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BUILDING A DIGITAL TWIN FOR ROBOT WORKCELL PROGNOSTICS AND HEALTH MANAGEMENT

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ABSTRACT

The application of robot workcells increases the efficiency and cost effectiveness of manufacturing systems. However, during operation, robots naturally degrade leading to performance deterioration. Monitoring, diagnostics, and prognostics (collectively known as prognostics and health management (PHM)) capabilities enable required maintenance actions to be performed in a timely manner. Noting the importance of data-based decisions in many current systems, effective PHM should be based on the analysis of data. The main challenges with robot PHM are the difficulties of relating data to healthy and unhealthy states, and lack of models to fuse and analyze up-to-date data to predict the future state of the robot. This paper describes concepts of digital twin development to overcome the above challenges. A use case of a digital twin modeling robot tool center point accuracy is provided. The proposed procedure for this digital twin will be applicable to different use cases such as reduced repeatability or increased power consumption.

1 INTRODUCTION

1.1 Industry challenge

Industrial robots advance manufacturing by performing intricate, repetitive, or dangerous tasks such as material handling, welding, assembly, and painting. Because of their flexibility, robot workcells can respond to demands for customized products, changes in orders, and changes in equipment status. Once put into operation, robots begin to degrade. If the degradation leads to a failure, the result can be expensive repair costs and significant production interruption. To minimize failure instances and enhance their decision-making with respect to maintenance practices, manufacturers turn to monitoring, diagnostic, and prognostic technologies (collectively known as prognostics and health management (PHM)).

Invoking any effective PHM capability involves equipment (or process) monitoring along with corresponding data collection. Analytics are applied to evaluate the status of robots, and if there are degradation problems, provide a diagnosis. In addition to diagnosis, prognostics can also predict the future status of the robot components and estimate the remaining useful life (RUL) (Lee et al. 2014).

There are a large number of diagnostics techniques and methods (Borgi et al. 2017; Izagirre et al. 2021). Many reviewed methods for diagnostics and prediction are for specific performance deterioration types while prognostics is relatively lacking in many case studies (Peng et al. 2010). A data-driven prognostics approach involves developing a fault "model" that must be trained with data representing anticipated faults. This data may be difficult to obtain or validate (Vogl et al. 2019). To be more effective, PHM methods should fill the gaps in physical sensor data and modeling virtual sensors to obtain data that cannot be obtained by physical sensors. The methods should also help model typical degradation scenarios, maintenance activities, and system impact. With such methods, predictions are based on real-time status, a rich historical data set, and anticipated events. A real-time digital representation of the robot workcell through digital twins would address these challenges. This work is part of research at the National Institute of Standards and Technology (NIST) to develop methods and measurement science to advance PHM in the manufacturing industry.

1.2 Digital twin technologies and tools

A digital twin is a data-driven, real-time virtual representation of a product, system, or process. Digital twins are enabled by recent technological advancement in modeling and simulation, sensors (to enhance data collection capabilities), data storage, and data analytics. There are three main types of digital twins that can be built using varying methods: (1) Physics-based digital twins, (2) Data-driven digital twins, and (3) hybrid digital twins, which leverage the advantages of physics and data-driven approaches while minimizing their shortcomings. The type of digital twin selected for a project depends on the amount of knowledge available and the purpose of the digital twin. A digital twin is context-dependent and could be just a partial representation of a physical system. Therefore, the digital twin only requires relevant data and models that are specifically designed for an intended purpose (Shao and Helu 2020).

1.3 Contributions and paper organization

This paper provides an overview of current trends in modeling, integration, and communication, and a standards based approach for implementing a digital twin to support PHM for robot workcells. This paper contributes to understanding how a digital twin can be built to support PHM for industrial robots. It provides a use case for constructing a digital twin based on the industrial robot arm testbed for PHM that is installed at NIST.

This paper is organized as follows: Section 2 provides background including discussion of the types of digital twins, requirements and challenges for a digital twin, and digital twin applications in manufacturing PHM; Section 3 describes the challenges of robot PHM, degradation types, and their relationships; Section 4 reviews a Draft International Standard (DIS) developed under the International Organization for Standardization (ISO). It is designated DIS ISO 23247 - Digital Twin Framework for Manufacturing, which can be applied to PHM use cases; Section 5 describes a use case for developing a digital twin to predict robot accuracy with end effector attached; and Section 6 discusses remaining work for implementing digital twins of real robots and concludes the paper.

2 BACKGROUND

2.1 Motivation for developing digital twins

Data analytics is becoming a cornerstone of decision-making in production planning and maintenance scheduling (Lee et.al 2014). To ensure accurate and timely decisions in these industrial activities, digital twins constantly fuse relevant data to create a continuous learning system to improve performance (Tao et al. 2016). A digital twin for PHM represents the different states of the system; healthy and degraded states because it is updated with real-time data. Data analytics within the digital twin determines the location, type, and level of degradation of the workcell and predicts the RUL (Tao et al. 2016). Through the digital twin, the condition and predictions of the state of the system and its components are made possible. The result is that better decisions regarding a degraded component, repair timing, and type of repair can be derived. PHM is one of the major areas for digital twin research and publications in manufacturing (Tao et al. 2019). By enhancing PHM with a digital twin, the high costs of reactive maintenance and repair from unexpected failure can be averted.

2.2 General requirements for a digital twin

This section discusses the major components of a digital twin. These are (1) data collection mechanisms, (2) virtual models (physics, data-driven, or hybrid), and (3) integration interfaces to support two-way communication between the digital twin and the real system. Figure 1 illustrates the components in a basic digital twin framework.

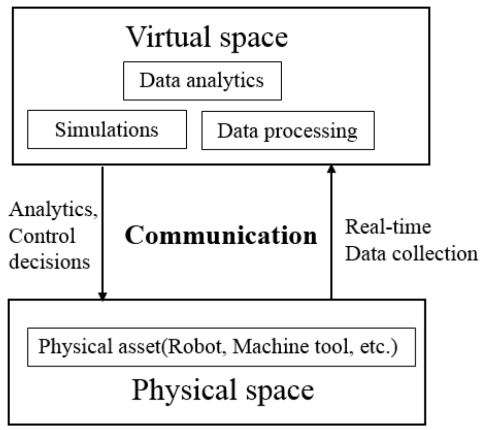

Figure 1: Basic Digital Twin Framework

1. **Data collection mechanisms**

The most widely used mechanisms for data collection are physical sensors, which monitor and collect data, such as, temperature, velocity, force, electrical current, object proximity, valve status (open/closed), flow rate, acceleration, pressure, position, orientation, and vibration. Where it is difficult to install physical sensors, virtual sensors in the digital twin can infer needed data indirectly from measured data. For computer numerical control (CNC) machine tools and robots, data can be obtained from supervisory programmable logic controllers (PLCs). For PHM, data such as maintenance logs, mean time between failure data, mean time to repair data, and product quality data can also be made available for analysis.

2. **Virtual models**

A virtual model is a representation of the elements that make up the physical asset (e.g., robot workcell) in the virtual space. This is where data from different sources is fused to create a representation of the behavior of the system. Data preprocessing transforms collected data into a form that is suitable for analytics. Data analytics models are often discussed in terms of data mining and machine learning. *Data mining* is the discovery of knowledge and insights from (often large) data sets. Figure 2 shows the relationship between data mining, machine learning, and deep learning. *Machine learning* is the creation and use of algorithms that provide the ability to learn without being directly programmed. Machine learning uses the principles of data mining. Deep learning is where the learning is through successive layers of representations, with each layer contributing to the learned model (Yu et al. 2009; Hou et al. 2003).

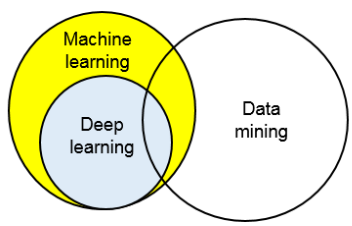

Figure 2: Relationship between machine learning, data mining and deep learning (Kulin et al. 2020).

3. **Integration interfaces and information exchange**

Interfaces enable exchanging data among different applications within the digital twin. Shao and Kibira (2018) outlined standards that support integration activities from distributed messaging and frameworks for the digital twin from the highest level to condition monitoring and diagnostics of machines at the lowest level.

3 DIGITAL TWIN FOR ROBOT WORKCELL DEGRADATION

3.1 Robot workcell PHM

A robot workcell typically features one or more robots with at least one type of end-effector (e.g., gripper, welding wand, adhesive applicator), sensors, safety equipment, controller, and other supporting automation (e.g., conveyor system) that is programmed to perform one or more tasks. Robot workcells are required to be of high reliability. Monitoring, analysis, prediction, and maintenance activities of a robot workcell can be carried out at different levels of control (e.g., workcell, individual robot, or a robot component such as a motor). A common framework to define interfaces between different levels of control in manufacturing is the America National Standards Institute (ANSI)/International Society for Automation (ISA)-95 standard (ISA 2014). ISA-95 provides five levels of control, from level 4 to level 0, i.e., business processes, manufacturing operations, monitoring, sensing, and processes. The PHM project at NIST promotes advanced sensing, prognostics and health management, and control from ISA-95 manufacturing levels 3 to 0 to result in improved decision-making support and greater automation (Hedberg et al. 2018). Previous NIST work has developed a hierarchy of PHM analyses and how faults in a critical element of a robot (at a given level) affect other elements based on their physical and functional relationships (Weiss et al. 2017).

3.2 Robot degradation

Degradation is the reduction in health, and usually in performance, that can lead to a failure to meet production expectations in terms of throughput and/or quality. Degradation is progressive and is more critical on some components in affecting the overall health and safety of the workcell. Most modern industrial robots have six axes, which provide them translation in the X, Y, and Z planes and orientation in roll, pitch, and yaw to achieve specific end effector positioning. However, the presence of multiple joints increases the possible points of degradation. And if degraded performance occurs, finding the root cause is more complicated. The potential errors due to degradations at any joint, along with errors in the end effector, sum up at the tool center point (TCP). Robot degradations affect TCP accuracy, repeatability, path straightness, and energy consumption. Of the degradation types, loss of TCP accuracy is the most difficult to overcome (Shiakolas et al. 2002). The major causes of robot degradation are mechanical wear, encoder slip ring failure, and thermal effects (or high temperatures). These are described below:

1. **Mechanical wear:** The loss of material due to wear depends on the friction between two surfaces and load carried. In robot joints, the main axes undertake greater load levels and the wear processes in these axes are usually more significant than in the wrist axes. Wear results in gear backlash, vibration, and noise.
2. **Encoder slip failure:** An encoder is a device that detects and converts mechanical motion, such as rotation, into a coded electrical signal. The common causes of encoder failure are mechanical bearing overload, surface wear, damaged insulation, loose fit, and high temperature (Bova and Tolio 2009).
3. **Thermal effects:** The internal components of a robot joint such as a motor, servo drive, gearing system, brake, encoder, torque sensor, and connecting cables are often enclosed in a single housing. Any thermal action in one affects the others. In case of the gearing system, excessive heat can lead to scuffing failure and reduced life of lubricant. In addition, elevated temperatures lead to expansion of the gears and shaft. The result is a tighter fit leading to additional wear and power loss. Without effective heat dissipation, increased temperatures result in diminished performance (Eitel 2019).

3.3 Challenges to robot workcell PHM

Some of the challenges for robot PHM are (1) lack of sufficient data related to degraded condition(s) of the robot, and (2) lack of models and methods to fuse and analyze robot data at different levels of detail and control. When data is insufficient, or if there are abrupt changes in operating environment and conditions, prognostics tend to be inaccurate in representing the system. Even where data is available, it is often unlabeled and uncertainties exist (e.g., probability distributions of the data may not be known).

In addition, as observed in Chandrababu et. al. (2009), it can be tedious and time consuming to diagnose even a "relatively" simple problem in robots due to complex interactions among system components including a faulty part or subcomponent. It is also non-trivial to relate sensor data with failure events in a practical industrial setting. Other issues are: (1) high cost for direct measurements from a robot to acquire data for the TCP (Qiao et al. 2018), (2) determining which variables (e.g., vibration, temperature, or power consumption) to monitor and for which to collect data, (3) selecting robot modeling and data analytics tools and integration, and (4) experiencing difficulty in modeling all factors and variables responsible for performance degradation due to limitations of robot simulation modeling tools.

3.4 Digital twin application for robot PHM

It was determined by Shangguan et al. (2020) that many prognostic approaches rely on historical data and some physically collected data, with little consideration for virtual data. They proposed fusing the two data types leading to a convergence of the physical with the virtual data through the digital twin. A digital twin plays the role of integrating and analyzing sensor data, virtual data, technical specification, and plant condition data thus enabling the PHM tasks of diagnosis and prediction (Shangguan et al. 2020). Figure 3 summarizes the activities involved in developing a digital twin to enhance PHM for robot workcells.

In a predictive role, deterioration scenarios can be created within the digital twin to determine what would happen in the robot workcell (Aivaliotis et al. 2019). Prognostics relies on both operational and environmental data so that algorithms assess the extent of deviation or degradation from expected normal operating condition (Tuchband et al. 2007). Prognostics with the digital twin also enables predicting the outcome of alternative maintenance scenarios or particular repair actions. These predictions are compared with actual experience to evaluate effectiveness. The experience then becomes part of the asset's history.

In summary, to support robot PHM, a digital twin can (1) generate degraded data conditions of interest that are not possible in real-life; this data can then be analyzed to identify interesting patterns, (2) generate data that cannot be captured by physical sensors or from the controller, (3) provide a platform to learn from collected physical sensor data by comparing it with digital twin data, and (4) analyze the robot workcell at different levels of detail; from robot sub component to workcell levels.

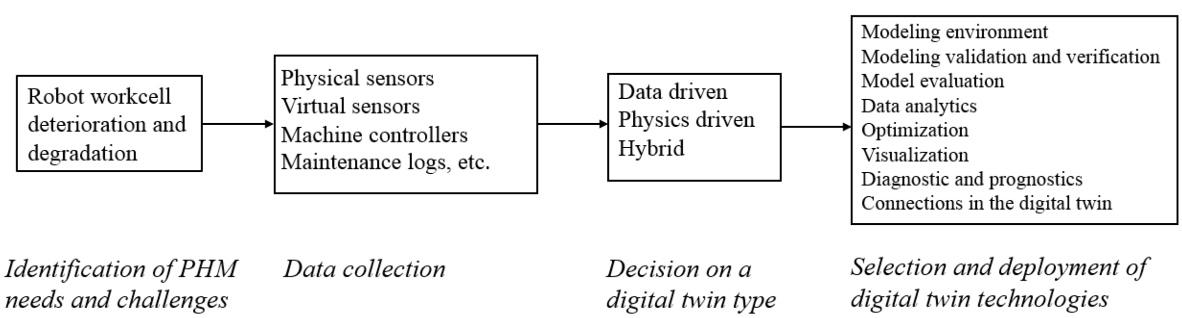

Figure 3: Activities of developing a digital twin for robot workcell PHM

4 STANDARD DIGITAL TWIN FRAMEWORK FOR MANUFACTURING

A survey by Lu et al. (2020) showed that current approaches for implementing digital twins in manufacturing face a number of challenges such as lack of (1) common definitions of digital twins, (2) common terminologies, and (3) standardized procedures for creating digital twin applications. To enable wider implementations of the digital twin in manufacturing, especially for small and medium enterprises, a standardized procedure and generic framework are needed. This framework is provided by the ISO 23247 – Digital twin Manufacturing Framework, which is the standard that is adopted for building the digital twin for the robot workcell for this project.

This section introduces the DIS ISO 23247 framework. There are four parts in the standard: (1) overview and general principles, (2) reference architecture, (3) digital representation, and (4) information exchange. The parts of the standard is briefly described as follows:

1. ISO 23247-1 provides general principles and requirements for developing digital twins in manufacturing; it defines terminologies used throughout the series (ISO 2020a). For example, the digital twin in manufacturing is defined as "a fit for purpose digital representation of an observable manufacturing element (OME) with synchronization between the OME and its digital representation." OMEs include personnel, equipment, materials, manufacturing processes, facilities, environment, products, and supporting documents. When implementing digital twins of OMEs with specific objective and scope, appropriate standards, methods, and tools need to be used.
2. ISO 23247-2 provides a reference architecture for implementing digital twins in manufacturing. It includes a reference model from domain and entity point of view. There are four domains and each domain has a logical group of tasks and functions, which are performed by functional entities. These are (1) observable manufacturing domain, (2) data collection and device control domain, (3) core domain, and (4) user domain. Figure 4 shows the entity-based reference model and an illustration of the four domains and their interactions (ISO 2020b).
3. ISO 23247-3 describes the basic information attributes for typical OMEs (ISO 2020c). Whenever possible, existing standards should be used to digitally represent OMEs. In a use case, the most appropriate information model shall be selected for the OME according to the requirements. Each OME shall use the unique enterprise identifier if possible.
4. ISO 23247-4 discusses technical requirements for information exchange between entities within the framework (ISO 2020d). The networks between domains and entities include (1) user network that connects the user entity and the core entity, (2) service network that connects sub-entities within the core entity, (3) access network that connects the data collection and device control entity to the core entity and to the user entity, and (4) proximity network that connects the data collection and device control entity to OMEs.

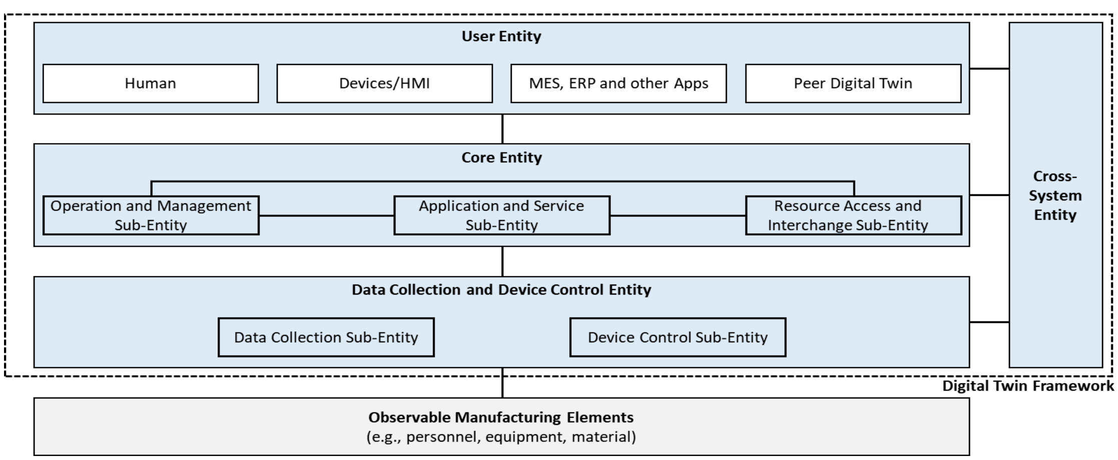

Figure 4: Entity-based digital twin reference model for manufacturing (ISO 2020b).

5 DIGITAL TWIN USE CASE FOR ROBOT PHM USING THE STANDARD FRAMEWORK

5.1 Description of the use case

This is a description of a digital twin of a single robot arm, which would represent one of the robots in the NIST PHM for robot systems workcell consisting of two robots. The workcell was installed to be used to develop different use cases for PHM research in robot systems (Weiss et al. 2017). One of the robots is tasked for material handling while the second robot is configured for performing a precision operation. A different end-effector is attached to each robot to carry out the specified operation. The two robots have overlapping work envelopes. As such, a supervisory PLC monitors and coordinates the activities in the workcell. Performing PHM within the workcell involves monitoring data such as robot joints and TCP to analyze data for each robot arm to determine the source and cause if deterioration in performance is observed. The scope of the work in this paper is a description of the activities and benefits that accrue by building a digital twin. This use case is targeted for robot accuracy, as an example, but the procedure is relevant to other forms of robot degradation. Table 1 is an instantiation of the ISO 23247 - Digital Twin framework for a digital twin for PHM of the robot in the workcell.

5.1.1 The problem

The use case is for PHM of a robot and end effector with respect to TCP accuracy. Robot accuracy degradation is the deterioration in a robot's ability to locate and orient the end-effector TCP as specified in the robot program. The end-effector at the robot arm's wrist allows the robot to interact with the task. The material handling robot is fitted with a gripper (for picking and manipulating objects). Figure 5 shows a UR5 robot fitted with a gripper picking up a part for dropping at a different location. The end-effector for the precision operation is a process tool for carrying out the operation. In the robot workcell, reduced TCP accuracy results in placing a part at a location or having the orientation that is different from the robot command. Robot accuracy is assessed by comparing the actual positions with the expected (or commanded) position. Reduced accuracy occurs because of joint friction, encoder slip failure, wear, or vibration. These effects may also result in increased power consumption during execution of a task. Before any analysis activity can proceed, data has to be collected.

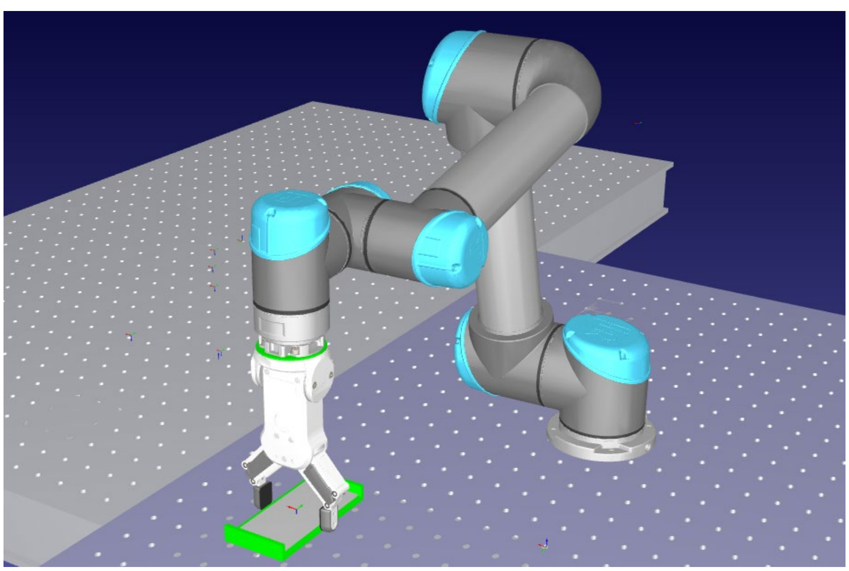

Figure 5: A Universal Robot with an RG2 gripper picking and dropping a part

Table 1: Robot TCP accuracy use case (table template adopted from work of ISO/IEC/JTC1/AG11)

Use case name	**Monitoring and control of a robot arm to maintain robot accuracy**
Application field	Manufacturing (PHM for Robot Workcells)
Life cycle stage(s)/ phase(s) coverage	Maintenance
Status	During operation
Scope	Accuracy of a robot workcell tool center point of a robot arm with an attached end effector Performance degradation of a robot workcell consisting of two robots (initial scope is accuracy of a single robot tool center point with end effector)
Problem(s)	1) Direct measurement systems of TCP and instead, relying on controller data 2) Selection of factors and variables to include in data collection 3) Selection and integration of data analysis tools with robot simulation 4) Limitations of simulation modeling tools in representing factors and variables that affect the accuracy of a robot and the end effector
Objective(s)	1) Understand how available technology can be put to develop a digital twin to improve decision-making in robot workcells 2) Understand the relationships among and between variables that affect robot workcell accuracy 3) Predict robot workcell accuracy based on these factors and variables
Short description	Robot workcell degradation due to faults in the robot or end effector leads to reduction in performance. Accuracy of the TCP is important because it determines the quality of the product. A reduction in accuracy in the TCP indicates a degradation in the robot's or end effector's health. The digital twin is built in a virtual environment to represent the robot or robot workcell. At a high level, data on TCP is monitored while executing a given task. Data on position, velocity, and acceleration of joints are monitored and obtained and used in the simulation model of the robot. Other data are collected and used directly in data model for analysis.
Stakeholders	1) Industries that use robotic systems in their operations 2) Robot Manufacturers 3) Robot system integrators 4) PHM software developers
Key technologies	1) Data collection from the robot's controller and used in the robot simulation environment. 2) PLC to record the process information and raw sensor data 3) Robot modeling and simulation technology and tools 4) Data-based analytical models developed in MATLAB - the robot simulation tool has a MATLAB application programming interface (API)
Relevant standards	ISO 23247-4
Standardization needs	The standardization of robot programming, interfaces for real-time data exchange between the robot systems, virtual models, and analytics provided by established vendors
Remaining issues and future works	1) Factoring the end-effector into the digital twin 2) Gathering and instantiating other data (e.g., temperature, current) from the controller that the digital twin cannot model and provide 3) Exploring suitable and integrable tools and algorithms for data providing the analytics with RoboDK simulation and the robot workcell 4) Integrating the various modules to form a digital twin of the robot workcell

5.1.2 Data acquisition from the robot workcell

Figure 6 illustrates the interactions between a robot workcell and its digital twin. Physical data is collected from the robot workcell using sensors and the controller. The collected data includes position, velocity, and acceleration of the robot joints. The data may require preprocessing. The data is updated at the same intervals as the position and orientation of the TCP and used to update the status of the simulation model. In addition to the robot simulation data, there are also joint temperature and power consumption that are obtained from the robot controller. This data is obtained from the workcell. This data is fused with robot simulation data for analysis to determine the cause of performance degradation and the extent of deterioration of the robot component(s).

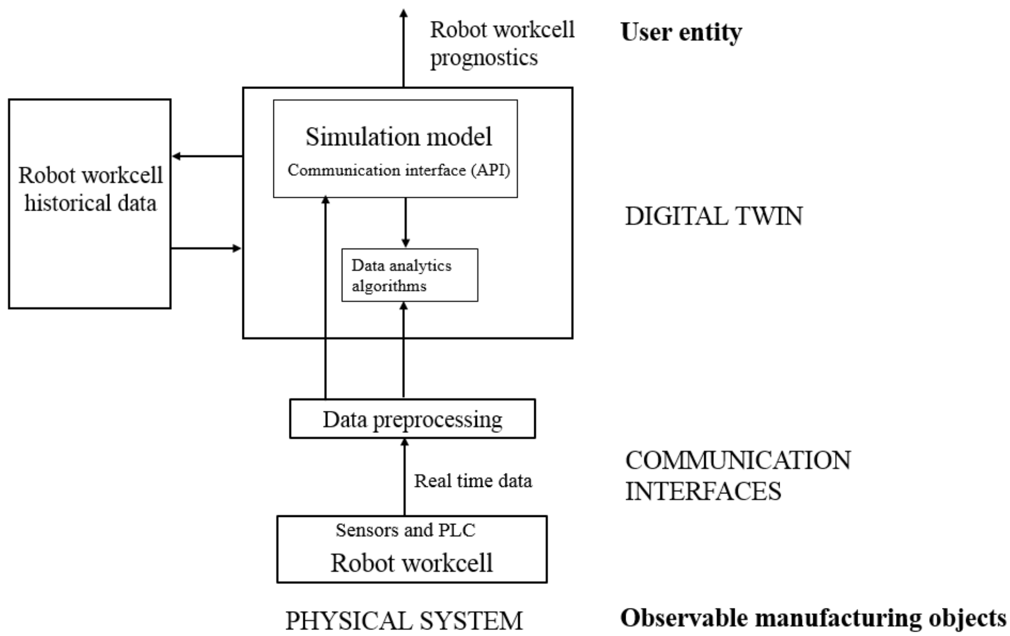

Figure 6: Illustration of relationships between different components of the digital twin.

5.1.3 Digital twin approach

More effective PHM has to be proactive, i.e., predict when failures are expected to occur so that maintenance actions are carried out prior to the realization of a failure. Many PHM prediction models assume that sufficient past failure data exists and that future system behavior would follow past trends (Aivaliotis et al. 2019). These assumptions may not always hold, especially for new equipment or new processes. The digital twin, as an updated virtual replica of the workcell, overcomes these limitations by (1) fusing real-time data from different sources, (2) simulating to determine future status of the robot or its components based on action carried out, (3) performing analytics for prognostics, (4) helping to develop failure models of a robot or its component and then keeping them updated with real-time data so as to make accurate predictions of future performance including failure, and (5) enabling multilevel analysis (from workcell to robot component). Regarding points (3) and (4) above, analytics in the digital twin lead to developing models of relationships among collected data, and between them and robot performance with respect to accuracy. Such models can be used to identify and predict faults and failures.

5.2 Digital representation and integration

A robot workcell is a complex system where the components, their interactions, and operations cannot all be modeled using mathematical formulations. However, the positions, velocities, and accelerations of the robot links, joints, and end-effector can be modeled using a robot simulation tool. We used RoboDK as the robot simulation environment with which to create the digital twin. This software uses a physics engine to calculate the values of the kinematic variables. Other data such as power consumption cannot be represented in such tools. This data, together with simulation data, are to be used to develop a data-driven model.

The simulation model is developed at a level of detail sufficient for the collected data described in Table 1 to be used to update the model in real-time. Robot accuracy is monitored at the high level. Robot simulation tools have an application programming interface (API) for MATLAB and other high-level programming languages. The API allows creating robot programs from generic programming code to simulate specific tasks beyond those provided by the graphical user interface. The robot simulation and the data-driven analytics model constitute the digital twin of the robot workcell for monitoring, analysis, assessment, and decision-making.

The different states of the system are saved to create a database of the workcell history. For example, if the digital twin is used to trace a specified degradation, the database will store the data related to both healthy and degraded states of that particular degradation type. Future data can be compared with this database to perform classifications based on this history. The history will also contain the robot performance before and after the maintenance action has been performed.

5.3 Robot drivers in RoboDK

A robot driver provides an interface between digital twin models and a physical robot. Robot simulation tools such as RoboDK provide such robot drivers to monitor and control a specific robot controller enabling a computer to control industrial robots (RoboDK, 2021). The reverse direction of communication is also possible. RoboDK has a macro that allows the analyst to monitor the state of a Universal Robot (UR) and update the position of the robot in RoboDK. This is how the robot simulation can update the position of the robot and will create targets as the robot is moved. It is also possible to monitor the robot position, speed, acceleration, and motor currents.

Although most robot drivers use a Transmission Control Protocol/Internet Protocol connection, the real-time data exchange interface provides a way to synchronize external applications with the UR controller, without breaking any real-time properties of the UR controller (Universal Robots, 2019).

6 DISCUSSION AND CONCLUSION

PHM for robot workcells helps them to maintain the efficiency and flexibility they offer to manufacturing. The challenges for robot PHM have been identified. They are mostly related to the difficulty in relating data to healthy and unhealthy system states and the lack of methods to relate faults at different levels of control. This paper proposed that a digital twin of a robot workcell can help overcome these challenges to train prediction models based on sufficient information. The ISO 23247 standard provides a framework to realize such a digital twin. The framework specifies digital twin definition, relevant terminologies, the requirements, and procedure for a digital twin implementation.

Implementing a digital twin for robot systems requires specifying the different components of the digital twin. This is followed by selecting an appropriate type of twin for representing the physical robot workcell. Some data of the robot can be represented directly by robot simulation models. Other data is used directly from the workcell for analysis. The combination of the robot simulation and data-driven model provides the needed PHM. The example used in the model is a six axis Universal Robot where the focus is the accuracy of the TCP with attached end-effector.

The causes of robot and end effector degradation are challenging to locate and determine especially since the workcell continues operating after degradation has occurred but produces inferior products or uses higher than expected energy. For example, degradations due to increased friction and wear leads to gear backlash, higher temperature of joints, or vibration. Vibrations on the other hand also increase wear. These are the variables affecting position, velocity, and acceleration of joints during execution of a task. Similarly, gripper pads can wear with repeated use leading to an erroneous pick or place activity of a part. The analytics on collected data within the digital twin through unsupervised learning can determine the relationships among the root causes (e.g., gear wear), intermediary effects (e.g., joint position), and the high-level effect such as accuracy. The analysis could be extended to other forms of performance degradations such as path straightness, (task and path) repeatability, or energy consumption.

Developing measurement methods and PHM validation efforts are continuing at NIST and the next digital twin activity is to implement this use case on the workcell testbed, with multiple robots performing different tasks under control of supervisory PLC.

7 DISCLAIMER

Certain commercial systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose. No approval or endorsement of any commercial product by NIST is intended or implied.

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