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DATA REQUIREMENTS FOR A DIGITAL TWIN OF A ROBOT WORKCELL

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ABSTRACT

The applications of digital twins continue to grow with the volume and variety of data collected. These data support the modeling of function, behavior, and structure of a physical element. However, successfully building a digital twin requires data identification, data fusion, and data management. Thus, despite the increase in data availability, there are still challenges of data usage, especially data scoping and scaling to implement a digital twin for a specific purpose. The objective of this paper is to identify data requirements for various types of digital twins for a robot workcell. The identification includes data description, source, method of collection, and data formats. The digital twin types include descriptive digital twins, diagnostics and prognostics digital twins, prescriptive digital twins, and intelligent digital twins. The outcome of this data requirements identification can be used as a guide for developing and validating digital twins for a robot workcell through its lifecycle.

1 INTRODUCTION

1.1 Background

The application of digital twins in manufacturing has greatly increased in recent years and this trend is expected to continue (Jones et al. 2020; Attaran and Celik 2023). Digital twins are built using data collected by sensors from a physical element such as a product, manufacturing system or equipment. This data enables the physical element and its digital twin to be synchronized at a desired frequency and fidelity. In this paper, a digital twin is defined to consist of (1) models (e.g., simulation) that represent the physical element, (2) data from a physical element that represents its attributes and status, and (3) model interfaces to support the two-way communication (Stojanovic et al. 2021).

The details of a digital twin depend on the physical element or process it represents and the intended purpose of the digital twin. The digital twin models describing the function, behavior, and structure of the physical element could be simulation models and/or mathematical models. Many digital twins are based on modeling and simulation of the physical element and enable seamless simulation along all lifecycle phases of the physical element (Boschert et al. 2016). A digital twin may also comprise models developed by data mining, machine learning, deep learning, or optimizations. These models are built based on historical data and are updated as more data is collected from the physical element or process. Therefore, complete, relevant, and high-quality data are indispensable in building, validating, and maintaining a digital twin, establishing communication sub-systems, and developing predictive models of the digital twin (Zhang et al. 2022). Data requirements are the foundation for the development and validation of digital twins and for fulfilling the intended purpose. Among others, these requirements include data identification, data fusion, data curation, and overall data management.

1.2 Objectives and Motivation

Building a digital twin involves a process of identifying, prioritizing, formulating, and availing data for the digital twin objective(s). This paper focuses on the above process for a digital twin of a robot workcell. Robot workcells are widely installed with new technologies, such as smart sensors and microprocessors to enable communication among industrial equipment and collection of data, which can be analyzed to improve performance. However, there are still challenges in how to identify and use the data to build a digital twin for a specific purpose. These challenges include dealing with unlabeled data, lack of clarity on the sufficiency of data, and lack of knowledge on preparing validation data sets (Weiss and Brundage 2021; Kibira and Weiss 2022). To build a digital twin, data should be complete, relevant, focused, and obtained on time (Zhang et al. 2022). Therefore, this paper explores and identifies a range of data needs for building and validating various types of robot digital twins. Part 2 of the ISO 23247 standard describes a reference architecture for digital twins in manufacturing, which is the basis for the identification of the observable manufacturing elements (OMEs) in the manufacturing environment including data collection elements (ISO 2021).

Figure 1 illustrates a generalized view of a robot system digital twin based on the ISO 23247 reference architecture. It shows the interactions between the physical world and its digital counterpart. In the OME domain, the physical system comprises the robots, end effectors, the workpiece, sensors, and fixtures. In the digital twin domain, there are digital and business service (comprising data management, intelligent decision-making, etc.) models. Data on product, equipment, operational, and process plans are collected and used to build, validate, and update the digital twin models. Optimal parameters and control commands are generated by the digital twin. Data collection and controls are synchronized with a specified frequency determined by the use case requirements. The digital twin of a robot system typically has the following components:

- Computer-Aided Design (CAD) models of the working environment and robot components, i.e., links, joints, parts, end effector, fixtures, tables, and supports.
- Communication and data links to sensors, models, and controllers.
- Operational data collected by various means such as sensors, controller, Programmable Logic Controller (PLC), standard protocols (e.g., MTConnect), and the meta data.
- A digital representation of the robot system, e.g., in the form of a simulation model.
- Analytic models based on machine learning, deep learning, or optimizations.

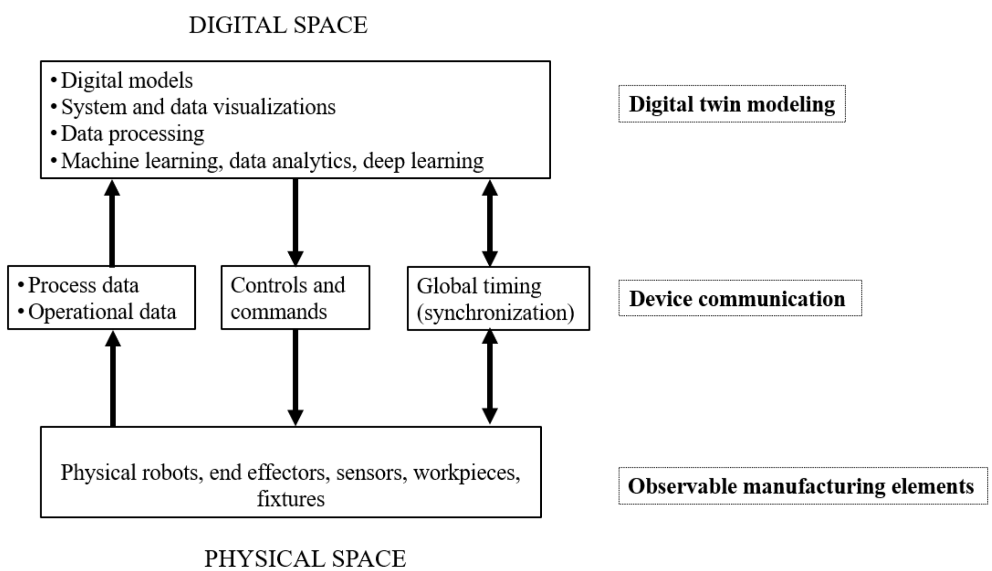

Figure 1: Interactions between physical and digital spaces in a robot system digital twin.

The data needed for digital twins varies from case to case because there are no systematic guidelines available for identifying the data needed to build a new digital twin in manufacturing. Figure 2 shows the digital twin architecture for visualization, monitoring, prediction, and prognostics and health management (PHM). This is an example of data acquisition from a robot workcell and its input and usage in the digital twin. The figure also depicts the three main elements of the digital twin: the physical element, virtual models of the physical element, and the communication network. This paper will help facilitate digital twin development by characterizing relevant data and sensing for different types of digital twins including descriptive, diagnostic and predictive, prescriptive, and intelligent digital twins (Shao et al. 2014).

1.3 Paper Contribution and Contents

This paper contributes to systematically understanding (1) the data required to build digital twins of a robot workcell, (2) different types and levels of data from a physical robot workcell, (3) methods and standards for data collection to support the development, validation, and update of a robot digital twin, and (4) technologies for collecting data from a robot workcell. The rest of the paper is organized as follows. The next section reviews current research in digital twins, data collection methods, and relevant standards and technologies. Section 3 identifies the data requirements for various digital twins. Section 4 provides a discussion and further work.

2 METHODS, TECHNOLOGIES, AND STANDARDS SUPPORTING ROBOT WORKCELL DIGITAL TWINS

This section provides an overview of relevant methods, technologies, and standards that support the development of robot workcell digital twins, especially on how these support data identification, acquisition, and management. Data for a robot system digital twin can be collected at different levels of sensing. Qiao and Weiss (2018) identified four levels of sensing. These levels are simplified in Figure 3. The highest (or system) level collects data that is used to determine the health condition or state of a robot system. The add-on sensing collects data, such as pre-designed part features, which can't be obtained from the controller. The environment level sensing provides data such as part design data, process data, system integration control data, and external programmable logic controller (PLC) data. The component (or lowest) level sensing collects data that is analyzed to improve operations or to determine the source of a problem.

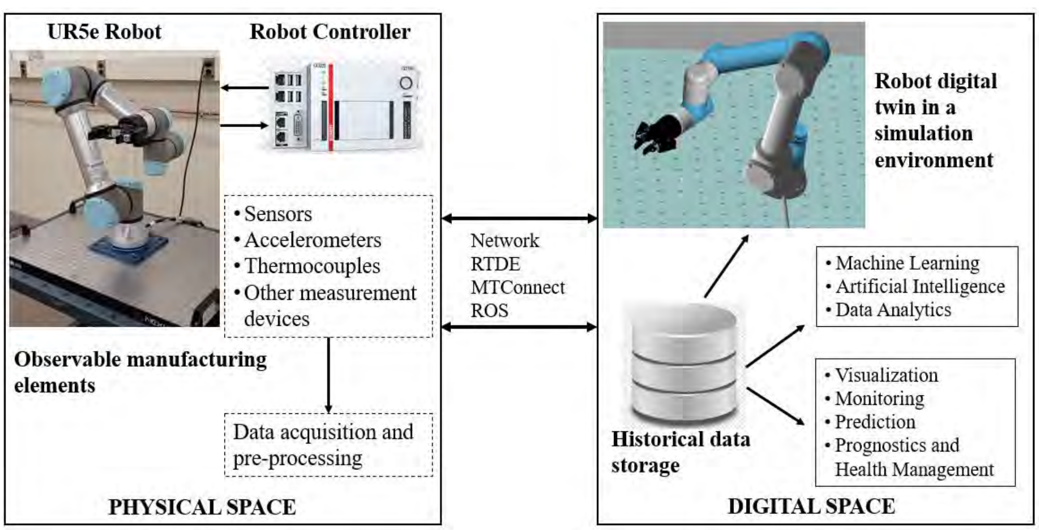

Figure 2: Data acquisition, usage, and exchange between the robot workcell and its digital twin.

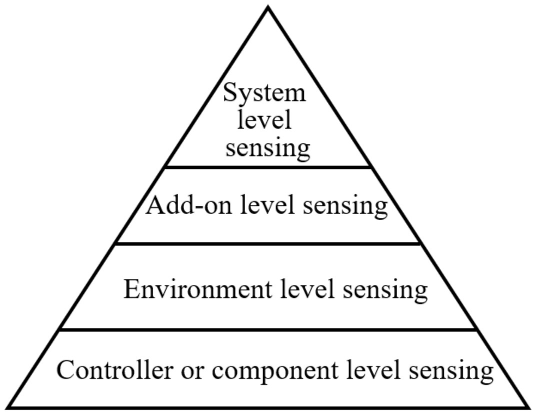

Figure 3: Different levels of sensing (Qiao and Weiss 2018).

2.1 Data Acquisition from Physical and Virtual OMEs

The technologies supporting data acquisition for digital twins include:

- Robot Controller: Robot controllers are the main source of data for a robot arm. For example, to collect data from a Universal Robot, a UR-Real Time Data Exchange (UR-RTDE) protocol is provided. Data collected includes joint position, velocity, acceleration, joint torque, temperature, and tool center point (TCP) force.
- Physical sensors: Sensors are a means by which large volumes of data can be collected. Sensor data includes temperature, speed, object proximity, acceleration, pressure, position, orientation, and vibration.
- Virtual sensors: Virtual sensors are needed in cases where it is not possible to directly measure the data. Aivaliotis et al. (2019) show how virtual sensors are modeled in the digital twin to gather data, which was analyzed to estimate the remaining useful life of a robot arm.
- Data from existing systems: Existing applications in an industrial environment are Computer-aided Process Planning (CAPP), Enterprise Resources Planning (ERP), Supervisory Control and Data Acquisition (SCADA), and Manufacturing execution system (MES).

2.2 Related Standards

Standards have been developed to support building a digital twin based on data (Shao and Kibira 2018; Farhadi et al. 2022). In this subsection, we briefly introduce ISO 23247: Digital Twin Framework for Manufacturing (ISO 2021), ISO 14306: Industrial Automation Systems and Integration (ISO 2017), ISO 13374: Condition Monitoring and Diagnostics of Machines (ISO 2007), and Robot Operating System (ROS). Data communication standards are also identified.

- The ISO 23247 standard series provides a generic development framework that can be instantiated for case-specific implementations of digital twins in manufacturing.
- ISO 14306 defines the syntax and semantics of a file format for the 3-dimentional (3D) visualization and interrogation of lightweight geometry and product manufacturing information derived from CAD systems, using visualization software tools. This standard provides guidance, especially for digital twins where data display is the primary function.
- ISO 13374 is for processing, communicating, and displaying condition monitoring and diagnostics information. Prognostics and health management are one of the main applications of digital twins in manufacturing (Errandonea et al. 2020).

- Robot Operating System (ROS) is a library for programming robots. ROS was designed to meet challenges encountered when developing large-scale service robots (Quigley et al. 2009). But its architecture is applicable to a wide range of robots and can support developing robot digital twins.

Since data is obtained from various sources using different methods, it is often available in different formats. For example, controller RTDE data from a robot can be obtained through an API developed using python and saved to a spreadsheet. Sensors include strain and temperature gauges, which also provide data in different formats. To utilize these data in a digital twin, a neutral data format may be needed for data sharing and modeling. Standards can provide protocols for this purpose. Lim et al. (2020) highlights data exchange protocols and case studies in manufacturing used by data acquisition systems for digital twin communication. The most used data standards for robot digital twins are OPC-UA (OPC Foundation 2023) and MTConnect (MTConnect Institute 2023).

2.3 Data Characteristics of a Robot Workcell

Data that supports digital twin development is identified in different categories depending on its characteristics. For example, data can be qualitative or quantitative. Quantitative data can be continuous or discrete (discontinuous). Data can also be operational data or metadata. Most data are collected, while some other data are computed or generated from a simulation. Zhang et al. (2022) identified data categories for digital twins as physical entity-related data, virtual model-related data, service-related data, and fusion data, which are briefed as follows:

- Physical entity-related data is from the physical robot such as the controller and sensors.
- Virtual-model-related data is from virtual sensors. Since such data is difficult to measure directly, data will need to be generated from simulations and computations.
- Service-related data is from services provided by the digital twin including scheduling or prognostics that use both physical and virtual data.
- Fusion data is the result of merging various types of data and processing by algorithms such as Neural networks and Bayesian methods.

3 DATA REQUIREMENTS FOR VARIOUS DIGITAL TWIN TYPES

A digital twin is context-dependent and therefore, only needs relevant data for the intended purpose (Shao and Helu 2020). Moyne et al. (2020) have observed that digital twins play larger roles as they evolve from descriptive and reactive to predictive and prescriptive digital twins. This section is a discussion of data requirements for descriptive digital twins, diagnostic and predictive digital twins, and prescriptive digital twins. Intelligent digital twins are also introduced.

3.1 Descriptive Digital Twins

Descriptive digital twins help identify what happened or what is happening in the system. This type of digital twin provides different views of visualizations in the form of text, numerical values, graphs, plots, tables, and charts to identify data patterns and trends. Data that are communicated between the physical equipment and virtual environment can be visualized and monitored in real-time for the entire lifecycle of the manufacturing system (Li et al. 2022). Figure 4 shows a digital model of a robot arm developed in a physical modeling tool using joint data from a real robot workcell performing a precision operation. The visualization of operation in the digital world contributes to system description and model verification. Description is often performed by system monitoring where data is collected on the flow of materials, status of production orders and equipment, and personnel in the production process to support decisions related to controlling the operation of the shopfloor (Zhuang et al. 2021).

The data requirements for descriptive digital twins support visualizing digital twin elements and associated data. The data should also be in a suitable format for developing the digital twin. A standard such as ISO 14306 helps to define the syntax and semantics of collected data for 3D visualization. Depending on the scope, the most crucial data for visualization of a robot system are environment data, CAD data of the robots and workpiece, robot joint data, and production data. The identification of data includes description, sources, methods of collection, purpose of collecting this data, and the data format.

(1) The environmental data
- Description: These are data regarding the operational space of the robot system. The virtual environment includes the table and base upon which the robot is mounted, the walls, floor, ceiling, and fences. This data is mostly static since the environment does not change during operation. The environment includes humans with whom the robot interacts. However, humans change positions and posture during operation.
- Purpose: To provide boundaries of the working space and locations of all OMEs.
- Source: CAD models of the environment can be developed from direct measurement of the existing workcell or from original designers of the workcell. Anthropometric data sources can be consulted to obtain human data.
- Methods of collection: This data is collected from designs of the robot workcell.
- Format: A neutral CAD format such as ISO 10303 (ISO 2021), Standard for the Exchange of Product model data (STEP), can be adopted.

(2) CAD data of the robots and the workpiece:
- Description: These are the robot 3D CAD model data. This data describes the geometry of each link and joint of the robot, end effector, and workpiece. Most of this data are described as robot kinematic data. Also required is data on spatial coordinate relationships between links.
- Purpose: To analyze the relationship between the dimensions and connectivity of kinematic chains and the position, velocity, and acceleration of each of the links in the robotic system. The result of the analysis helps plan and control movement and determine whether the robot and end effector can perform required tasks in terms of reachability. This data is also needed to compute forces and torques at the robot joints.
- Source: Robot CAD data (including those for end effectors) could be provided by manufacturers. Typically, individual links are imported into the digital twin modeling environment to create a digital twin of the robot. However, robot link models are often provided as solids, yet they are hollow to accommodate components such as motors, encoders, gears, electronics, and wiring. CAD data for components inside the links may have to be developed in some cases.
- Methods of collection: Obtained by examining robot and workpiece design documents.
- Format: The models are often available from the manufacturer in the STEP format as a complete robot assembly.

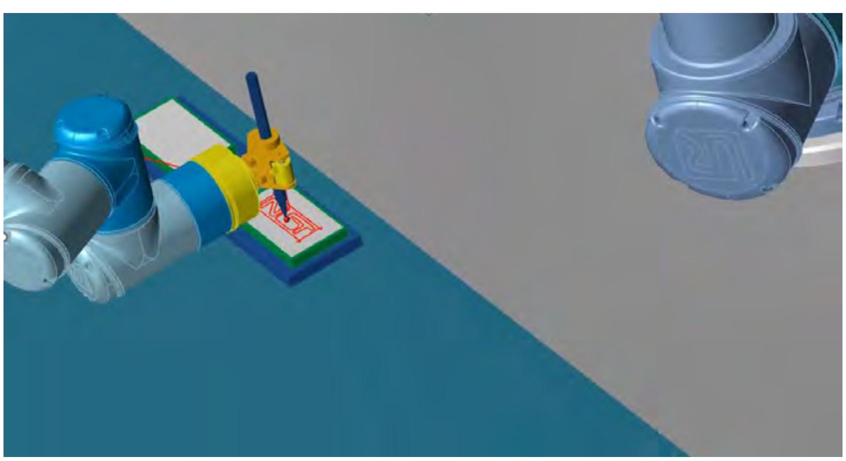

Figure 4: Simulation in a digital twin to help verify a robot program through visualization.

(3) Robot joint data:
- Description of data: This data shows the movement of the robot links relative to the base and the relative movement between the links. This data includes joint and TCP positions, velocity, and acceleration. This data is sampled at a selected frequency or when a predefined event happens. For the TCP, the data includes the position and orientation. In the development of the visualization component of a digital twin, it is important to take note of the differences in the coordinate system between the physical robot and the virtual one. The data for the end effector is also needed whether it is open or closed, if open, the angle.
- Purpose: To determine the trajectory of each robot component as it executes tasks defined in the robot program. This data especially determines the position of the end effector and the needed working envelope.
- Source: This data is obtained from the robot instruction program. This program can be developed by direct programming or by use of a teach pendant.
- Methods of collection: APIs are available in C++ and Python for most robots. Using the API, a socket-based adapter that sends MTConnect compliant data to the agent can be developed.
- Format: This data is provided in the Extensible Markup Language (XML) format but can be saved as text, csv (comma-separated values), or a spreadsheet file. It can also be input directly into the (physical or digital twin) robot joint with minimal programming effort.

(4) Production data:
- Description of data: This data provides information about the status of production orders, which can be compared with the original production plan. Data is needed from all stages of the production cycle such as the number of workpieces moved by the robot, machined by computer numerical control (CNC) machine tools, or whose geometries are measured by the coordinate measuring machine (CMM). The efficiency of operation of equipment should be tracked as well as the frequency of nonscheduled stops of equipment during production. The other data is the current progress in execution of preplanned production, and uncertainty quantification of projected performance. This data includes the number of rejects and those that need rework. For a descriptive digital twin, key performance indicators (KPIs) such as schedule attainment, availability, quality rate, and overall equipment effectiveness are needed to effectively monitor and assess the manufacturing process.
- Purpose: To determine the status of production operations, equipment status, and progress of production orders to guide in decision-making.
- Source: Production plan, enterprise requirements planning, computer-aided process planning, supervisory control and data acquisition, and maintenance logs.
- Format: Database format such as xlsx (Excel) and JSON (JavaScript Object Notation).

3.2 Diagnostic and Predictive Digital Twins

Diagnostic digital twins help identify why an unexpected event happened or why it is happening. Robot diagnostics is the ability to identify any degradation in performance, to determine the cause, and its location. Predictive digital twins help identify what is going to or likely to happen and when. This is often performed through simulation. For example, a predictive digital twin can be used to predict the cycle time and throughput based on current strategies for order release and dispatching, scheduled material arrivals, and machine and worker availabilities.

PHM is one of the major applications of the digital twin in manufacturing (Tao et al. 2019). PHM relies on monitoring, diagnostics, and prediction. PHM data, for example, is the type of data required to understand the type and source of failures in a robot. Within the digital twin, this data helps predict the types and timing of faults and failures. The levels of sensing described in Section 2 can further be summarized into two major types. These are upper-level sensing and add-on, and lower-level sensing, which provide data as follows:

(1) Upper-level sensing data:

- Description: Upper-level sensing or monitoring provides the data needed to determine the health state of the robot. This sensing level data requires algorithms that can assess the state of health of the robot based on the sensor data. This is the data related with position accuracy, resolution, velocity accuracy, TCP force, repeatability, and path straightness. Other data include energy consumption, which is observed through the current at the joints. This data also includes add-on data such as vibrations and temperature.
- Purpose: To quantify performance based on collected data and to compare this performance with the planned (expected) performance. Methods have been developed to assess accuracy, repeatability, path straightness, and productivity (Qiao et al. 2016).
- Source: Advanced sensing methods involve external sensors such as vision sensors, laser tracker-based systems, and optical tracking systems. Energy consumption is obtained through metering at the robot's electrical power input port. External vibration and temperature data are obtained through accelerometers and temperature gauges.
- Format: This data is available in a spreadsheet file and can be converted to any format.

(2) Lower-level sensing data:

- Description: The lower level of sensing collects data that is analyzed to determine a relationship between observed health degradation and the robot component responsible for the degradation. Most of the measurements include joint kinematic data, dynamic data, and individual joint currents. Kinematic data includes joint positions, joint velocities, and joint acceleration. Dynamic data includes joint torques and TCP force. Dynamic data for robot components includes link mass, link center of mass, and link moments of inertia. The mass or weight of the workpiece(s) is also needed. Other data include joint temperatures. Figure 5 shows an example of the role of data and the digital twin in PHM. The digital representation is used to generate data through simulation, which together with physically generated data can be used for predictive maintenance.
- Purpose: Lower-level data is collected and analyzed to determine a relationship between the observed health degradation and the robot component responsible for the degradation.
- Source: Most of this data is internally collected or available from the production plan. There is data that can be collected externally using sensors, for example, vibration and temperature data can be collected by using accelerometers and thermocouples.
- Format: This data is available in a spreadsheet.

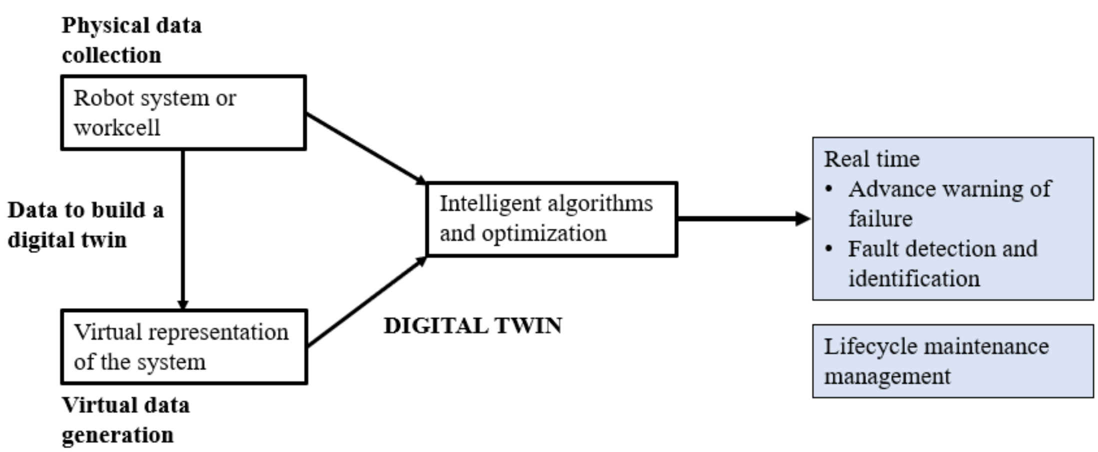

Figure 5: Role of data to support a PHM digital twin of a robot workcell.

3.3 Prescriptive Digital Twins

Prescriptive digital twins extend the functions of descriptive, diagnostic, and predictive digital twins to propose courses of action that need to be taken to obtain a desired outcome. Decisions are evaluated based on a projection of the outcome of alternative decisions often through simulations. Prescriptive digital twins add intelligence for recommending corrective and preventive actions on the robot system based on results of data analytics, machine learning, or optimization algorithms. For example, prescriptive analytics may include identifying changes in input parameters and strategies that will enable cycle-time reduction and throughput increase. The prescriptive capacity of the digital twin is based on the correlation of certain parametric data with subsequent events. For example, events such as noise, vibration, and temperature increase may precede component failure and therefore, guide part replacements when similar patterns are observed in future. However, many digital twin approaches today lack mechanisms that convey elements of prediction quality, such as prediction uncertainty and model accuracy, with respect to the application environment (Grieves 2022). The details of the requirements are as follows:

- Description: The data required for prescription includes all the data already mentioned for diagnostic and predictive purposes, and more. It may include the data to assess the current and anticipated health states of equipment. In addition, current and anticipated production levels, and equipment loading and subsequent health status are needed for prescriptive analytics. These data include production plan data (expected number of units to be handled in each period in the future), process plan (the sequence of activities of each unit), current equipment status (busy, idle, faulty, and waiting for repair, or being repaired), time since repair or service, MTBF (mean time before failure), MTTR (mean time to recovery, repair, response, or resolution), MTTF (mean time to failure), and MTTA (mean time to acknowledge), current and expected health states of the robots, and expected time to failure. Parameters such as expected bearing friction, gear backlash, and production rates that should be synchronized between the real world and the digital twin need to be identified.
- Purpose: The purpose of this data is to provide inputs to prediction models.
- Source: This data is obtained from the production plan, which determines equipment loading. Equipment data is obtained from maintenance logs, manufacturer recommendations, and from similar equipment. Degradation data, which provides anticipated health states of equipment, can be obtained from published data on similar mechanisms that are installed in robot arms such as, bearings, gears, and motors.
- Format: Production data loading is often provided in the form of charts and tables in various formats.

3.4 Intelligent Digital Twins

The intelligent digital twin is an extension of the classical digital twin by enriching it with ability to automatically adapt and update models and provide benefits and new capabilities as the physical system and its environment change (Maschler et al. 2021). The intelligent digital twin observes the environment using the operating data (sensor and actuator values) and analyzes it to gain new knowledge beyond the explicitly defined information in the existing models. Artificial intelligence algorithms are an integral part and must have an information coupling to the models and process data of the digital twin.

Grieves (2022) defined intelligent digital twins as those characterized by being (1) active, (2) online, (3) goal-seeking, and (4) anticipatory. For intelligent digital twins, data is continuously collected and transmitted to the virtual world rather than on a periodic basis. Intelligent digital twins automatically control their physical counterparts based on the strategies and parameters identified by the prescriptive digital twins. These digital twins may also be able to dynamically adjust themselves to keep them valid and trustworthy. Technologies such as Artificial Intelligence, machine learning, data stream mining, and process mining is the main modeling technique for this kind of digital twins.

Data requirements for intelligent digital twins are the same as those for prescriptive digital twins. Both prescriptive and intelligent digital twins emphasize the importance of prediction and anticipation of change for the system and the data. For this reason, the information transfer takes place in two directions: from the digital twin to the asset providing predictions and what-if analyses, and from the asset to the digital twin providing not only reference data to validate the predictions but also information about changes in the environment and the system itself (Müller et al. 2022). Therefore, the major difference in requirements for intelligent digital twins is the timeliness, collection continuity, and rapid analysis algorithms. Table 1 is a summary of the digital twin services and the associated data.

Table 1: Services of the robot digital twin and associated data requirements.

Digital twin service	**Data type required**	**Source**
Descriptive (visualization, real-time monitoring, etc.)	Environmental	Direct measurement or original workcell designers
	CAD models of robot and workpiece	Robot manufacturer Part design
	Robot joint data	Robot program or controller
	Production data	Production plan, ERP, CAPP, SCADA,
Diagnostic and predictive (diagnosis, prognosis, quality control, simulation, etc.)	Robot level performance data	vision sensors, laser tracker-based systems, and optical tracking systems
	Robot component data	Sensors, accelerometers, thermocouples
Prescriptive (assessment of realizability, simulation, prognostics, and health management, etc.)	All above data	
	Current and anticipated health state, robot maintenance data (MTTR, MTBF, MTTA), Health state parameters	Maintenance logs, manufacturer recommendations, similar equipment. Degradation data, similar mechanisms installed in robot arms such as, bearings, gears, and motors
	Production plan data, Process plan data	Production plan, product design, which determine equipment loading.
Intelligent, self-adaptive services	All above data	Same as prescriptive digital twins but with emphasis on timeliness, collection continuity, and rapid analyses algorithms

4 DISCUSSION AND FURTHER RESEARCH

This paper has discussed data requirements for building digital twins for a robot workcell. Since data is indispensable for a digital twin, the value of a digital twin depends on the quality of the data used for building it. It has been observed that since the requirements for digital twin data extend beyond the needs for the usual simulation, the key enabling technologies and standards have been identified. The components of the physical system that need to be represented in the digital twin depend on the intended purpose. Similarly, the digital twin only requires relevant data for the intended purpose from all that is available from the physical system (or robot system). This data should also be a sufficient description of the OME. However, there are still some challenges with data such as a lack of complete understanding of the sufficiency, relevance, and sensing needs to successfully implement a digital twin. Data requirements for digital twins have been identified to serve as a guide for digital twin analysts and developers for robot workcell. Other data issues such as data curation including data denoising, data cleansing, data balancing, data imputation, and data annotation need addressing to support a digital twin throughout its lifecycle.

In further research, technologies for implementing a robot workcell digital twin are being investigated. The workcell consists of small collaborative robot arms for material handling and machine tending, a machine tool for cutting a part, and a coordinate measuring machine for product geometry measurements and quality control. The workcell will act as a testbed to identify and develop use case scenarios representing common manufacturing processes and challenges faced in industry. The testbed will also be used for standards enhancement, demonstration, and testing. Scenarios representing different digital twin types and objectives will be developed and prototypes of each scenario will be built using available tools and standards. Each scenario will require that data be identified, and the work of this paper will be a guide in data identification. Digital twin verification and validation is one of the major concerns for further development and adoption of the digital twin. Just as a digital twin can be used to validate a program, data from a physical robot workcell can be used to validate a digital twin before the digital twin is deployed for various purposes. PLC datasets from a real robot and the robot program can be developed and used by industry to validate their digital twins.

There will also be a research focus on enhancing approaches for integrating digital models with real-time streaming data. Many digital twin concepts in literature lack full integration, especially the feedback loop. This is partly due to the significant challenge of data identification, data gathering, filtering, and processing in real time, as well as data collection device malfunctioning and poor calibration that may create anomalies or missing data points. The MTConnect/ROS (Robot Operating System) approaches will be adopted for the feedback loop, from the digital twin to the physical world. The experience from these activities will result in methods and guidelines for building digital twins and hence, wider adoption of the digital twin in manufacturing.

DISCLAIMER

No approval or endorsement of any commercial product by NIST is intended or implied. Certain commercial software 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.

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