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TOWARDS A DIGITAL TWIN OF A ROBOT WORKCELL TO SUPPORT PROGNOSTICS AND HEALTH MANAGEMENT

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ABSTRACT

Current maintenance research often includes modeling equipment degradation to support determining when any degradation will exceed a specified threshold. Such models provide critical intelligence to determine an impending failure and promote the timely scheduling of maintenance, yet, the models require equipment data. While healthy state data can be readily captured from a system, degraded or failure state data is more difficult to acquire because equipment are normally operating in a healthy state. The degradation process can be modeled in a digital twin to generate failing health data. This paper presents work that is a step in the process of realizing a digital twin for this purpose. A procedure for modeling a robot workcell in a healthy state is described. We discuss how degradations will be incorporated into the robot to generate degraded data that can be used to predict future states of the robot and support decision-making.

1 INTRODUCTION

1.1 Robot PHM data challenge

Ideally, manufacturers who employ industrial robots would seek maintenance practices that are based on the prediction of the future health state of their robots. Currently, the use of predictive analytics and other health forecasting capabilities is relatively limited across the manufacturing ecosystem (Jin et. al. 2016; Helu and Weiss, 2016). Manufacturers rely on some combination of preventive and predictive maintenance while seeking to minimize their reactive maintenance. Enhancing monitoring, diagnostic, and prognostic (collectively known as prognostics and health management (PHM)) capabilities directly advances maintenance strategies in an industrial environment.

To build prediction models, which would enhance overall PHM and a predictive maintenance strategy, previously collected data or knowledge of the robot's physics must be available. This data should encompass healthy and unhealthy states, and knowledge should include the system degradation process (Izagirre et al. 2020). A data-driven model learns from collected data to classify degradations and failures. A challenge is that, often, there is insufficient data on all possible faults and failures, especially for a new system. In addition, many operators of high precision applications, such as military or aerospace, rarely want to operate their equipment until failure. However, a digital twin of a robot workcell would model the prevailing state of the system in addition to generating data representing projected future health states. The data would be used for monitoring and prognostics to optimize workcell productivity and reduce downtime. This paper addresses a procedure for building a digital twin for a robot workcell.

1.2 Motivation

A digital twin refers to a virtual representation of a system that is frequently updated with real time data from the actual system. Kibira et al. (2021) discussed the significance of a digital twin in enhancing PHM for robot workcells. However, building a digital twin that reflects the structure and functionality of a physical asset, i.e., a high-fidelity multipurpose digital twin, can be a labor-intensive or even an impossible activity. A digital twin should be context based and driven by use-case objectives (Shao and Helu 2020). This implies that a digital twin should be tailored for a specific application. The objective of this paper is to demonstrate a procedure for efficiently building a digital twin by identifying and including those elements of the digital twin to improve PHM for a robot workcell.

1.3 Framework for the digital twin and scope of current work

Building a digital twin for a robot workcell representing a healthy state is the first step. The use case is described in section 3. Robot degradations and failures will be identified and classified along with the associated robot components such as motor, gears, or encoder. The types of degradations will be incorporated in the model. Additional detail modeling of robot joints will be needed. Data representing these degradations will be generated and analyzed.

The scope of this effort is on modeling the kinematics and the dynamic forces in robots of an existing workcell. The current model is based upon healthy state of the workcell and is validated against previously collected data. This paper presents the procedures to 1) identify data and parameters of the robot, 2) select the model type and modeling process, and 3) verify and validate the model. These activities are key elements to building a valid and functional robot workcell digital twin. The work of this paper represents a work-in-progress to ultimately realize a twin that supports robot PHM.

1.4 Contribution and paper organization

This paper presents a procedure for building a data-driven multibody digital twin of a robot workcell. This work contributes to identification of robot elements and procedure to realize a robot workcell digital twin. The development of the digital twin is guided by the ISO 23247 standard, digital twin framework for manufacturing (ISO 2021). This procedure enables the development of a PHM digital twin for industrial robots more effectively and efficiently. The rest of the paper is organized as follows: Section 2 provides background on the effort to develop a robot workcell digital twin model, Section 3 introduces a case study, Section 4 describes the digital twin modeling process, Section 5 describes the validation of the digital twin, and Section 6 presents discussion, conclusion, and future work.

2 BACKGROUND

This section gives background and a review of modeling a robot or robot workcell and the requirements for building a robot workcell digital twin.

2.1 Related work on robot arm modeling and simulations

The research work in this paper is based on a robot workcell that is installed at the National Institute of Standards and Technology (NIST) (Klinger and Weiss, 2018). The details of this workcell are described in Section 3. The workcell includes two, six-axis industrial robot arms. This section reviews some of the previous efforts to building a digital twin for robot workcells.

A review shows that many digital twins for robots have been built to improve efficiency and safety of human-machine interaction in a collaborative work environment (Pairet et al. 2019; Wang et al. 2021; Malik et al. 2018). Tavares et al. (2017) built a digital twin for robotic workcells to improve manufacturing efficiency in processes such as welding and cutting. Other works such as Verner et al. (2019) have used a digital twin for training in control and operation of a new workcell.

A literature review uncovers several digital twins that have been built for predictive maintenance. Margargle et al. (2017) built a digital twin to generate failure data for inputs into analytics and support predictive maintenance of automotive an braking system. Digital twins built for predictive maintenance of computer numerical control (CNC) machine tools are described in Luo et al. (2020). Digital twins built for PHM of robot systems or workcells are scarce in literature. For example, a recent review of the digital twin for predictive maintenance does not mention any for robot systems (Errandonea et al. 2020).

However, Aivaliotis et al. (2021) built an "advanced" model of a robot within the context of a digital twin for predictive maintenance. The twin was built to capture the degradation process of a robot and develop a prediction model to calculate its remaining useful life (RUL). The research does not include details of the types of faults or their locations. This work's RUL is established by monitoring and determining when the quality of the manufactured product starts becoming unacceptable. No significant published efforts were found regarding robot digital twins using dynamic data such as loading, torque, current, and power to generate and fuse data to support PHM decisions.

2.2 Requirements and procedure for building the digital twin

The first category of requirements, the functional and structural requirements, are defined to determine what a digital twin should do and what stakeholders decide to include in the digital twin. The procedure specifies the framework and process of developing the digital twin.

2.2.1 Functional and structural requirements

Functional requirements refer to the specification of behavior or what the digital twin should do to augment robot workcell PHM awareness and intelligence. A major functional requirement is to generate data representing the state of health for a robot workcell and predict future health state of the robot. Structural requirements refer to the digital twin components and the connections among themselves to provide the needed functions. Table 1 summarizes these requirements. This discussion is for structural requirements of the tools and software to effectively represent the physical system.

Building a digital twin requires selecting appropriate modeling methods and tools. A digital twin can be used for simulation purposes but not every simulation can be described as a digital twin. The major difference between digital twin and simulation lies in the volume and ways in which they acquire and use data. A digital twin architecture is oriented to capture and communicate large volumes of data, perform analytics, and support decision-making in real or near-real time. However, for representing a system in the digital twin, simulation tools can be used or adapted for the purpose. Suitable simulation tools and methods are needed for the digital twin for our robot workcell. The tool should model both kinematic and dynamic data such as joint torques, joint temperature, joint control current, and tool center point (TCP) force.

Table 1: Summary of digital twin requirements.

Category	**Requirements**
Functional	• Generate data representing the health state of the robot workcell • Predict future state of robot health • Determine when and what types of interventions are needed
Structural	• Model the robot workcell in sufficient detail and capture data that is relevant to the goal of the digital twin • Store historical data of past states, repair requests, repair activities in the physical system, and other health management information in a database so that it is available for future prognostics needs • Model the progression of the robot workcell from a healthy to an unhealthy state and generate data representing these states • Update the digital twin with data collected from the robot workcell

2.2.2 Digital twin standard framework

Harper et al. (2019) and Jacoby (2020) provided an overview of standards for building a digital twin for various applications. These standards mainly address data interoperability, the internet of things, data acquisition, data generation, data storage, and data consumption. The ISO 23247 series standard defines a framework to support the implementation of digital twins of manufacturing elements including personnel, equipment, materials, manufacturing processes, facilities, environment, products, and supporting documents. This reference architecture will be used as a guide for our twin development.

3 CASE STUDY

3.1 Overview of the robot workcell

The workcell supports research efforts in manufacturing robot PHM by providing the infrastructure to generate use cases and develop measurement techniques to evaluate monitoring, diagnostic, and prognostic technologies. Weiss et al. (2017) describe the workcell and the use case. Figure 1 shows a photograph of the workcell with two robots, end effectors, parts, input location, output bin, and fixtures. One of the robots (a Universal Robot UR5) performs material handling operations while the second robot (a Universal Robot UR3) performs a precision path manufacturing operation. A supervisory programmable logic controller (PLC) coordinates the robot activities. Data are collected from the robots' controllers and from the PLC.

3.2 Workcell robots

The UR5 and UR3 robots each have six degrees-of-freedom and are capable of performing a range of tasks including packing, welding, and assembly. The robots have similar structure to one another with the same number of links and joints (see Figure 2). The six joints are: base joint, shoulder joint, elbow joint, wrist1 joint, wrist2 joint, and wrist3 joint. All six joints contribute to the transformational and rotation movements of the tool flange onto which the end effector is attached. These links are connected using revolute joints. At the joints are located the motor, gearbox, encoder, controller, electronics, brakes, and bearings. The movement of the robot links are affected by the motor rotation of the joints according to the commanded velocities and accelerations.

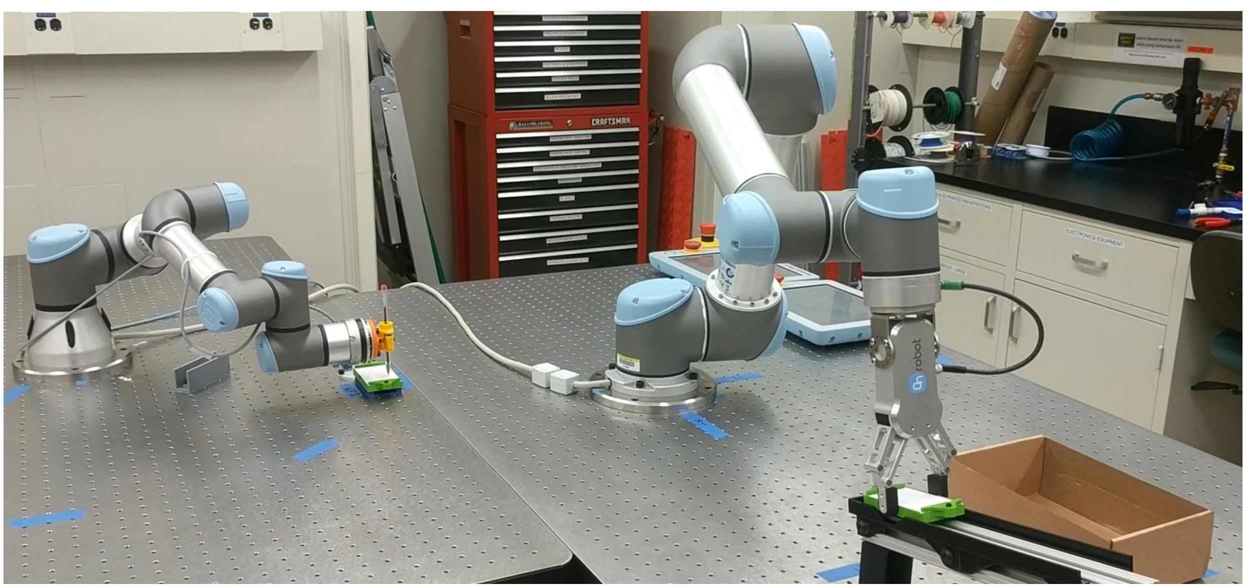

Figure 1: Photograph of the workcell (the UR3 robot on the left and UR5 robot on the right).

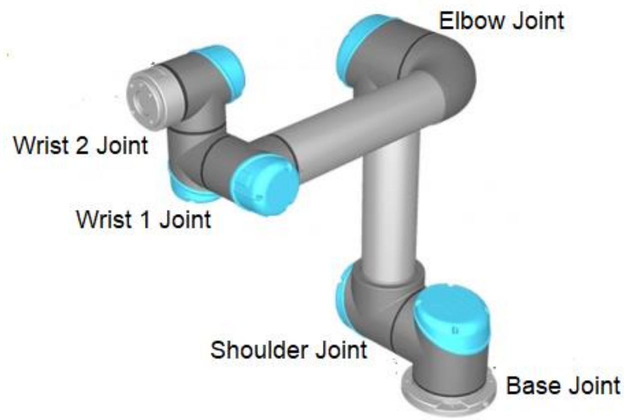

Figure 2: Joints of a UR5 (Universal Robots 2021b).

3.3 Development procedure for workcell digital twin

The procedure starts with determining the requirements for building a digital twin. The required data need to be specified such that it is aligned with the PHM objective, i.e., to generate data that represent both healthy and unhealthy states. This data are input into analytics and the results are used to predict future state of health of the workcell. This is followed by determining the modeling type, modeling environment, and modeling tools. The means of exchanging data between the virtual and the physical worlds are determined. Data are captured from the robot workcell and saved from where it is used to run the twin. This is followed by determining data analytics methods. Building the digital twin then follows. The digital twin is verified and validated by comparing data generated by the twin with data collected from the physical system, which is not part of the data set used in the construction and running of the twin. A validated digital twin is executed to generate data and produce actionable recommendations.

The initial digital twin models kinematic and dynamic data. This is the model that will be verified and validated and extended to encompass additional data. For example, data such as electrical energy consumption, temperature, and current will be incorporated in future research. In addition, the expansion should proceed by adding layers of functionality maintaining performance to meet the extra data that needs to be gathered and managed.

4 BUILDING THE MODEL FOR THE ROBOT WORKCELL DIGITAL TWIN

This section describes the procedure of building a digital twin of the robots in the workcell. The software and data required for the robot arms are presented. The mapping of robot arm components to the modeling software blocks are described.

4.1 Modeling method, tools, and software

The modeling method for this research is physical modeling, where the model consists of the real physical components of the system. Physical modeling does not require sophisticated programming, is reliable, and can easily to be transferred to industry. The arrangement of elements in a physical model resembles that of its real-life counterpart. The modeling tool used in this research is Simscape, which is an integrated package within MATLAB's Simulink toolbox (MathWorks 2020). MATLAB code is used to define robot parameters, import and manipulate input data, and visualize and export output data.

Simscape uses 'blocks' to model physical elements such as motors, links, and joints. A model consists of interconnected 'blocks' along with their geometric and kinematic relationships. Forces, torques, motions, and constraints are specified within the 'blocks' of the physical elements. The equations of motion are formulated and solved in the blocks. Data are collected through sensors modeled in the blocks. It is believed that the model reflects the physical robot workcell along with its kinematic and dynamic behaviors. This belief is tested by performing simulation experiments and comparing digital twin generated data with physical system data. For example, torque that is computed by the model is compared with the actual torque for each motor. Concurrency in the torque data between the physical and the digital twin implies accuracy in not only the dynamic model but also the kinematics used in its computation.

4.2 Modeling procedure

Building the model requires an understanding of the three-dimensional geometry of the links, link masses, centers of mass, and inertias of the links. Nominal values of some of these parameters are provided by the manufacturer of the robots. The modeling steps are summarized as follows:

a) Obtain, or develop, Computer Aided Design (CAD) models of the robot links
b) Define or identify robot parameters and properties
c) Map robot components to the software blocks and build the model starting from the base link to the end effector
d) Determine data input method into the model
e) Verify and validate the model

4.2.1 Obtain CAD models

The CAD models are obtained from the robot manufacturer (Universal Robots, 2021a; 2021b). The models are available in the Standard for the Exchange of Product model data (STEP) format and provided as a complete robot assembly. The assembly is imported into the CAD workspace where individual links are separated (see Figure 3). The individual links are imported into the twin modeling software environment to create a digital models of the robots.

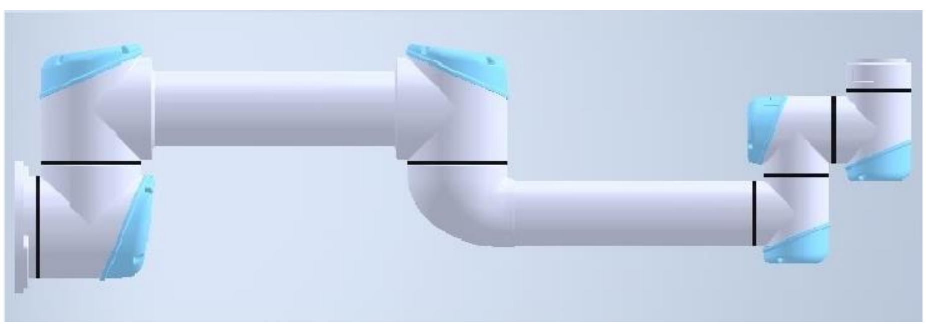

Figure 3: Model of the UR5 robot in the CAD workspace.

4.2.2 Define robot parameters and properties

Controlling a robot arm requires computing torques at the joints to produce the required motion of the end effector. Robot motions need to be accurately modeled with respect to its kinematics and dynamics. These activities require knowledge of kinematic and dynamic parameters. The Denavit-Hartenberg (DH) parameters are provided by the manufacturer (Universal Robots, 2020). However, the inertia matrices are not provided. Although the robot links take geometric forms that are close to a uniform cylinders, they are not of uniform density since the masses are concentrated at the joints where the motors, gears, and brakes are located. Previous researchers such as Kufieta (2014) have tried to calculate inertias by taking into account the mass concentration close to the joints. Lynch et al. (2017) also lists values of kinematic and inertial properties, which together with those from the MATLAB robotics tool are used in the robot models of this paper.

4.2.3 Map robot components to software tool blocks

There are three main sections of blocks in a multibody model for a robot arm: ground, joint, and link blocks.

a) Ground block
The ground section needs three basic blocks, i.e., Solver, World frame, and Mechanism configuration blocks to define the environment and its properties, such as gravity, and properties for a simulation (see Figure 4). Figure 4 shows an example of a rigid transform block that translates and rotates the follower port frame (F) with respect to the base port frame (B). This transformation creates and relates nonidentical frames on an object. For example, rotations take place only on the z-axis and, unless the axes of rotations are coincident on all ends of the object, such transformation would be needed for some of the frames. The Conn1 connector links the model to the optical tables onto which the workcell is mounted. The output port of this block is labeled Joint1 and is the revolute joint between the Ground and the next block.

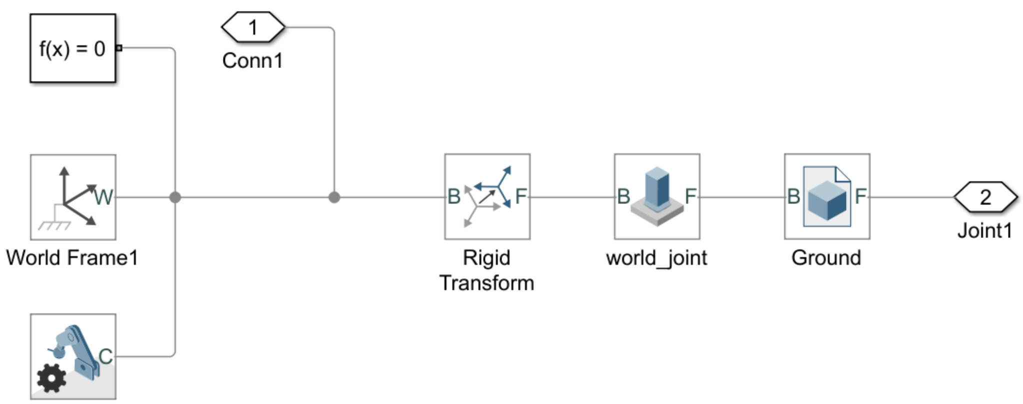

Figure 4: The Ground block details.

b) Joint block
The joint block consists of a revolute joint connecting the robot links so that they can rotate with respect to one another. One of these blocks is shown in Figure 5. There are six joint blocks in the model. The position data, or angle of rotation of the motor at the joint, is obtained from the real robots. This data is input at the joint block. The angular velocity and acceleration are set to be the first and second derivatives of the joint position. The torque at the joint required is computed by the model and displayed by the scope.

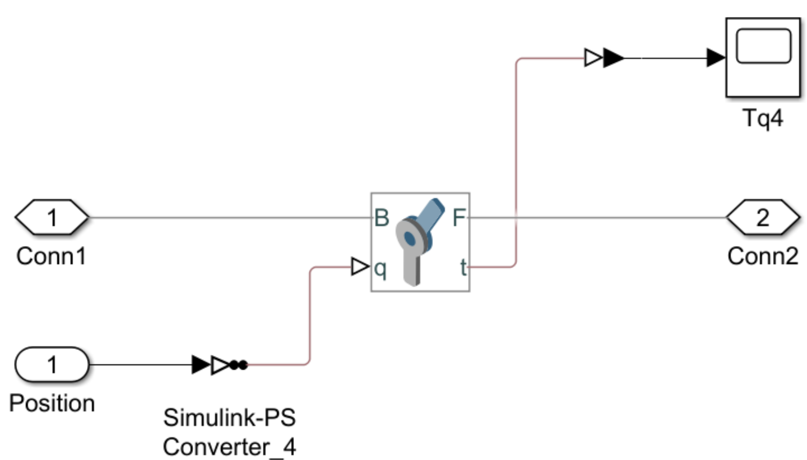

Figure 5: Block representing a joint between two links.

c) Link block

The link block represents one of the segments that constitute the robot arm. Figure 6 shows each link block. All blocks have a similar structure. The rigid transformation blocks are used to align the reference coordinate frames between different links. The link properties, including mass, center of mass, and mass inertias are determined for each link and defined in the solid block.

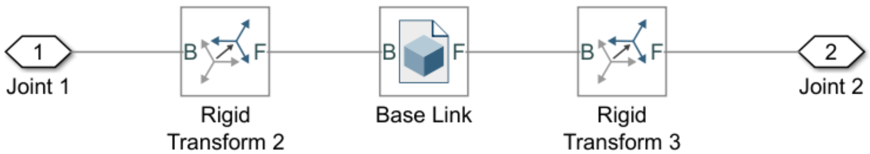

Figure 6: Details of the Base link.

d) End effectors

The end effector is attached to the robot's last link (tool flange). The end effector mounted to the UR5 is the two-finger RG2 gripper. The robot controller issues commands to the gripper to open and close during specific time intervals within the work cycle. The UR3 robot is fitted with a spring-loaded pen holder end effector and performs the operation of drawing on a part. The act of drawing transforms the part into a finished product. Both end effectors are shown in Figure 7.

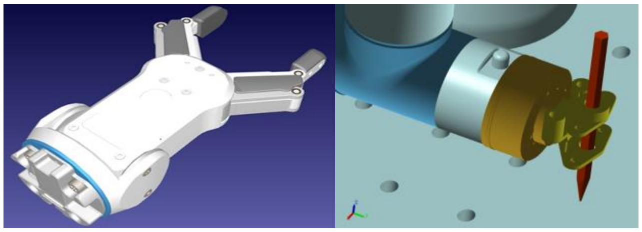

Figure 7: The RG2 Gripper (left) and pen holder end effector (right).

4.2.4 Determine data input method

Data are captured from a robot workcell where one robot is performing material handling operations while the other robot is performing the drawing operation. The data are mainly collected from the robot joints and the TCP. The torques applied to rotate robot joints enable movement of each link and the TCP along a programmed trajectory to execute the required tasks. This data has been collected and the goal is to provide robot level and process level measurements of the workcell operating in nominal parameters (NIST 2018). Samples are collected at a frequency of 125Hz. The data are collected such that each row of the data represents the conditions at each joint corresponding to the given time stamp. The time stamp is the first column of the data. This data generated from the physical world is saved to a database as a spreadsheet file from where it is input into the model.

5 MODEL VERIFICATION AND VALIDATION

Simulations are performed with the digital twin executing "operational cycles" of the workcell. The joint positions, velocities, and accelerations data are input from the physical robots. The model computes the actuation torque required to move joints to the desired positions during the cycle. The model also computes the TCP pose. Data representing the last seven runs was charted. Figures 8 and 9 represent a sample of charts showing TCP pose and moments at the joints.

5.1 Comparing data from physical robots and the model

Figure 8 shows the comparison of actual (data directly captured from the real system) and the model (data generated via the digital twin) of positions and velocities of the TCP in the X and Y axes for the UR5. Figure 9 shows the controller (from the real system) and the model (from the digital twin) torques for the UR5 robot. The charts show similar trajectories of the moments generated. This indicates an accuracy by the model in representing the physical robot. The TCP data shows greater accuracy than the moment data. The greater accuracy of TCP data, which depends on data used for all links in the model, verifies and validates the kinematic representation of the robot workcell.

An examination for joint 1 and joint 2 shows that the torques predicted by the model are slightly lower than those from the controller. Physically, Joint 2 carries the most load of all the joints in the UR robots. This could also explain the significance of the difference in the estimated torque. The accuracy of the dynamic model for this joint depends on how closely the estimated inertial parameters match those use in the controller. Figure 10 shows the TCP positions in the Y and Z axes for the UR3 robot, which also produce results that are closely matched for both physical robot and the model (only TCP charts for the Y and Z axes are shown).

5.2 Discussion on the results from the charts

The results from the plots are as much affected by accurate Simscape modeling as by the robot component data. If the data used for robot components is not accurate for the particular robot, the digital twin will not generate accurate data. The digital twin used nominal values of component and link data provided by the manufacturer, which may vary slightly from the particular values for the actual robots in the workcell. The inertial properties for the end-effector are also unavailable. These values used in the model are estimated based on the mass, geometry, volume, and the assumption of uniform density. The effect of the end effector on the difference between the model torques and the actual torques are more pronounced in the joints closer to the flange than at the base.

Each of the six robot joints and the TCP generates data. The data used at the joints are the robot positions, which are defined by the angles of rotation from a reference (zero-angle) position. From simulation, the values velocities and accelerations are equal for both the twin and the physical models. Therefore, they are not charted. The values charted for torque are the estimates from the controller. These quantities could differ from the actual values measured by physical sensors attached to the robot links. Our effort is a first step to build a digital twin. Future work will investigate whether more accurate values can be obtained through direct measurements. Evaluation of the results of the charts are also done by visual observations alone. Vigorous verification and validation approaches in future work will compute differences between digital twin and the actual values.

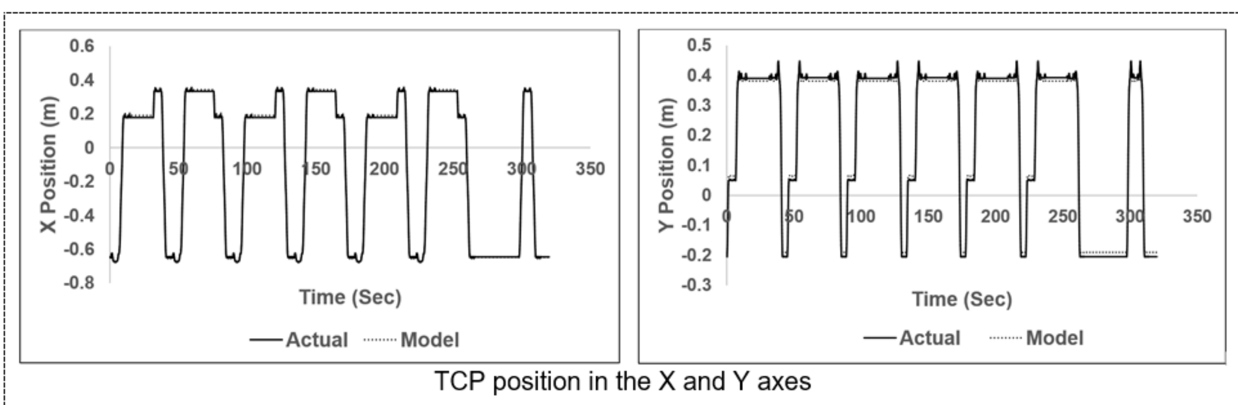

Figure 8: Positions for Tool Center Point for UR5 robot.

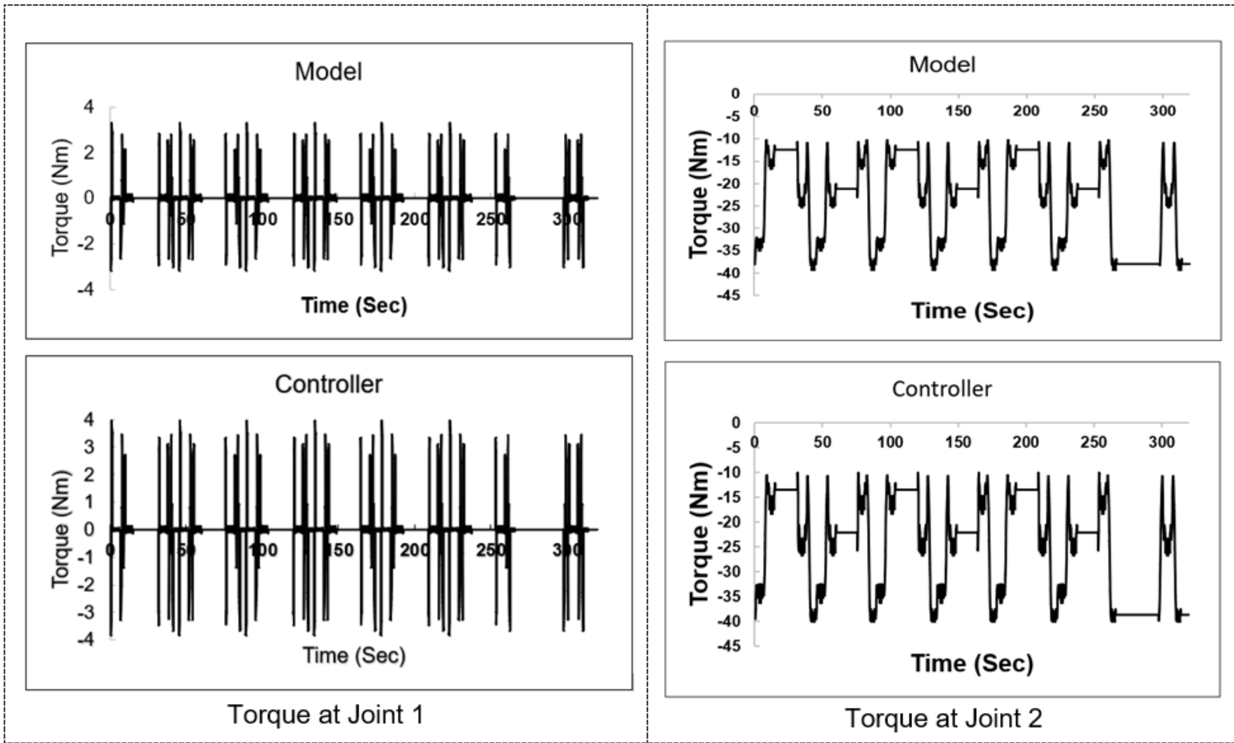

Figure 9: Torques at the joints for the UR5 robot.

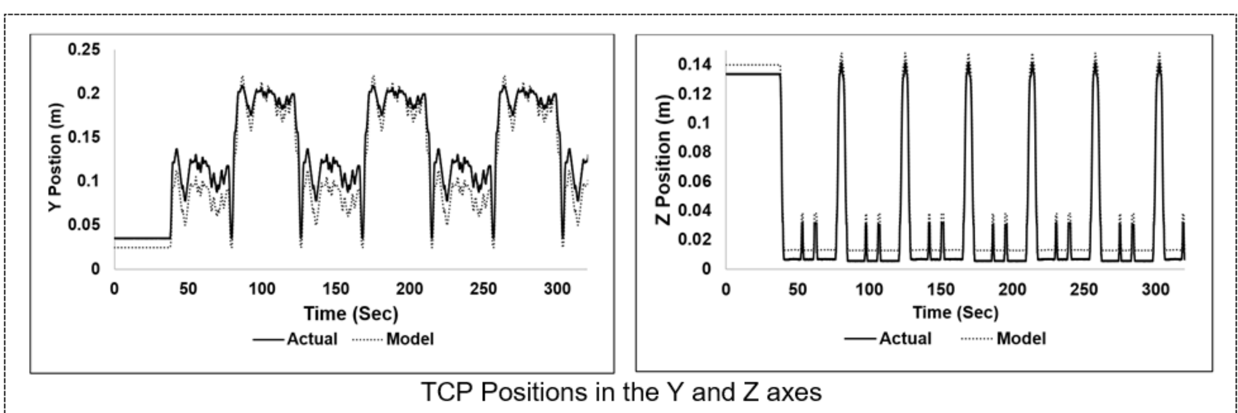

Figure 10: Position data for Tool Center Point for UR3 robot.

6 CONCLUSION AND FUTURE WORK

This paper has shown a procedure for building a digital twin for a healthy state of a robot workcell involving two robots, whose activities are coordinated by a supervisory PLC. The accomplished tasks are a work-in-scope
progress to build a digital twin that can generate both healthy and unhealthy states. The digital twin would generate and fuse data and perform analytics predicting future state of the robot and thereby guide in determining the scheduling of maintenance activities. The methods thus developed would be transferable to industry.

One major challenge was determining accurate inertial properties of the robot links; nominal data was minimally available. Future work will attempt to obtain more accurate estimation of these parameter values without dismantling the physical robot. The use of captured performance data will be investigated. However, the visual examination of the results of the plots of digital twin generated data shows similar profiles and correspondence with data from the physical system, especially for the kinematic model. The development of robot digital twins is a work in progress as the current version models only kinematic and dynamic data. Additional data such as TCP force, electrical power and currents that were collected from the physical system will be included.

Future work will also include degradation curves in model components. Mechanical degradations are a major contributions to deteriorations in mechatronic systems. Other degradations can be caused by conditions such as electrical power surge, loose connections, ambient temperature, or high humidity. Research is continuing in how faults, such as gear backlash, can be injected into robot components in the model to generate data associated with those faults. Modeling robot components at lower levels of abstraction will be required to achieve this objective. In theory, faults can occur in any robot component. These include gears, motors, actuators, link, speed reducers, and bearings. At the robot level, a joint may be identified to have deteriorated and therefore be pinpointed as the source of performance degradation. But a model will be needed to identify the faulty component such as a gear or bearing. The granularity of data collected will play a major role. Research will also be conducted to identify and classify robot failure types and develop a fault tree to further guide the degradation modeling (Jiao et al. 2017). A knowledge base of faults derived from knowledge experts or historical data will be consulted. The completed digital twin will be validated and used for making decisions such as predictive maintenance scheduling.

DISCLAIMER

Certain commercial products and 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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