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Open Process Automation- and Digital Twin-Based Performance Monitoring of a Process Manufacturing System

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ABSTRACT Open Process Automation (OPA) and Digital Twin (DT) technologies show great promise to reduce risk, downtime, and energy consumption, while improving safety and efficiency in manufacturing systems. OPA defines a reference architecture for the construction of scalable, reliable, interoperable, and secure automation systems with products from multiple vendors as a single, cohesive system. DTs are purpose-driven dynamic digital replicas of physical assets, processes, systems, or products. Both technologies enable increased options and competition for accelerating future innovation. However, there are significant challenges to adopting these technologies, including ‘‘plug-and-play’’ interoperability, access to data, access to equipment, and the combination of different DTs for system-wide improvements. This paper demonstrates and evaluates a DT Framework solution for performance monitoring in process manufacturing systems that aims to avoid unplanned downtime, a prevalent challenge that pressures profitability in manufacturing. The DT framework is built and demonstrated through an OPA testbed system that allows seamless gathering and analyzing of data from a process manufacturing line. The proposed DT framework solution provides guidelines to develop, test, and evaluate new system-wide DT solutions without interrupting production operations and without costly R&D investments.

INDEX TERMS Smart manufacturing, Industry 4.0, automation, predictive maintenance, virtual commissioning.

I. INTRODUCTION

Digital transformation has become a fundamental topic for executive leadership in almost all manufacturing companies today. Digital transformation adoption across industries has become cost-effective thanks to the recent advancements in information and communication technologies, including cloud computing, visualization capabilities, Industrial Internet of Things (IIoT), additive manufacturing, big data, advanced analytics, artificial intelligence, blockchain technology, and autonomous robotics. These technologies have enabled cyber-physical integration that allows data collection, analysis, and visualization to help make well-informed decisions and thus optimize the manufacturing operations.

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Digital solutions promise significant value for an organization spanning the improvement of productivity, efficiency, and quality as well as the reduction of costs. Of particular interest recently is the concept of a Digital Twin (DT): a purpose-driven software replica of a physical asset, system, or process, which combines modeling information with data analytics to help optimize business performance [1]–[5]. One of the key benefits of DT technology is that it can provide time-critical comprehensive convergence between the physical world (e.g., machines, equipment, etc.) and digital world (e.g., computation, networking, etc.). This convergence promotes richer models that yield more realistic and holistic measurements of unpredictability throughout a product lifecycle spanning design, manufacturing, operation, service, upgrades, etc. [6]–[9].

Discrete and continuous process manufacturing companies and other asset-intensive industries such as oil and gas, mining, energy, and utilities, believe that DT technology should be at the center of digital transformation efforts [10]. However, compared to discrete manufacturing, DT adoption in process manufacturing is still at an early stage with implementations limited to isolated one-off solutions instead of industry-wide DT applications, which limits the benefits of DT technology implementation [11].

To gain the full potential of DT technology, different DTs need to interoperate across the manufacturing value chain. Interoperability could be achieved through system openness to extensions by interoperable components from various vendors. Most recently, there is a tendency towards embracing Open Process Automation (OPA) in industrial systems by adopting communication protocols that allow applications by multiple vendors to seamlessly interoperate, such as the Open Platform Communications Unified Architecture (OPC UA) [12]. Additionally, a number of companion standards to define new operational technology system architectures are underway such as the Open–Process Automation Standard (O-PAS) [13] and the User Association of Automation Technology in Process Industries NAMUR Open Architecture (NOA) [14]. The combination of OPA and DT technologies shows great promise to reduce risk, down-time, and energy consumption, while improving safety and efficiency in manufacturing systems.

In addition to providing high quality products, to stay competitive, manufacturing systems are required to discover unexploited efficiencies across the value chain to reduce costs and increase profitability [15]–[17]. A prevalent challenge that impedes profitability in manufacturing is unplanned downtime. This challenge arises from the absence of transparent insight into the performance of the manufacturing assets required to detect, predict, and prevent failures. Performance monitoring through DT technology is a promising approach to minimize the risk of unplanned downtime. Performance monitoring gives real-time visibility into specific equipment or process parameters including health status, condition, and performance through key performance indicators (KPIs) that are used to inform when assets need to be inspected. OPA and DT technologies enable the collection, visualization, and analysis of asset health data to derive KPIs that can be combined and shared across departments to create a more comprehensive view of the manufacturing system. Plant operators and maintenance personnel can coordinate using this aggregated information to preserve throughput targets, and improve product quality, while reducing downtime for an enhanced customer experience.

This paper presents a performance monitoring approach that is based on OPA and DT technologies to help perform maintenance at the right time and thus avoid unplanned downtime. The performance monitoring approach was developed as part of an open automation testbed framework that consists of an OPA and DT sandbox with a self-contained Integration Test Environment (ITE) platform. The testbed combines system and software platforms that demonstrate and evaluate OPA and DT technologies through cross-vendor systems.

This paper focuses on the software portion of the testbed. It illustrates the steps towards the development and implementation of a system-wide DT framework including an emulation of the manufacturing process system, for performance monitoring. Similar steps can be followed to generate comprehensive unified DT solutions beyond performance monitoring. The paper provides the following contributions:

1) Development of a manufacturing process system emulator that provides a physics-based virtual model of the manufacturing process. The emulator is used to generate data for initial training and testing of the DT functions prior to the actual hardware being available. Such a process emulator might be broken into subsystems that can be replaced by actual hardware subsystems as they become available, thus accelerating the ability to test the system as part of a virtual commissioning approach, including its DT components.
2) The development of a DT Framework (a combination of DTs) to support system-wide performance monitoring in process manufacturing systems. Within the scope of this work, the DT framework consists of the following components:
    a) An equipment (e.g., pump) performance monitoring DT that is used to detect degradation onset, classify equipment health state, and estimate the overall equipment health percentage.
    b) A Control Loop Performance Monitoring (CLPM) DT that monitors the performance of the Proportional Integral Derivative (PID) controller within the process closed loop.
    c) A process performance monitoring DT that is used to detect anomalies in the process and estimate the health percentage of a process unit.

The DT framework presented in this work illustrates an approach towards an extensible DT solution that scales up from equipment, to units, to process manufacturing lines, to support multi-facility operation. Practitioners should be able to adapt the framework to other tools and data in cooperation with OPA computing frameworks to enable organizations to more quickly evaluate operations, test assumptions for innovation, and improve capabilities.

The rest of the paper is organized as follows. Section II provides background on DT and DT applications in process manufacturing. An overview of the baseline DT framework used to guide the design and development of the proposed performance monitoring DT solution is also given in Section II. Section III describes the development of the manufacturing process system emulator. Section IV details the development of the performance monitoring DT framework solution. Section V discusses how the KPIs provided by the DT models can be leveraged to help plant operators and maintenance personnel perform just-in-time maintenance and thus reduce downtime. Section VI discusses the results and potential extensions of this work. Finally, Section VII summarizes the contributions of this paper and presents some future research avenues for this work.

II. BACKGROUND

A. RELATED WORKS

With the emergence of Smart Manufacturing and Industry 4.0, manufacturers are currently considering a wide range of digital technologies to improve productivity, efficiency, and safety of their operations, while minimizing variability, health and environment risks, as well as costs. Embracing emerging digital technologies allows companies to construct DTs of their assets and systems to gain a comprehensive visibility over the entire manufacturing value chain.

DT technology has been extensively investigated in discrete manufacturing. The literature search in [3] found that industrial applications of DTs focus on the areas of design, production, and prognostics & health monitoring. In [18], the author pointed out that there are seven ways in which DTs are used to improve manufacturing operations, namely, product design, process optimization, quality management, supply chain management, predictive maintenance, cross-discipline collaboration, and customer experience analysis. For instance, in product design, Tao *et al.* proposed a DT-based product design approach that connects the physical and virtual products to improve product customization [9]. In production, Leng *et al.* proposed a DT conceptual framework for monitoring and optimizing physical manufacturing workshops based on context data [19]. In the predictive maintenance field, Liu *et al.* proposed a DT approach for the evaluation of process plans with dynamic changes in machining conditions and DT-related uncertainties as presented in [20]. Wang *et al.* [21], presented a health monitoring approach that leverages data analytics and subject matter expertise for online machine-part state classification and estimation for improved performance monitoring. Guerra *et al.* proposed a DT method for the optimization of ultra-precision motion systems. The DT combines virtual representations of mechanical and electrical components to emulate non-linearities (backlash and friction) and the corresponding control system [22]. A thorough review of existing literature concerning the concept of Digital Twin for maintenance applications can be found in [23]. In human-machine interaction, De Magistris *et al.* propose a dynamic digital human model that is capable of computing dynamic, realistic movements and internal characteristics in quasi-real time, based on a simple description of future work tasks, in order to achieve reliable ergonomics assessments of various work task scenarios [24].

Compared to discrete manufacturing, DT adoption in process manufacturing is still at an early stage with implementations limited to isolated one-off solutions instead of industry-wide DT applications, which limits the benefits of DT technology implementation [11]. The literature search in [11] found that asset integrity monitoring, project planning, and life cycle management are the key application areas of DT technology in the process industry. In asset integrity monitoring, the authors in [25] presented a DT concept that provides estimates of fatigue life for assets in the oil & gas industry aimed at extending the life of these assets. In project planning, Aivaliotis *et al.* investigated the adoption of a representative DT of the production system used to conduct a detailed analysis of various alternative configurations of the production system to assess the possibility of increasing productivity in short and medium time horizons [26]. In lifecycle management, the work in [27] investigated the use of simulation to resolve the conflicts involving costs, time, and quality in process plants throughout their lifecycle. The majority of these works presented theoretical concepts rather than actual industrial implementations. Also, these works focus on one-off solutions instead of system-wide DT applications. To address this issue, this paper uses the baseline O-O concepts and systematic methodology for DT solution development proposed in [5] and [28] to demonstrate how a practical system-wide performance monitoring DT solution could be easily derived.

B. FOUNDATION: THE DT BASELINE FRAMEWORK

In this subsection, the DT baseline concepts adopted to structurally and easily deliver practical DT solutions are briefly recalled. These concepts include a DT definition and Object-Oriented (O-O) constructs that allow DT capabilities to be extended, reused, and interchanged [5], [28].

- *DT definition*: The DT definition used within this paper is the the following. A DT is a purpose-driven dynamic digital replica of a physical asset, process, system, or product that is driven by a need for improvement of the manufacturing environment (e.g., reduce unplanned downtime, generate a production plan, improve quality, etc.). A DT provides a capability in terms of detection, prediction, and/or prescription so that it can deliver on its intended purpose and provide a value-add capability to a DT information client in the manufacturing ecosystem. To provide its capability, a DT combines a modeling resource with a computational engine. The modeling resource, which can consist of one or more models, is used to emulate some aspect of the physical asset, process, system, or product. Models generally use analytics technology to define behavior within a particular environment defined by context. The DT computational engine coordinates the use of the models and provides the required DT outputs (i.e., deliver on the DT purpose) to the DT client [5].
- *DT class*: A type of DT that describes a set of DT objects that share the same attributes, operations, methods, relationships, and semantics in order to deliver a specific capability for the DT user [5], [29].
- *DT object*: Particular entity in the manufacturing ecosystem, such as an asset, system, component, process, product, person, etc. with a well-defined boundary and identity that encapsulates state and behavior [5], [28], [29].

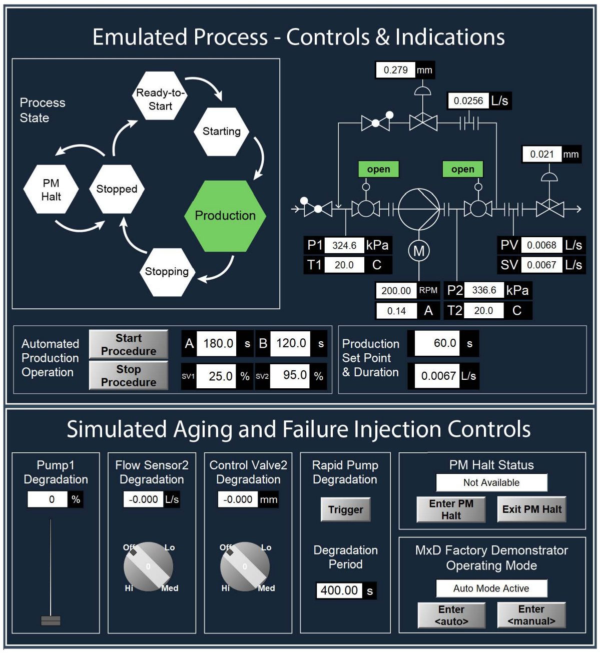

FIGURE 1. Emulated factory framework panel.

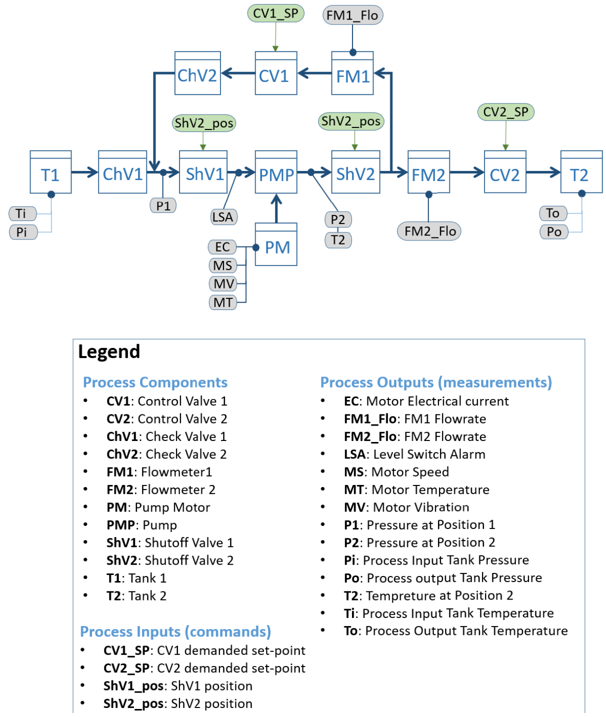

FIGURE 2. The factory process piping and instrumentation diagram.

- *Generalization/specialization*: A relationship in which objects of the specialized element (the child) are substitutable for objects of the generalized element (the parent). This relationship allows for the extrapolation of capabilities usually from general to specific [5], [28], [30].
- *Aggregation*: A ''has-a'' relationship, meaning that an object of the whole has objects of the part. Aggregation is used to model a ''whole/part'' relationship, in which one class represents a larger thing (the ''whole''), which consists of smaller things (the ''parts'') [5], [28], [30].
- *DT O-O hierarchy model*: General O-O conceptual model that structures the DT classes that constitute the entire DT solution.

III. THE EMULATED FACTORY FRAMEWORK

This section introduces the emulated factory framework supporting the DT development. First, we provide an overview of the assemblies constituting the emulated framework. Then, we describe the development of the manufacturing process model assembly, its simulation results, and its real-time performance as well as the simulation and generation of healthy and faulty data.

A. OVERVIEW OF THE EMULATED FACTORY FRAMEWORK

The factory emulator framework is built using Applied Dynamics International's ADEPT Framework product, which allows multiple real-time execution assemblies to be designed, distributed, and coordinated as a single integrated real-time framework [31]. The assemblies may be distributed across multiple servers, with each assembly being assigned to a single CPU core on a multicore server, which could be cloud-based.

Several real-time servers are used for the emulated factory framework, with particular assemblies assigned to generate the emulated factory process data, to package it into industry standard communication protocols, and to send it across the integration test environment network. Data are transferred via dedicated data protocol interface assemblies within the OPA-DT framework, and then used by the OPA-DT assemblies to monitor process and equipment performance.

As a portion of the factory emulator framework, the two model assemblies discussed below run on a single Nvidia Jetson AGX Xavier server, with an Ubuntu Linux OS and ADEPT run-time support. These are the manufacturing process model assembly, which supports the Graphical User Interface (GUI) illustrated at the top of Fig. 1, and the simulated aging and failure injection model assembly, which supports the GUI illustrated at the bottom of the figure.

B. THE MANUFACTURING PROCESS MODEL ASSEMBLY

A Piping and Instrumentation Diagram (P&ID) of the manufacturing process being modeled by the assembly is shown in Fig. 2. The diagram illustrates a typical plant process, using pump *PMP* and control valves *CV1*, *CV2* to transfer fluid at a controlled rate from tank *Ti* on the left, to tank *To* on the right. A tachometer on motor *PM* provides feedback signal *MS*, which is required to control the pump at a constant speed, high enough to satisfy the maximum flow demand. Flow meters *FM1* and *FM2* provide the feedback required to successfully operate the control valves such that they produce the commanded fluid flow rate.

A simplified representation of this P&ID is also shown in the panel on the top right of Fig. 1. The entire process manufacturing simulation model is implemented using a Simulink model, together with a Simscape subsystem for physical process modeling, imported as a real-time assembly into the emulated factory framework. Note that depending on the DT purpose, other aspects of the system physics (e.g., heat and mass transfer, etc.) can also be modeled and added to the emulated factory framework.

C. REAL TIME PERFORMANCE OF THE MANUFACTURING PROCESS MODEL ASSEMBLY

The nonlinear and numerically stiff nature of the differential equations describing fluid flow in the manufacturing process model precludes using an explicit integration algorithm to achieve a fixed numerical integration step size in Simscape. An implicit trapezoidal rule was found to give satisfactory integration accuracy with fixed step size, but the variable number of iterations required to achieve a specified accuracy with an implicit integration algorithm makes it difficult to guarantee each step will complete within the allotted 10 ms frame time. Some model features were added (e.g. pump leakage), and some removed (e.g. fluid compressibility), to reduce the number of frame overruns. The best numerical integration performance was obtained by consolidating all continuous-time modeling features into the Simscape subsystem, leaving Simulink to handle only discrete-time modeling features.

D. SIMULATED AGING AND FAILURE INJECTION MODEL ASSEMBLY

The simulated aging and failure injection model assembly is designed to allow demonstration of DT manufacturing equipment performance monitoring and failure detection. Specifically the assembly simulates pump vibration accelerometer spectra, with time-based evolution of the spectral characteristics, from normal operating conditions, through failing and failed operating conditions.

The assembly simulates 100 frequency bins of 100 Hz spectral width, representing an underlying sample rate of 20 kHz for the pump accelerometer data. Each sampled frequency bin is represented as an independent and exponentially distributed random variable, with its mean value a function of the frequency bin index. The simulated spectra are averaged at a 100 Hz rate, and averaged spectra are supplied to the DT for pump performance monitoring, which is further described in Section IV.

Mean frequency bin amplitudes were derived from approximately 600 experimental spectra, representing time-evolution of the spectra through the three operating conditions. A time-dependent four-parameter representation of the spectrum was then derived from the bin amplitudes, and these parameters are used by the assembly to compute mean bin amplitudes as a function of time and frequency bin.

The assembly simulates pump wear at an accelerated rate by time-varying the θ parameters on an accelerated schedule, controlled and initiated by operator input to the lower section of the GUI panel illustrated in Fig. 1.

IV. DIGITAL TWIN-BASED PERFORMANCE MONITORING

This section describes the components of the performance monitoring DT framework solution developed for the studied process manufacturing system. First, an O-O DT hierarchy combining different individual DTs is described. Then, each of the individual DTs developed for equipment, process, and controller are detailed separately.

A. OBJECT-ORIENTED HIERARCHY OF THE PERFORMANCE MONITORING DT SOLUTION

The O-O hierarchy of the performance monitoring DT solution presented in this section highlights the need to incorporate instances of different DT classes to provide benefits above and beyond what is provided by the individual DTs. Each of the DT classes complies with aspects of the DT definition (see section II-B), and their collaboration can be facilitated through the DT O-O hierarchy.

Small deviations in capacity and downtime in process manufacturing systems may have substantial economic impacts. A DT solution that provides the ability to determine the health state of the equipment, process, and control, understand what might be wrong, and thus avoid unplanned downtime or failures is indispensable. Based on this need, three DT classes are identified for the process manufacturing system, namely:

- A DT class that monitors the performance of equipment (here we chose a pump object as an example of equipment). The pump performance monitoring DT class uses data collected from the pump to detect degradation onset, classify the health state (three health states are classified, namely: normal, degrading, and faulty), and estimate the overall pump health percentage
- A DT class that monitors process performance by merging data from the process and PID controller. To detect process anomalies, the process performance DT monitors whether the set-points are tracked or not while predicting and observing the behavior of the PID controller action
- A DT class that monitors the PID controller performance. This DT provides an indication of the health state and performance of the PID controller.

Figure 3 shows the hierarchy of the overall DT solution. The DT hierarchy combines the three individual performance monitoring DT classes for equipment (pump), process, and controller. The combination of these three individual DT classes builds up to a system performance monitoring DT, where each DT class delivers a set of KPIs that relate to the DT purpose as well as a confidence interval metric that quantifies the quality of the DT output. Details about the development of each of the individual DT classes follow.

B. EQUIPMENT PERFORMANCE MONITORING DT

1) CONCEPT

The purpose of the pump performance monitoring DT is to provide KPIs that allow a DT client to make decisions on scheduling just-in-time maintenance to avoid pump

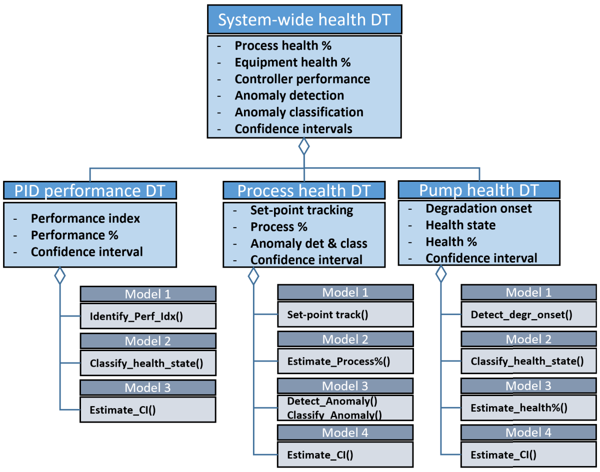

FIGURE 3. DT solution hierarchy.

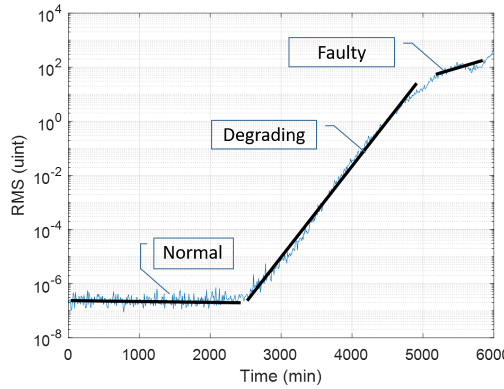

FIGURE 4. Pump degradation trend example.

unplanned downtime. The KPIs that the pump performance monitoring DT outputs consist of: (1) degradation onset detection, (2) health state classification (i.e., normal, degrading, and faulty), and (3) overall pump health percentage. In addition to these three output KPIs, the DT provides a confidence interval output that quantifies uncertainty around the degradation onset detection and state classification.

Data from the simulated aging and failure injection model assembly described in Section III-D are used to train and evaluate the pump performance monitoring DT. Different health indicators extracted from the data are combined to detect pump degradation onset, classify its state, provide confidence intervals, and estimate the health percentage.

2) DATA ACQUISITION AND PREPROCESSING

Sensor data are collected and provided to the DTs at a rate of 100 Hz. For instance, vibration data are delivered to the pump DT in the form of single-sided frequency spectra that consist of 100 frequency bins of 100 Hz spectral width, representing an underlying sample rate of 20 kHz. The acquired raw vibration spectra must be preprocessed to extract and select the descriptors that help to reveal any deviations in the pump behavior. Vibration data preprocessing aims at transforming the provided spectra into signals in a different domain (time or time–frequency) that represents the degradation dynamics. Temporal features focusing on calculations of the statistical parameters of the signal are useful for classifying state, detecting degradation, and performing diagnostics of failures [32]. Using a set of run-to-failure vibration data, multiple features were extracted and compared in terms of trendability [33], i.e., which features show clear degradation profiles. Based on this comparison, the RMS and Peak-to-Peak vibration, as well as the Kurtosis, and Skewness of the vibration signals were extracted and used as health indicators, as they exhibited clear trends of pump degradation. For instance, Figure. 4 shows an example full trend in a pump run-to-failure test using vibration signal RMS values.

Due to the high rate at which data are captured (100 Hz), for each extracted feature, a circular buffer is implemented to allow for retaining only the most up-to-date values of RMS, Peak-to-Peak vibration, Kurtosis, and Skewness over a predefined period of pump operation. If for instance the predefined period is 1 hour of operation, a new data value will overwrite one that is 1 hour old. The buffered data are split into a batch of size n that includes the newest sample and a baseline of 1 to $n-1$ samples. These data are then used to detect degradation onset, compute confidence intervals, and estimate overall pump health percent.

3) DEGRADATION ONSET DETECTION ALGORITHM

Algorithm 1: Degradation Onset Detection Algorithm

Input : sensor data (e.g., vibration data)
Output: degradation onset detection

initial_base_size=100;
batch_size=30;
base ← data(0 : initial_base_size);
batch ← data(initial_base_size + 1 : (initial_base_size + batch_size));
while *in production state* **do**
  Compute the feature vector $F = \{Kurtosis, Rms, Peak2Peak, Skewness\}$, for both the baseline and batch data;
  forall *features* $f_i \in F$ **do**
    $\mu^{f_i}_{base} = \frac{1}{len(base)} \sum_{j=1}^{len(base)} f_{ij}$;
    $\sigma^{f_i}_{base} = (\frac{1}{len(base)-1} \sum_{j=1}^{len(base)} |F_{ij} - \mu^{f}_{base}|^2)^{1/2}$;
    $\mu^{f_i}_{batch} = \frac{1}{len(batch)} \sum_{j=1}^{len(batch)} f_{ij}$;
    if $\mu^{f_i}_{batch} > (\mu^{f_i}_{base} + 3 \times \sigma^{f_i}_{base})$ **then**
      $Onset^{f_i} \leftarrow 1$;
    end
    if *Onset == 1 in at least two features* **then**
      Degradation Onset ← TRUE;
    else
      Slide batch with the new data point;
      Extend base with the previous data point;
    end
  end
end

Algorithm 1 describes the steps for the pump DT to detect degradation onset. The algorithm uses a moving average concept that consists of the following. For each health indicator f_i in $F = \{RMS, Peak2Peak, Kurtosis, Skewness\}$, a batch window W^{f_i} of n newest health indicator values is set up and the mean $\mu^{f_i}_{\text{batch}}$ of these n values in the window W^{f_i} is calculated. At the same time, the mean $\mu^{f_i}_{\text{base}}$ and the standard deviation $\sigma^{f_i}_{\text{base}}$ of all of the values (baseline) of f_i seen before W^{f_i} are calculated as well. The DT degradation onset detection algorithm uses a statistic approach that assumes that the distribution of each of the features $f_i \in F$ in the pump healthy state is approximately normal. In this case, about 99.7% of the data points should lie within three standard deviations of the baseline mean value. Therefore, a dynamic threshold is set as

$$\mu^{f_i}_{\text{batch}} < \mu^{f_i}_{\text{base}} + 3 \times \sigma^{f_i}_{\text{base}} \tag{1}$$

As the window W^{f_i} moves, the mean value of the batch window $\mu^{f_i}_{\text{batch}}$ is continuously compared to the mean of the values in the baseline $\mu^{f_i}_{\text{baseline}}$. Degradation onset is detected when the mean value of the batch window is above the threshold in at least two condition monitoring features f_i in F. Note that the detection rule can be relaxed or constrained by the decision maker (for instance, degradation onset can be classified as when the mean value of a single feature is above the threshold, or more robustly, once all of the features are above the threshold).

4) CONFIDENCE INTERVAL MODEL

A Confidence Interval (CI) estimate is associated with the degradation onset detection and health state classification. The CI estimate is calculated from the sample data to determine the range likely to contain the population parameter (mean, standard deviation) of interest. The CI is determined by calculating the probability that the mean of the batch μ_{batch} data falls within the $\mu_{\text{base}} + 3 \times \sigma_{\text{base}}$ range, which contains the healthy data population. A statistical model is used to find the number of standard deviations between the mean of the batch data distribution and the third standard deviation of the baseline distribution as follows:

$$A = \frac{(\mu_{\text{base}} + 3 \times \sigma_{\text{base}}) - \mu_{\text{batch}}}{\sigma_{\text{batch}}} \tag{2}$$

The CI is then found by evaluating the normal cumulative distribution function of the values in A.

5) DECISION MAKING MODEL

The decision making model consists of a state machine that classifies the health state of the pump and provides a health percentage indication (see, Fig. 5). As long as a degradation onset is not detected, the state machine is at its initial state, where it reports a healthy state with a 100% health indication. At the same time, the CI associated with the health state and percent is reported by the CI computation model. When degradation onset occurs, the state machine transitions to the degrading state. For the studied system, degradation was observed to be linear in the data (see, Fig. 4), thus, a linear model was defined to estimate the health percent while the pump is in the degrading state. When the mean value of the condition monitoring feature reaches a very high limit, the state machine transitions to a faulty state. The parameters (e.g., the high level limit of the condition monitoring feature) for the linear model can be learned from data or adjusted by the user. The state machine can be manually triggered to enable the transition to a maintenance state from the degrading and faulty states to clear the degradation before going back to the initial state (normal operation state) after a maintenance action is performed on the pump.

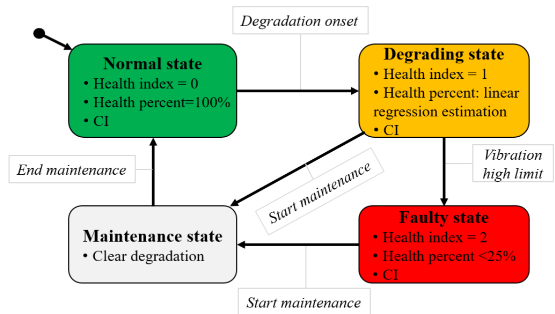

FIGURE 5. Pump DT decision maker's state machine.

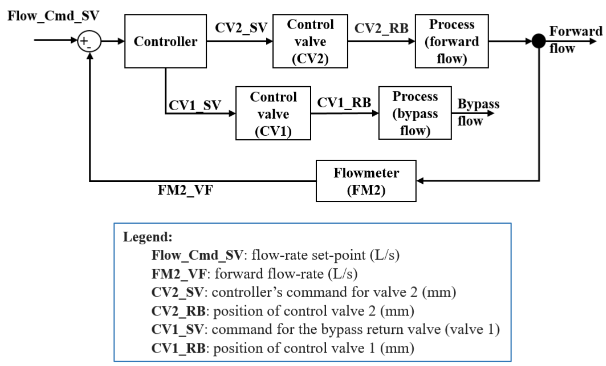

FIGURE 6. Process scheme.

C. PROCESS PERFORMANCE MONITORING DT

1) CONCEPT

The purpose of the process performance monitoring DT is to asses a control loop in terms of set-point tracking evaluation, process anomaly detection, and process health percentage estimation with confidence intervals.

A schematic of a control loop in the system is illustrated in Fig. 6. The monitored process variable is the flow rate. The loop consists of forward flow and bypass flow branches that are controlled with a PID controller such that the control commands to the two branches add up to a constant.

The process performance monitoring DT uses data from the measured flow rate, set-points, and the controller command to identify any deviations from the expected normal behaviors and classify abnormal behaviors. The DT uses a model that outputs a set-point tracking index, which is an evaluation of whether the measured flow rate matches the set-point or not with a confidence interval.

The DT decision making model uses the output of the process DT model as well as the output of the PID performance monitoring DT model, which will be described in section IV-D, to detect and classify process anomalies. Thus, the decision making model of the DT will be discussed after the PID performance monitoring DT is introduced in section IV-D.

2) PROCESS DT MODEL

The process DT uses Algorithm 2 to check whether the measured flow rate matches the input set-point or not. The algorithm mainly monitors the flow rate in the production steady state. During the production state, the DT model buffers flow data sampled at 100 Hz over a one minute period batch and compares them to the actual set-point with limit bounds set at three standard deviations from the set-point value. The standard deviation is calculated from the measured flow rate variability. If the flow rate is within the limit bounds, then the algorithm reports that the behavior is normal through the tracking index. Else, the DT model reports an abnormal behavior (i.e., flow rate does not match the set-point).

Algorithm 2: Set-Point Tracking Assessment Algorithm

Input : set-point (sp = Flow_Cmd_SV)
measured flow rate (Flw = FM2_VF)
Output: tracking vs not tracking index (*Flw_Idx*)
while *in production state* **do**
  foreach *batch of a 1 minute period* **do**
    Get all measured *Flw* values;
    $\mu_{Flw} = \frac{1}{N}\sum_{i=1}^{N} Flw_i$;
    $\sigma_{Flw} = (\frac{1}{N-1}\sum_{i=1}^{N} |Flw_i - \mu_{Flw}|^2)^{1/2}$;
    $UL = sp + 3 \times \sigma_{Flw}$;
    $LL = sp - 3 \times \sigma_{Flw}$;
    $Flw_{Err} = sp - \mu_{FM2\_VF}$;
    if $Flw_{Err} < LL \,||\, Flw_{Err} > UL$ **then**
      $Flw\_Idx \leftarrow 1$;
    end
    else
      $Flw\_Idx \leftarrow 0$;
    end
  end
end

A confidence interval associated with the set-point tracking index is estimated in a similar way to the pump DT confidence interval (see section IV-B4). It is calculated by evaluating a normal cumulative distribution function for the values of the range determined by how far the mean of the batch data is from the limit of three standard deviations from the set-point.

D. CONTROLLER PERFORMANCE MONITORING DT

1) CONCEPT

The purpose of the PID controller performance monitoring DT is to assess a control loop in terms of control behavior evaluation. The PID controller output is monitored by using a control command prediction model to evaluate the controller output for a given behavior. This model uses the input set-point to predict the output of the PID controller provided to the control valve.

The output of the prediction model is combined with the output of the process DT model to detect process and controller anomalies. Details about these combinations will be discussed in the process/controller DTs decision making subsection (Section IV-E).

2) DT MODEL

The PID performance monitoring DT uses a machine learning model that provides an indication on whether the control command is as expected for a given behavior or not. Expected normal behaviors are learned from historical normal operation data. For instance, Figure 7 shows example normal operation data used to train the prediction machine learning model. It can be observed from Figure 7 that the relationship between the set-point and the PID controller output is a linear relationship. Linear regression is a machine learning algorithm commonly used to find the relationship between a dependent variable Y and input variables $x_i = x_1, \ldots, x_n$ for some constants b (intercept) and a (linear regression coefficient).

A linear regression model is developed to predict the output of the PID controller at a given set-point. The problem of predicting the controller output is described as follows. Given a set of data points $D = \{(x^{(1)}, y^{(1)}), \ldots, (x^{(n)}, y^{(n)})\}$ with $x^{(i)}$ and $y^{(i)} \in \mathbb{R}$ for $n = 1, \ldots, m$, the goal is to predict the output $\hat{y} \in \mathbb{R}$, the PID controller output $CV2\_SV$, to a new input $\hat{x} \in \mathbb{R}$, a new set-point $Flow\_Cmd\_VF$. A linear regression model $y = a \times x + b$ is used for the prediction. The linear coefficient a is learned from the data. To estimate the parameters that yield the minimum variance with zero bias for the estimate, minimization of the least squares error between the values predicted by the model, $a^{(n)}$, and the actual target outputs $y^{(n)}$ for each data point is used. Finding the regression coefficient $a^{(n)}$ is to minimise

$$\Theta = \arg\min_{a} \frac{1}{n}\sum_{i=0}^{n}(y^{(i)} - x^{(i)}a^{(i)})^2 \tag{3}$$

The prediction model has been trained and validated using sets of normal operation data. The model is then used to predict the output of the PID controller for a given set-point (the *C_Predict* function) within Algorithm 3.

The PID controller performance DT uses Algorithm 3 to monitor the action of the controller in production steady states. In a similar fashion to the process DT, a one minute batch of PID controller data is accumulated and compared to the control output predicted by the machine learning model. If the actual control command matches the predicted one, then Algorithm 3 reports that the behavior is normal through the control index. Else, the controller DT model reports that the controller is excessively compensating, which is then used in

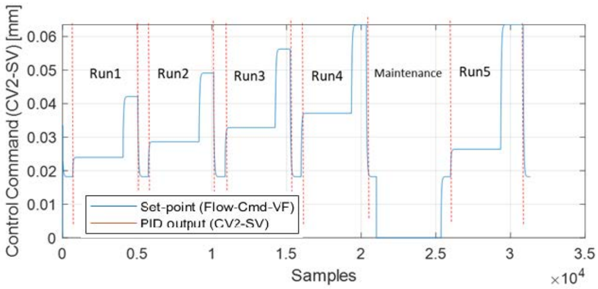

FIGURE 7. **Example normal operation data for training the the machine learning model.**

Algorithm 3: PID Controller Action Assessment Algorithm

Input : set-point (sp = Flow_Cmd_SV)
PID controller output ($C = CV2\_SV$)
Output: normal vs excessive control index (C_Idx)

$N = 60(\mathrm{s}) \times 100(\mathrm{Hz})$;
while *in production state* **do**
  foreach *batch of a 1 minute period* **do**
    Get all measured C values;
    $\hat{C} = C\_Predict(sp)$;
    $\mu_C = \frac{1}{N}\sum_{i=1}^{N} C_i$;
    $\sigma_C = (\frac{1}{N-1}\sum_{i=1}^{N} |C_i - \mu_C|^2)^{1/2}$;
    $UL = \hat{C} + 3 \times \sigma_C$;
    $LL = \hat{C} - 3 \times \sigma_C$;
    $C_{Err} = \mu_C - \mu_{\hat{C}}$;
    if $C_{Err} < LL \,||\, C_{Err} > UL$ **then**
      $C\_Idx \leftarrow 1$;
    end
    else
      $C\_Idx \leftarrow 0$;
    end
  end
end

---

the decision making part to detect and classify process and/or controller anomalies.

A confidence interval is associated with the control index that the controller DT outputs to the decision maker. The confidence interval is calculated in a similar way to the pump DT and process DT confidence intervals. It is calculated by evaluating the normal cumulative distribution function between the mean of the batch data and the limits at three standard deviations from the mean of the predicted control value.

E. PROCESS/CONTROLLER DTs AGGREGATION FOR DECISION MAKING

The decision making model combines the outputs of the process and controller DT models to detect and classify behaviors. Figure 8 shows the concept of the decision making model. Decisions are made as follows:

- If the controller output is as expected (from the prediction model of the controller DT) for a given behavior and the set-point is tracked (from the process DT model), the decision making model reports a normal behavior and confidence intervals for both the process and controller indexes.
- If the controller is excessively compensating (i.e., the controller is providing more control than expected for a given behavior), and the set-point is tracked, then a process anomaly is detected and classified. This first type of process anomaly is described as an anomaly that the controller can compensate. An example of this anomaly is a small leakage in the forward flow loop.
- If the controller is excessively compensating, the set-point is not tracked, and the controller is railed (i.e., controller hits its maximum and still cannot compensate), then a process anomaly is detected and classified and the controller DT indicates that the controller is railed. This second type of process anomaly is described as an anomaly that the controller cannot compensate for as it hit its maximum. An example of this anomaly could be due to a control valve clogging.
- If the control command is different than predicted, the set-point is not tracked, and the controller is not railed, then a controller anomaly is detected. Note that this could be a controller and process anomaly. Currently, we focus on a controller anomaly.

As shown in Fig. 8, the overall process/controller DT outputs include, process health index, controller performance index, process anomaly detection, controller anomaly detection, process health percentage, controller health percentage, and confidence intervals. Health percentages are estimated based on the process and control health indexes.

The next section describes how all the DT outputs are leveraged to provide value, i.e. how the outputs are combined together to assign recommendations to the user and thus realize a predictive maintenance DT solution.

V. LEVERAGING THE DT OUTPUTS FOR PREDICTIVE MAINTENANCE

DTs for live monitoring may be integrated within a manufacturing line to support operations and system sustainment via quality prediction, operations optimization, predictive maintenance, and anomaly detection. Experimental data generated by the emulated process plant described in Section III are used to demonstrate the applicability of the developed DT framework. The graphical user interface shown in Fig. 11 provides performance monitoring summary for equipment (pump), process (flow-rate), and control (PID controller). The pump performance monitoring DT provides an anomaly detection indication (detection of when degradation onset occurs), a state classification, a health percentage indication, and a confidence interval associated with the state classification. Figure 9 shows the output of Algorithm 1 for the feature "*Skewness*". The algorithm used dynamic thresholds

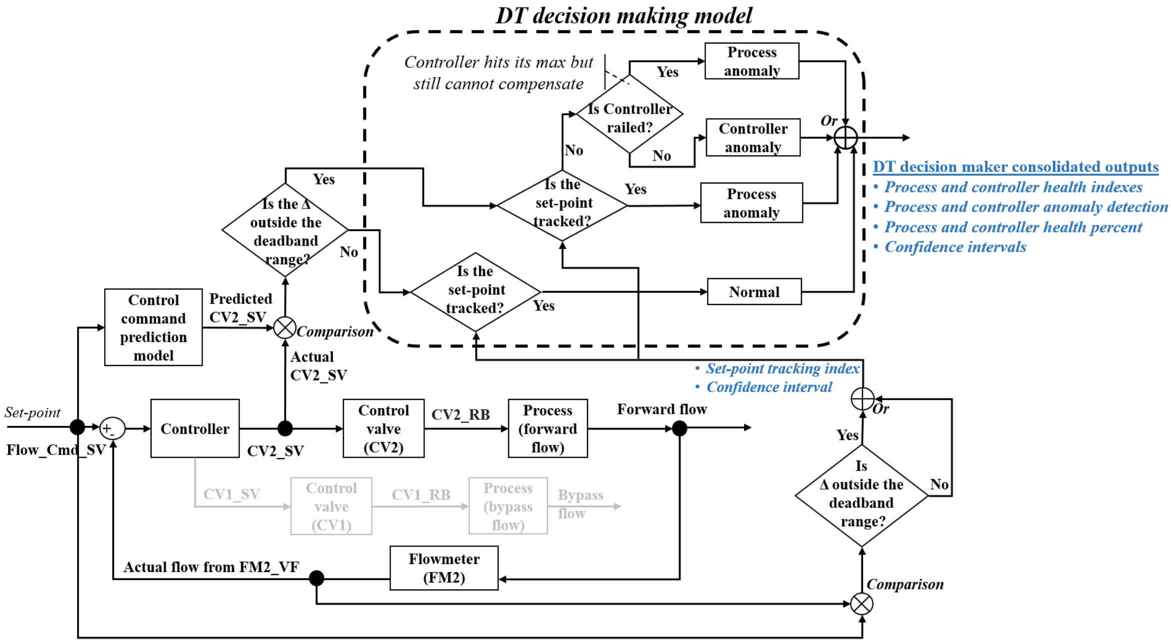

FIGURE 8. The decision making component for the process and controller DTs.

calculated by a moving window. The mean value of the batch window was continuously compared to the mean of the values in the baseline (all seen data). Degradation onset using "*Skewness*" was detected when the mean value of the batch window breached the dynamic thresholds.

Pump degradation onset is reported when at least two condition monitoring features detect its occurrence. Figure 10. shows the values of the four features used by Algorithm 1 to detect the occurrence of pump degradation onset over the course of a normal operation (in green) and a run-to-fail (in red) tests. For each feature, the pump remained healthy for the duration of the normal operation test, while it showed severe signs of degradation after the run-to-fail test. In the run-to-fail test, pump degradation onset event occurrence was confirmed after approximately 275 hours of operation with the four features. After the degradation onset event happens, the pump DT switches to the "*Degrading state*" (see Figure. 5). In parallel to Algorithm 1, a submodel is calculating the detection (state classification) confidence interval using Equation 2. In the user interface shown in Fig. 11(a), the unit PUMP1 Health displays the outputs of the pump performance monitoring DT. The state classification is shown through three colors that the unit's box could take, namely, green for normal state, yellow for degrading state, and red for degraded or failure state. The health percentage is shown in the middle left box of the unit, and the confidence interval is shown in the middle right gauge. The bottom box displays the detected anomaly type. Fig. 11(b) shows a scenario where the unit PUMP1 Health transitions to degrading state after a degradation onset is detected by the DT. The unit's box color turns to yellow to indicate that the pump is in a degrading state and that it needs attention. The health percentage estimated by the DT is 67% and the confidence interval indicates

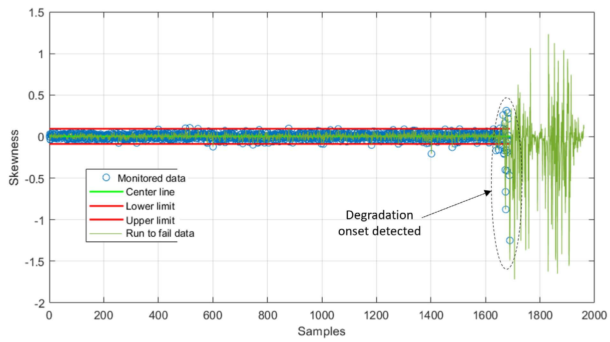

FIGURE 9. Pump degradation onset detection concept with signal Skewness.

a high certainty that the pump is degrading. The bottom box of the unit displays the detected anomaly as a bearing wear. The machine operator or maintenance personnel can use this information to immediately schedule just-in-time maintenance before the pump fails.

The unit called Flow Unit1 Health shown in Fig. 11 displays the outputs of the process performance monitoring DT. This DT provides indications of the health state, health percentage, anomaly type, and a confidence interval associated with health state classification of the process. Similar to the pump DT, the health state classification is shown through three colors that the unit's box could take, namely, green for normal state, yellow for needs attention, and red for faulty state. The health percentage is shown in the middle left box of the unit, and the confidence interval is shown in the middle right gauge. The bottom box displays the detected anomaly type. Fig. 11(c) shows a scenario with a process anomaly that the controller cannot compensate, i.e., the controller is excessively compensating until it is railed (hits its maximum

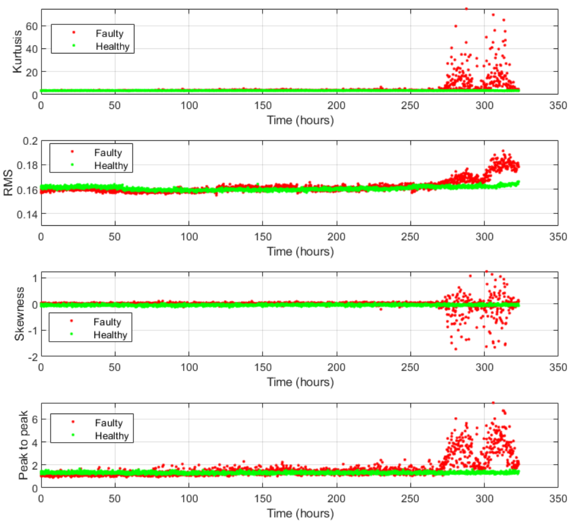

FIGURE 10. **Pump degradation onset detection using four features.**

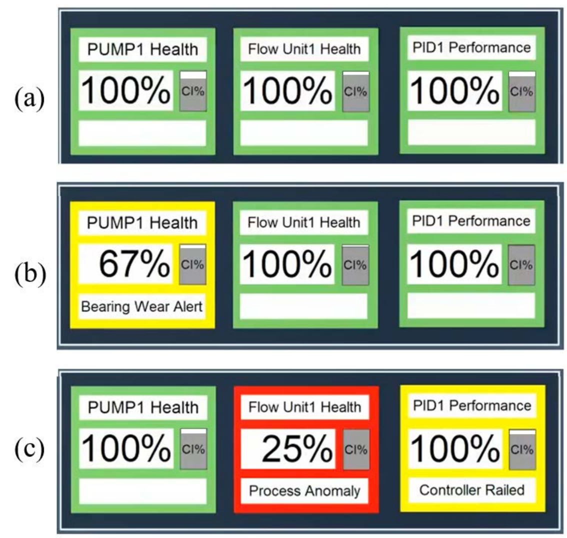

FIGURE 11. **Digital Twin & Open Automation Framework Panels. (a) Scenario where the pump, process, and controller are in healthy states. (b) scenario where the pump is in a degrading state. (c) Scenario where the controller is railed and the process is in a faulty state.**

compensation value), but the set-point is still not tracked. In this case the unit's box color turns to red to indicate that the process is in a faulty state and that it needs maintenance. The DT classifies and displays this type of process anomaly in the bottom box of the Flow Unit1 Health, estimates the health percentage to 25%, and a confidence interval of this classification is displayed in the middle right gauge. Additionally, the controller DT shows that the controller is railed.

The unit called PID1 Performance shown in Fig. 11 displays the outputs of the PID control performance monitoring DT. This DT provides an indication of whether the controller is normally or excessively compensating, an indication on when the controller is railed, a controller health percentage, an indication of controller anomaly, and a confidence interval associated with the controller state. Similar to the pump and process DTs, the state classification is shown through three colors on the unit's box, namely, green for normal state, yellow for needs attention, and red for faulty state. The health percentage is shown in the middle left box of the unit, and the confidence interval is shown in the middle right gauge. The bottom box displays when the controller is railed or when there is a controller anomaly. The controller is railed when it hits its maximum control value but still cannot compensate. A controller anomaly is detected when the set point is not tracked and controller is not railed. Fig. 11(c) shows the scenario where the PID1 Performance DT indicates the controller is railed, but still can not compensate for the process to match the set-point. This detection is used to help detect the type of process anomaly.

The three DT functions support live monitoring of the process manufacturing system. These DTs can be used by the operators and maintenance personnel to schedule timely maintenance actions and thus avoid unplanned downtime. Figure. 11 shows different operating scenarios where the DT functions support the operators and maintenance personnel decision making about scheduling maintenance. The DTs detect degradation onset which helps acting on the system before failures occur. They also detect and classify anomalies, which helps identify which parts of the system need attention.

VI. DISCUSSION

Given the equipment characteristics used for this work, vibration measurements were used in a univariate DT model to monitor the equipment performance. Univariate modeling is often less comprehensive than multivariate modeling, and thus has limitations for performance monitoring DTs. Although using only vibration measurements may introduce limitations to the performance monitoring solution, the methodology for DT development presented in this paper remains the same. This is possible because the DT uses one or more modeling resources to support the calculation of its output KPIs identified to fulfill the DT purpose, i.e., address a manufacturing need. Hence, different parameters such as temperature and pressure measurements can be introduced to the DT solution in a multivariate modeling resource in a similar way. The DT can combine univariate and multivariate models to provide a comprehensive performance monitoring solution.

For the process performance monitoring, the DT focused on three types of anomalies (see Section IV-E) that we simulated in the emulated factory process. Additional anomaly classes can be added to the emulated factory process and the anomaly detection and classification modeling approach. This will need additional historian data or anomalous behavior characterization using data collected from similar equipment and process. We note that a databank of manufacturing equipment and process data, including nominal conditions and failure cases, would have been very helpful for this project and could be very helpful for future efforts.

The DT solution introduced in this paper is aimed at anomaly detection and classification and predictive maintenance through equipment and process performance monitoring. In the future we expect to develop more DT capabilities to realize a system-wide DT framework that would allow for live monitoring, scheduling optimization, yield optimization, quality assessment, test What-If scenarios, and prescribe recommendations.

VII. CONCLUSION

In this article, we introduced a health monitoring approach that uses OPA and DT technologies to provide a predictive maintenance solution to help perform maintenance at the right time and thus avoid unscheduled downtime resulting from equipment and process failures. First, we presented an emulated factory process that is a physics-based virtual model of the manufacturing process system. This emulated factory process is used as a stand-in for the actual manufacturing process during initial development and testing of the DT functions prior to actual hardware being available. The virtual model of the manufacturing process supports the development of the DT functions for health monitoring of the physical process manufacturing system. Second, we presented three types of DT functions that were developed and tested as a DT framework solution for monitoring the health of equipment, process, and controller. Each of these DT functions provide a set of KPIs that are used to address the predictive maintenance purpose of the DT solution.

The emulated factory model and the DT functions were implemented in a physical integration testing environment platform as a proof-of-concept that demonstrates and evaluates OPA and DT technologies with cross-vendor systems. The implementation showed that such an approach allows manufacturers to develop, test, and evaluate new technologies without interrupting production operations and without costly research and development investments.

Future research directions include the following:

- Integrate the DT functions with the physical process system in addition to the emulation when the hardware becomes available, as DT technology emphasizes the synchronization and consistency of the physical and digital worlds.
- Extend the modeling approach used within the DTs to include additional system measurements such as temperature and pressure, etc. The objective is to combine univariate and multivariate analyses for a more comprehensive health monitoring approach.
- Develop additional DT capabilities for the process manufacturing system such as scheduling and yield optimization, quality assessment, etc. in order to realize a system-wide DT framework.

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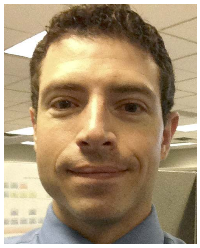

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