Network
DTA	Digital Twin Aggregate
DTI	Digital Twin Instance
DTP	Digital Twin Prototype
EWMA	Exponentially Weighted Moving Average
GT	Gas Turbines
LBO	Lean Blowout
M&D	Monitoring and Diagnostics
NPSS	Numerical Propulsion System Simulation
OEM	Original Equipment Manufacturer
PI AF	OSISoft® PI Asset Framework
RUL	Remaining Useful Life

CONCEPT OF THE DIGITAL TWIN

One early definition of digital twin was introduced by Grieves back in 2003, which consisted of three parts: a physical product, a virtual product, and a communication link in between the first two. (Grieves, 2015). The "physical" part of an asset uses sensors to gather operational and environmental data pertaining to the physical product in the real world. These sensors communicate data to the digital space through transmission technology. The "digital" part of an asset is an application that combines collected data and applies into a real-time digital model of the physical system. While a cyber physical system (CPS) is also defined as this connection between physical and digital systems, its concept primarily emerges from a system engineering and control perspective (Lee et.al., 2008). Whereas a digital twin has perspective of understanding, learning, and reasoning, often based on machine learning algorithms (NIC, 2017). Obviously, there are ambiguities in these definitions; for example, what constitutes a "digital model?" In 2012, NASA revisited the concept of digital twin and defined the term as *an integrated multiphysics, multiscale, high-fidelity, and probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates to mirror the remaining useful life of the physical product* (Shafto et.al., 2012). Based on the three-dimension model for the digital twin, Tao et.al. (2017) further proposed that a complete digital twin should include two additional dimensions: data, and service. In this five-dimension model, data lies in the center of a digital twin, because it is the core source of communication between physical and virtual world.

Figure 1 represents a functional model of a real-world asset and its related twin in the digital space. The digital twin serves as a virtual replica of the asset in real time. Enough sensors are located within the asset to measure and collect the real-world operational and environmental data. This data is continuously transmitted to, and aggregated, by the digital twin application. The application then it performs collective analysis on the incoming data streams. Over an appropriate period, the analytics techniques are used to detect the state of the asset or process. Such comparative insight could trigger investigation and a potential refinement to the physical model.

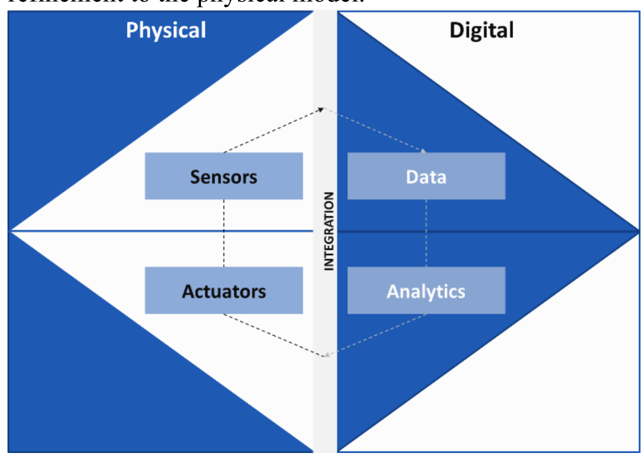

Figure 1. Digital Twin Functional Components

Furthermore, Table 2 summarizes five major characteristics of a digital twin observed in literature for a digital twin features distinct characteristics. Each unique characteristic of a digital twin related to the power industry is discussed in the subsequent subsections.

Physics-based vs. Data-driven Digital Twins

In this paper we will focus on physical asset digital twins. Data-driven analytical digital twins too represent the physical relationship among performance variables of assets and are constructed using historian sensor data from plants, which provide modeling capability when physics of an asset are inaccessible (Vilim). However, physics-based digital twins are constructed based on the real-world data, which may incorporate plants' historian data to enhance the analysis and validation capabilities beyond a model development. Hence, physics-based digital twins are preferred over data-driven digital twins with a greater resolution of the state of an asset for they are capable of estimating unmeasured sensor data through the virtual sensors and applying the models outside the region of nominal calibration (Vilim). In a similar manner, process-driven twins are just as important, but require a different level of discussion, tools, and techniques.

Connectivity

Most importantly, a digital twin provides a real-time comprehensive linkage between the physical and digital models. This linkage serves as a bridge between the physical product and the operation services, as a digital twin covers the entire lifecycle of the asset (Marr, 2017). When a digital twin is embedded in a cloud network (Porter and Heppelmann, 2015), the distributed analysis and processes across an entire fleet can be integrated easily to manage prognostic, diagnostic, and planning needs.

Adaptability

A digital twin continually refines the existing model through the collected sensor data on the actual physical product, artificial intelligence (AI) technologies, and advanced analytics. Then, the refined model provides pre-cursor to future high-risk events to adjust parts or even the entire model (Boschert and Rosen, 2016).

Modularity

Modularity in digital twin technology allows asset owners to gain additional insights for possible improvements of the asset, particularly in late phases of a product's lifecycle–production and operation–when a digital twin has already amassed a plethora of data (Boschert and Rosen, 2016). This collected data then can be used for service lifetime calculation or other analysis.

Virtual Analysis

One of the most important features of a digital twin is its diagnostic and prognostic abilities. Virtual, or soft sensors of a digital twin allows deeper analysis on the performance metrics that may or may not be measurable. The analysis from the virtual sensors can provide new insight into the health. If an advanced pattern recognition software is a part of a diagnostic toolset, this expanded data set enables better training of data models.

Table 2. Major Characteristics of a Digital Twin

Characteristics	Description
Physics-based	• Evolves along with the real system along the whole life cycle and integrates the currently available knowledge about it (Boschert and Rosen, 2016) • Not only used to describe the behavior (operation) but also to derive solutions (maintenance) relevant for the real system • The physical part is a basis of building the virtual part (Tao et.al., 2019)
Connectivity	• Digital twin covers the entire lifecycle of an asset or process and forming the foundation for connected products and services (Marr, 2017) • The components are connected to a system, which may or may not be cloud based, that receives and processes all the data the sensors monitor • The linked collection of the relevant digital artefacts including engineering data, operation data, and behavior descriptions via several simulation models (Boschert and Rosen, 2016) • *Network Communication*: The products that enable communications between the product and the cloud, which runs on remote servers and contains the product's external operating system (Porter and Heppelmann, 2015)
Adaptability	• An executable simulation model can serve as an assist system module of the automation software (Boschert and Rosen, 2016)
Modularity	• To transfer data and information into other DT in later phases (production and operation) (Boschert and Rosen, 2016)
Foresight/Virtual Analysis	• Forecasts the health of the system, the remaining useful life and the probability of mission success (Boschert and Rosen, 2016) • Capable of mitigating damage or degradation by recommending changes in mission profile to increase both the life span and the probability of mission success

CHARACTERISTICS OF DIGITAL TWIN

Grieves and Vickers (2017) further divided the concept of a digital twin into two types depending on the system's lifecycle: digital twin prototype (DTP) and digital twin instance (DTI). The prototype phase of a digital twin was to create a virtual model of a physical system before manufacturing a part or entire physical product. This is the initial stage where a series of tests and simulations could be performed to validate design sets that are necessary to realize and produce a physical version, and ultimately save cost and time. In this phase, a DTP is used to predict future behavior and performance of the designed product with the intention of varying within its set tolerance. DTP is often referred to as "Digital Twin Class" or "Digital Twin Blueprint" (GE Digital).

Transitioning from models design to development and physical realization of an asset begins to shift the system from the digital to the physical world. When a part or entire physical asset is built, real-world data is presumably available alongside the simulated models, where digital twin instance becomes the twin of an actual physical asset.

The parts of an asset are built based on its tolerances but can have variant real-time data. This type of digital twin only exists when an asset is manufactured and stays linked during the lifecycle of the asset (Grieves and Vickers, 2017). While a DTI starts with the baseline information from its prototype, DTI gets enhanced with operational data throughout the lifecycle of the asset.

A Digital Twin Aggregate (DTA) is an aggregation of multiple DTIs. Where individual DTI can be investigated for the current and past histories (diagnostic), multiple instances of assets would provide insightful data that correlates and predicts future states of the asset (prognostics). The aggregate of actual events and failures can provide Bayesian probabilities for predictive uses (Grieves, 2019).

A digital twin model can be further categorized based on data types. The data types are non-transducer type data, including geometry or pictures. By combining data from multiple types and sources, a digital twin can be modelled to provide a holistic real-time view of an asset that are monitored (Schalkwyk, 2019). The data from various sources may have a linear relationship corresponding to a physical asset. Alternatively, a graph-based framework can be used to map how the data relates to the asset and other data sources.

Analytical Models

An analytical model of a digital twin is used to analyze data, often using machine learning algorithms, to produce deeper insights into an asset. This procedure of the analytical model is to quickly obtain an initial estimate about the margin of tolerance (Zambal et.al., 2018) and detect any abnormal activities from the manufacturing database in real-time. Once the physical data of an asset is trained, the analytical model has ability to predict and diagnose faults that the asset has not experienced before.

Process Models

A process digital twin serves as a virtual representation of what is happening within a production process in real-time. A process digital twin consists of three attributes: interface, computing, and control elements (Bao et.al., 2019). The interface part of the digital twin integrates communication between physical and virtual spaces, in which digital twin can simulate and reflect the process status via operational and environmental data streams. The computing element of a process digital twin refers to the computability of the digital twin (Bao et.al., 2019). The collected data can be mapped to a process digital twin, which then combines machine learning capabilities to compute processing quality. The purpose of control is to analyze, optimize, and predict the process based on historical and real time simulation and production data (Bao et.al., 2019).

Visual Models

By combining 3D scanning and analytical models, a digital twin provides knowledge about the condition of an asset and enables better management of the asset throughout its service life. For example, consider a digital twin developed on the parallel aspects of two models: physical 3D models with structural damage and analytical models examining structural parameters by the damages. The accumulation of damage history of the physical and analytical models then provides reliable prediction of future performance and maintenance procedure throughout service life of an asset (Dang et.al., 2018).

EXAMPLES AND APPLICATIONS IN INDUSTRY

As the concept of digital twin was first introduced in 2003, numerous digital twin applications have been implemented in various industries including product design, manufacturing and production, prognostics, and health management (Tao et.al., 2019).

The details on industrial digital twin will be briefly discussed in this section.

Digital Twin in Product Design

A product digital twin can simulate how a physical asset performs under various test conditions. The flexibility to assess the physical asset through a digital twin allows developers to design collaboratively with the user groups in a responsive and time-efficient manner. Boschert et.al (2018) emphasized that the information created during design of an asset is useful and enriches the quality of information that interpreted during the asset's operation cycle.

Digital Twin in Manufacturing and Production

A production digital twin can qualify how a manufacturing process can proceed before any production of an asset. It helps make production process more reliable, flexible, and predictable. First and foremost, digital twins can visualize and update the real-time status, which is useful for monitoring a production process. Numerous sensors are enabled throughout the physical manufacturing process which then collect and capture data about a wide range of information to deliver consistent optimized products (GE Power Digtal Solutions, 2016). Application of the digital twin continuously analyzes incoming data that compares actual with an ideal and tolerable performances of the manufacturing process (Parrott and Warshaw, 2017). Soderberg et. al. (2017) also highlights data models necessary for real-time geometry assurance can help mass production to more individualized production.

Digital Twin in Prognostic and Health Management

Compared to traditional prognostic and health management systems, the digital twin driven system has significant advantages. On the prognostic side, digital twins are incredibly useful for accurately predicting future performance. This is especially useful for predicting how much energy to bid for in the power market. Another use is updating the physical model to accurately predict the future performance of the units after performing a large-scale hardware upgrade. This allows an owner to accurately calculate ROI on the upgrade based on real data, not just marketing materials for the upgrade. These predictions are also useful for maintenance planning because the performance degradation over time will be forecasted to see if operators can postpone certain maintenance until a later outage.

Moreover, a digital twin could facilitate the management of product service life. Tao et.al. (2017) prescribed nine principles to improve the maintenance efficiency and reduce maintenance failure. Digital twin assisted fault diagnosis methods using deep transfer learning (DFDD) and deep neural network (DNN) were developed in order to detect any faults throughout the lifecycle of an asset (Xu et.al., 2019).

Some practical applications of a digital twin model are linked to the definition of a complex and integrated control system that uses the network of cyber-physical systems (Bevilacqua et.al., 2019). The model provides control and monitoring logic in order to ensure stability of monitoring system in any abnormal operation of an asset. Based on actual data and reliable forecasts from the model, maintenance technicians are able to make safe repair decisions as any risk events evolve (Bevilacqua et.al., 2019).

Repackaging of Existing Technologies

While the marketing hype suggests that digital twins are the new fascinating emerging technologies for prognostic and diagnostic needs, they are commonly just an intelligent integration of many of the underlying tools that already exist.

USE CASES OF DIGITAL TWINS FOR GAS TURBINE MONITORING & DIAGNOSTICS

The EPRI Digital Twin

EPRI has been developing a digital twin of simple and combined cycle gas turbines over the last 5+ years to provide owners and operators with improved capabilities that typically reside in the expert domain of OEMs and 3rd party service providers. The digital twin is a physics-based representation of the actual asset. The model is thermodynamic and is created with the intent to support 5 M&D support areas:

- Integrate with existing M&D tools such as advanced pattern recognition (APR)
- Power plant performance prediction and trending
- Health Monitoring and Fault Diagnostics
- Monitoring and prediction of both base and part load performance.
- Outage and repair impacts including "what-if" capability

Characteristics of the EPRI Digital Twin

Following the characteristics defined in Table 2, the EPRI Digital Twin for Gas Turbines is described.

<u>Physics-Based Model</u>

The first step in the construction of a digital twin is the creation of the model. Tt is important to distinguish the terms software and model. Software is the underlying simulation code which contains the physics and building blocks required to represent a physical system. The model is a specific instance of the software used to represent a specific asset or even a specific aspect of an asset. Commercially available software was preferred for the EPRI digital twin to maximize cost benefit and enable this effort to focus on the modeling activity. For the digital twin a down selection of available cycle modeling software was performed to select a package that met the current needs and would remain flexible for future use including, but not limited to, modeling the steam turbine and heat recovery steam generator, transient (dynamic) simulation, and modeling both large frame and aeroderivative gas turbines.

After surveying available options, the Numerical Propulsion System Simulation (NPSS) was selected for the thermodynamic modeling portion. The software can simulate any gas turbine. The level of fidelity is adjustable by the and can mimic the real-life operation of the unit.

<u>Connectivity</u>

The purpose of this digital twin is to integrate into any industry standard M&D software. This is accomplished using a series of virtual sensors that are constantly calculated by the M&D software to provide constant model calibration. To do this, the physical model of the digital twin is encapsulated through a series of closed-form, linear equations has been tested and shown to provide good accuracy at detecting faults and at predicting day and week ahead performance. This approach uses historian data and transforms it to virtual sensors capable of more directly detecting faulted operation. Historian data, such as power, heat rate, and thermal measurements are used as inputs to the digital twin equations. These equations are created from the physical NPSS model and are customized to a specific GT. The output of these equations are estimates of virtual sensors, which de-noise the historian data and provide a cleaner estimate of individual module performance.

The "corrector" equations are a set of virtual sensors that represent the current health of the unit. They are not directly measurable but can be used to estimate component health on a normalized basis. The health parameters currently used in the digital twin are listed in Table 3.

Once estimated, the corrector, or health parameter, values can be used with a set of "predictor" equations capable of predicting expected values of performance such as power output or heat rate.

<u>Adjustable</u>

The described approach is adjustable to any model of gas turbine providing an underlying physical model exists. A reference gas turbine model is calibrated using a year or two of historical performance data. The exact inputs are described in the next subsection. The data is then used with a Bayesian calibration routine to tune the model to the specific data set. The outputs of the calibration are a calibrated, physical reference model (EPRI, et al., 2019).

Once a calibrated model exists, the health parameters and ambient conditions are varied over a range of inputs to

Table 3. Digital Twin Health Parameter List

VIRTUAL SENSOR	DESCRIPTION / USAGE
COMPRESSOR EFFICIENCY PARAMETER	Unbiased estimate of compressor efficiency
COMPRESSOR PRESSURE RATIO PARAMETER	Unbiased estimate of compressor pressure ratio (CPR)
COMPRESSOR FLOW PARAMETER	Unbiased estimate of compressor mass flow capability
STAGE 1 NOZZLE AREA	Turbine nozzle choke area
TURBINE EFFICIENCY	Unbiased estimate of turbine efficiency
COOLING FLOW	Unbiased estimate of chargeable and nonchargeable cooling flow from the compressor to the turbine
COMBUSTOR DP	Unbiased estimate of combustor pressure drop
AMBIENT PRESSURE INSTRUMENTATION BIAS	Estimated error in inlet total pressure measurement
CDP INSTRUMENTATION BIAS	Estimated error in compressor discharge pressure (CDP) measurement
EGT INSTRUMENTATION BIAS	Estimated error in exhaust gas temperature (EGT) measurement
IGV INSTRUMENTATION BIAS	Estimated error in inlet guide vane (IGV) measurement

Table 4. Virtual Sensor Equations - Master Input Output List

INPUTS	OUTPUTS
GENERATOR WATTS [KW]	CPR HEALTH
COMP INLET FLANGE TEMP [DEG F]	TURBINE EFF SCALAR
RELATIVE HUMIDITY [%: 0 TO 100]	COMP EFF DELTA
INLET AIR TOTAL PRESS TRANSMITTER [IN H2O]	TURB EFF DELTA
EXHAUST PRESS TRANSMITTER [IN H2O]	NOZZLE AREA SCALAR
FUEL HEATING VALUE [BTU/LBM] – LOWER HEATING VALUE	BURNER dP SCALAR
FUEL TEMPERATURE [DEG F]	NC COOLING SCALAR
COMPRESSOR DISCH PRESS [PSI]	CH COOLING SCALAR
COMPRESSOR DISCHARGE TEMP [DEG F]	COMP FLOW SCALAR
COMBUSTION REFERENCE TEMPERATURE [DEG F]	AMB PRESSURE BIAS
EX TEMP MEDIAN CORRECTED BY AVG [DEG F]	CDP BIAS
GAS FUEL FLOW [LBM/S]	EGT BIAS

Table 5. Performance Prediction Using Virtual Sensors – Master Input Output List

Inputs	Outputs
COMP INLET FLANGE TEMP [deg F]	Predicted GENERATOR WATTS [kW]
RELATIVE HUMIDITY [%: 0 to 100]	Predicted COMPRESSOR DISCH PRESS [psi]
Inlet Air Total Press Transmitter [in H2O]	Predicted COMP DISCHARGE TEMP [deg F]
Exhaust Press Transmitter [in H2O]	Predicted COMBUSTION REFERENCE TEMPERATURE [deg F]
Fuel Heating Value [BTU/lbm] – lower heating value	Predicted EX TEMP MEDIAN CORRECTED BY AVG [deg F]
Fuel Temperature [deg F]	Predicted Gas Fuel Flow [lbm/s]
CPR HEALTH	
TURBINE EFF SCALAR	
COMP EFF DELTA	
TURB EFF DELTA	
NOZZLE AREA SCALAR	
BURNER dP SCALAR	
NC COOLING SCALAR	
CH COOLING SCALAR	
COMP FLOW SCALAR	
AMB P BIAS	
CDP BIAS	
EGT BIAS	

create a large training matrix. This matrix is created by executing the NPSS model several thousand times. Alternatively, a neural network representation of the NPSS model could be used if there is a desire to run on a user system.

The result of the training matrix is used to perform a partial least squares regression. The regression is performed twice, once for estimating the virtual sensors (an update or corrector), and another for estimating performance given a set of virtual sensors (a prediction).

Modularity

The exact inputs and outputs can be changed as unit instrumentation availability and reliability require. The current full set of inputs is shown for the virtual equations in Table 4Table 3. Digital Twin Health Parameter List

VIRTUAL SENSOR	DESCRIPTION / USAGE
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IGV INSTRUMENTATION BIAS	Estimated error in inlet guide vane (IGV) measurement

Table 4 and the prediction equations in Table 5.

In a monitoring and diagnostics setup, the two sets of equations can be used. First, the virtual sensor predictions may be used to directly estimate unit health. Then future performance predictions can be made with the current estimated values of each virtual sensor. In this setup, the user would directly monitor for shifts in virtual sensors. In the second option, although potentially less accurate, the user would compare future performance estimates against real-time data to detect faults.

Foresight/Virtual Analysis

Fault Diagnostics

The closed-form virtual sensor approach was applied to two 7EA units over two years of data to identify its effectiveness. Two evaluations were carried out. First, a plot was made examining the compressor specific health parameters that examine efficiency, pressure ratio, and compressor flow relative to expected values. A perfectly health unit would have a COMP EFF DELTA value of zero and CPR HEALTH SCALAR and COMP FLOW SCALAR values equal to one, as shown in Figure 2. In this figure, the black lines represent offline water washes. This is an ideal control experiment since the expected impact of compressor washing is to recover performance. A clear recovery in efficiency and pressure ratio is observed before and after most of the washes. Recoveries in flow capacity are also noted, but to a lesser extent.

A more extensive examination was undertaken at for all the parameters, shown in Figure 3. A step change in several of the parameters, noticeably the sensor bias terms and the compressor flow scalar are apparent to the eye. (These excursions would also be obvious to automated monitoring software.)

There are also several small jumps in the compressor flow virtual sensor (COMP FLOW SCALAR) seen around the June 2018 timeframe. This region is zoomed in and shown in Figure 4.The red circle indicates the bottoming cycle bypass issue just discussed; however, the blue circle warrants further investigation.

An examination of performance data was made just before and after the blue circled excursion in Figure 4. The compressor inlet temperature plotted in Figure 5, immediately showed a large difference between the normal (or good, shown in green) points and the excursion points (or bad, shown in red). During this time there was obviously an issue with the compressor inlet cooling system, or it was shut off intentionally.

Based on this small use case the virtual sensors have immediate use for detecting faulted, or abnormal operation. When the health parameters are useful for fault detection, they can also be used to estimate the state of the machine to aid in future performance prediction.

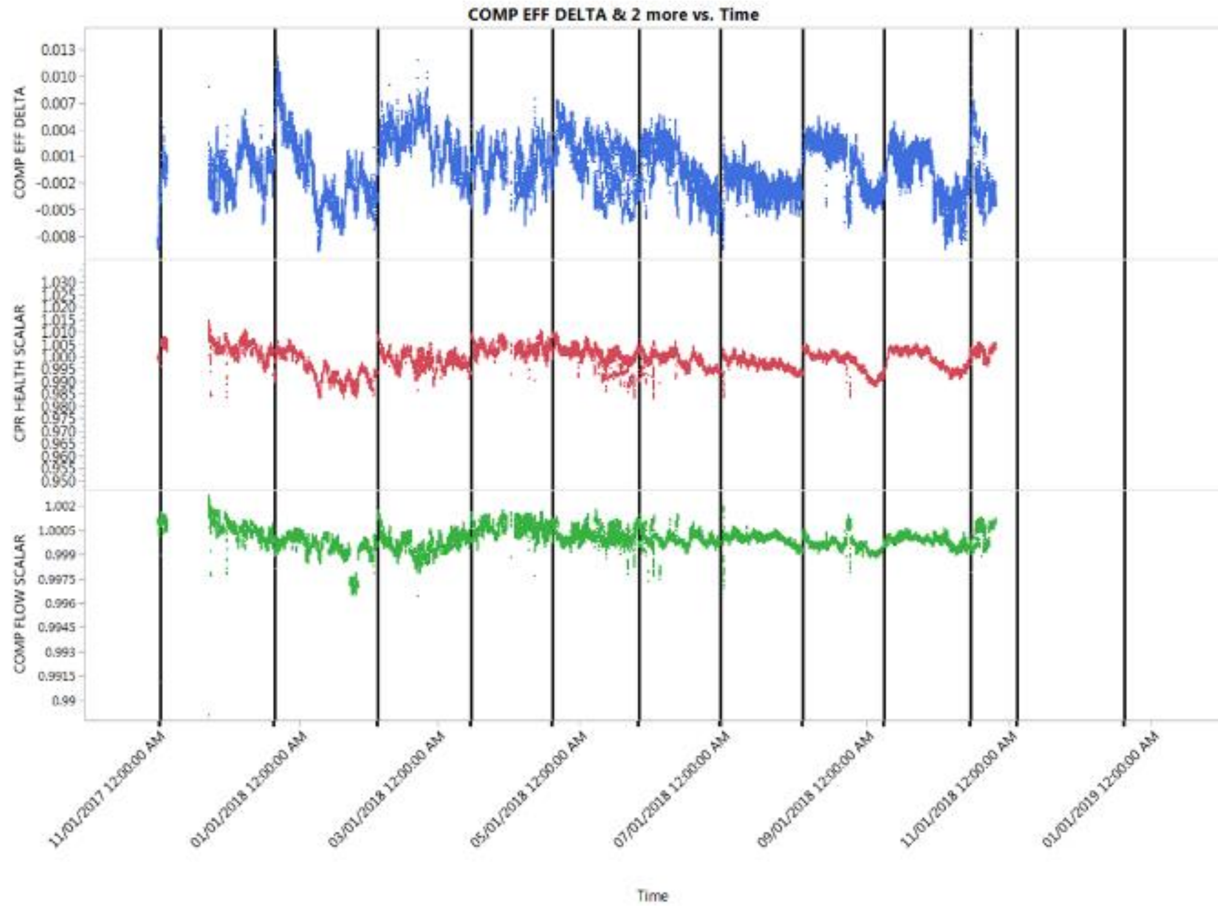

Figure 2. Using Virtual Sensors to Estimate Water Wash Impacts

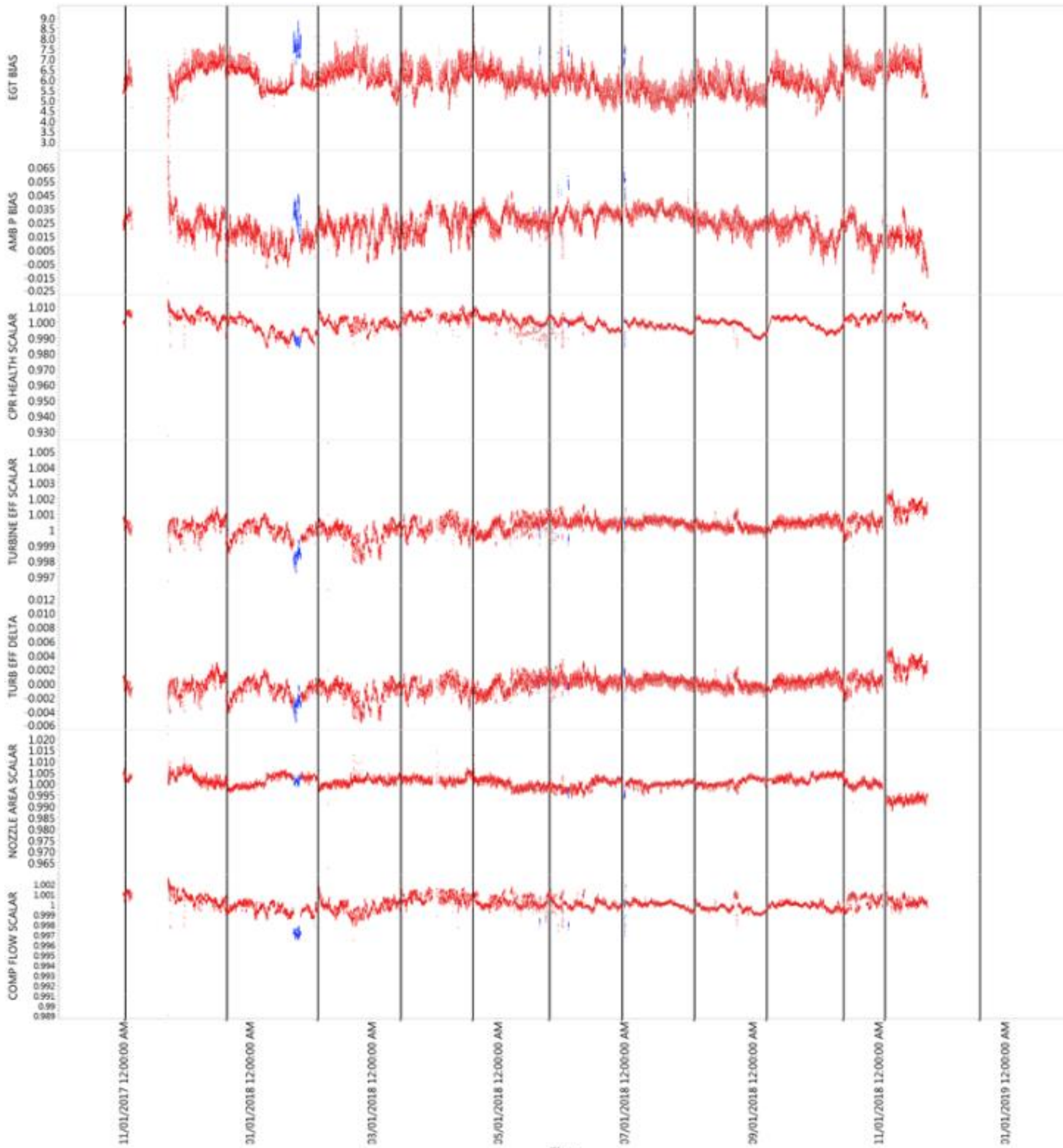

Figure 3. All Virtual Sensors – 7EA – Blue Represents Virtual Sensor Excursion

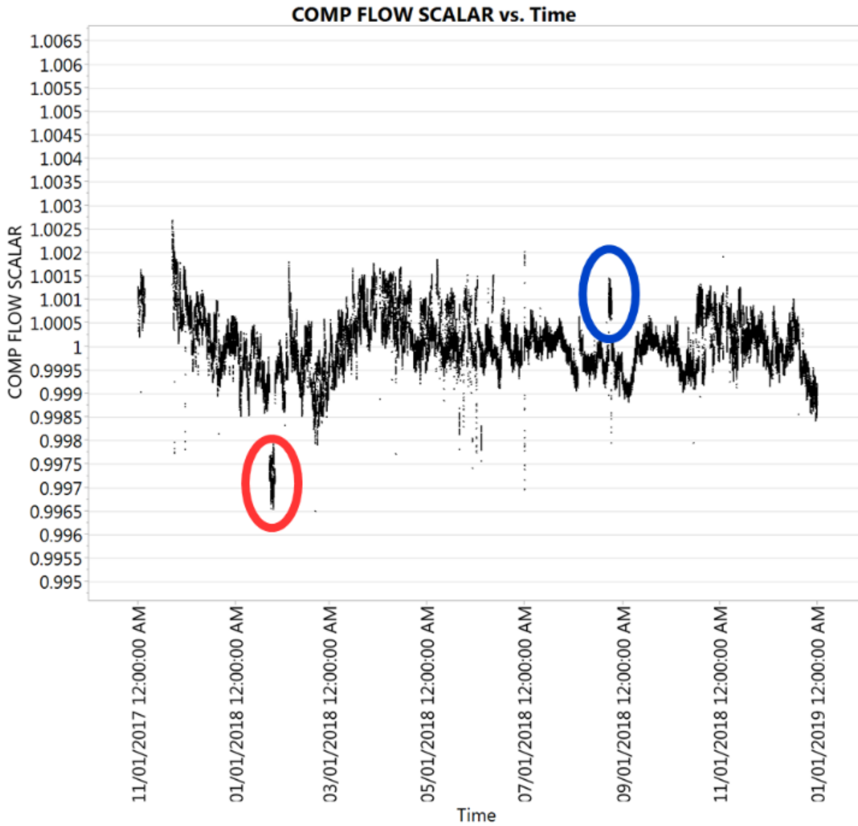

Figure 4. Virtual Sensor - 7EA - Compressor Anomalies

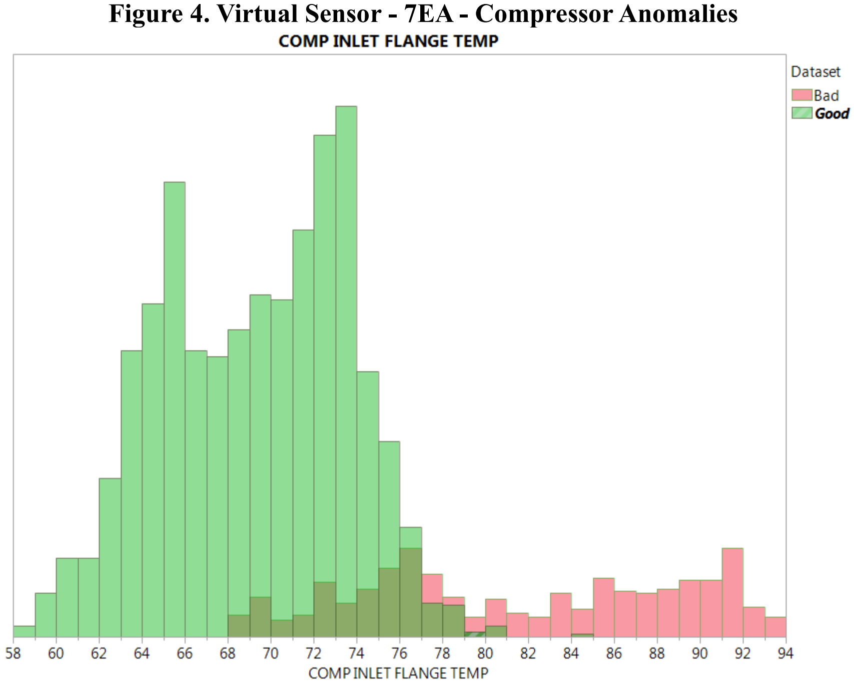

Figure 5. Investigation of Performance Excursion for Compressor Inlet Temperature

Future Performance Prediction

The predictive accuracy of the closed-form equation approach was also tested. This was performed by calculating a moving average of the estimated virtual sensors over 6, 12, and 24-hour periods. The moving average was then used to estimate performance one day and one week ahead. This test was carried out on a 7EA. Both linearly weighted and exponentially weighted (EWMA) moving averages were tested. The results are shown graphically for power output accuracy in Figure 6. Each plot shows the magnitude of error between the digital twin prediction 1 day (left column) or 1 week (right column) ahead of the current measurement point. Moving averages are applied over the last 6 hours (top row), 12 hours (middle row), and 24 hours (bottom row) to each of the virtual sensors. The grey histogram shows the EWMA averaging, and the red histogram shows linearly weighted averages. The linear moving average underperforms in every case. There is also little difference between 6, 12, and 24-hour moving averages of the virtual sensor parameters in terms of predictive accuracy, therefore a recommendation is made of an EWMA over six hours with a weighting factor of 0.935. The tabular accuracy is shown after the plots in Table 6.

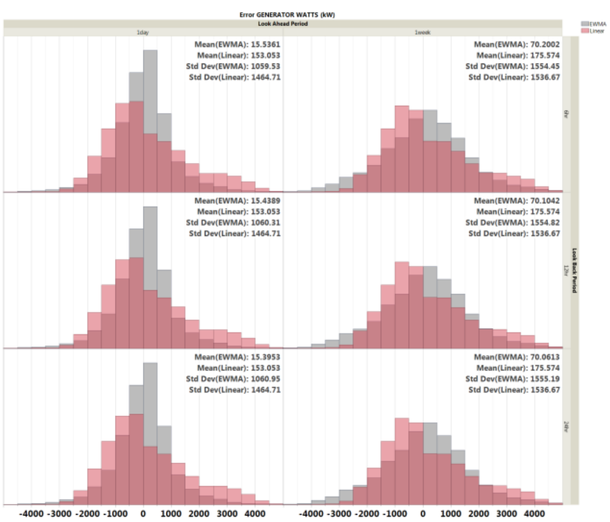

Figure 6. Predictive Accuracy of EPRI Digital Twin Equations – Power Output

Table 6. Summarized EPRI Digital Twin Predictive Accuracy

Prediction	One Day Ahead	One Week Ahead
Generator Watts (kW)	+/- 1,758	+/- 2,556
CDP (psig) [bar]	+/- 1.78 [+/- 1.12]	+/- 2.5 [+/- 1.17]
CDT (deg F) [deg C]	+/- 4.7 [+/- 2.6]	+/- 6.77 [+/- 3.39]
TTRF (deg F) [deg C]	+/- 15.94 [+/- 8.86]	+/- 23.5 [+/- 13.1]
EGT (deg F) [deg C]	+/- 9.4 [+/- 5.2]	+/- 14 [+/- 7.8]
Fuel Flow (lbm/s) [kg/s]	+/- 0.158 [+/- 0.072]	+/-0.23 [+/- 0.104]

Finally, a comparison is made between the actual and predicted data using a 6-hour EWMA average of the most recent virtual sensor estimates. This is shown for the week ahead in Figure 7. The green points show the digital twin prediction, the grey points show the historian data. The prediction error noise is well within the actual measurement or random noise of the machine itself.

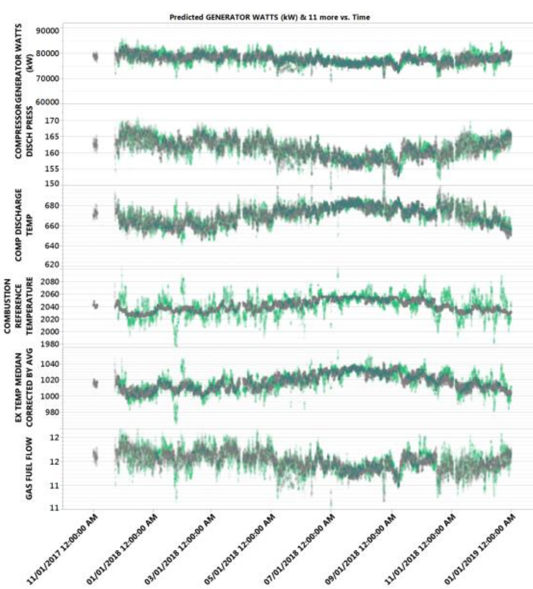

Figure 7. Week Ahead Prediction Comparison

CONCLUSION

This paper provided the reader with a concise summary of types of digital twins. All twins, regardless of type, make use of physical asset or process data, a simulation model, and a communication and interface method between the two worlds. Many twins make use of existing simulation capability. This is not a negative thing as it often means proven technology continues to be used in an expanded capacity.

The examples provided show how digital twin techniques can be used to extract additional value from existing asset data. Digital twins fundamentally enable new simulation tools and techniques to better merge improved physical sensing capabilities and analytics to extract additional value from asset data.

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