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DEGRADATION MODELING OF A ROBOT ARM TO SUPPORT PROGNOSTICS AND HEALTH MANAGEMENT

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ABSTRACT

Robots are increasingly being adopted in manufacturing industries and this trend is projected to continue. However, robots, like all equipment, degrade once in operation and eventually fail. Yet today's manufacturing systems are highly paced requiring high equipment availability. Tools and methods are being developed for monitoring, diagnostics, and prognostics to support maintenance activities. These tools require the presence of data representing both healthy and unhealthy states of the robot. Robot unhealthy data is usually not available because robots are normally operated in a healthy state. A digital twin, which is a virtual real-time representation of a system, can support generating this data. This paper demonstrates the building of a digital twin of a robot workcell that uses data from the real system as input. The most frequent robot degradations are identified as increased bearing friction and gear backlash, which are modeled in the digital twin. The digital twin is then used to generate data representing degraded states of the workcell, which are plotted against healthy state data to reveal patterns associated with the respective types of failure. The results show that modeling degradations in the digital twin can provide data which, when analyzed, can support prognostics and health management.

Keywords: Robot systems, Robot Degradation, Prognostics, Predictive Maintenance, Digital Twin

1. BACKGROUND AND INTRODUCTION

More manufacturing companies are adopting robot technologies in their operations because robots have shown capacity for success in increasing productivity, safety, and product quality [1]. However, once put in operation the robots begin to degrade. A robot arm, for example, is a complex system with many potential points of faults and failure. These faults and failures result in performance degradations, the origins of which could be due to wear and tear in any of the robot's links and joints. The most common degradations are position accuracy, velocity, tool center point (TCP) force, torque, and energy usage. Yet, today's manufacturing systems are competitive and highly paced requiring maximum equipment availability. This section reviews common approaches to robot maintenance and discusses a strategy to result in timely response leading to minimum failures and optimum maintenance activities.

1.1 Maintenance of Industrial Robots

Industrial robots' maintenance practice follows either the time-based preventive strategy or corrective maintenance strategy [2]. Preventive maintenance is performed at regular intervals irrespective of the equipment condition, which can lead to unnecessary maintenance and still not prevent all failures. On the other hand, corrective maintenance is performed after a failure has occurred with a potential for costly downtime, repair, and safety. It is estimated that one-third to one-half of all maintenance expenditure is wasted in ineffective maintenance activities [3]. These shortcomings led to the development of methods to identify initial signs of faults in equipment and prevent them before they happen. It is observed that 99% of mechanical failures are preceded by noticeable indicators [4]. The condition-based maintenance strategy uses real-time robot data to identify potential faults by monitoring data such as actuating torque, vibration, velocity, and acceleration. These variables are compared against reference data to determine the likelihood of failure and the remaining time before failure. Maintenance is performed only when there is impending failure.

The main challenges for condition-based maintenance are to detect that an equipment has deviated from its normal operating condition and to predict when a fault will occur. Recently, predictive maintenance systems through prognostics have been developed. Whereas machine diagnosis comprises the detection and classification of faults, machine prognosis is the determination of likelihood of a fault and estimation of the remaining useful life (RUL). The collection of tools and methods for monitoring, diagnostics, and prognostics is called prognostics and health management (PHM).

Deploying PHM methods requires previously collected robot data representing both healthy and failure performance. This data is compared with real-time system data to ascertain the health state of the system. However, robot unhealthy condition data is usually not available, and any prediction model developed with insufficient data would likely be inaccurate in representing the system. Further, manufacturers also need PHM systems to measure the effectiveness of current methods to monitor, diagnose, and predict failures impacting a robot's performance with respect to required specifications [5]. Therefore, a method is needed to supplement physically collected data. Secondly, the approach should also support the generation of data representing future health state of the robot workcell for prediction of impending failure. This data is input into analytics and the output used to support planning of maintenance activities.

1.2 Data Driven Robot PHM Approach

The possible approaches to addressing the data challenge are i) building a degradation model based on the fundamental physics of the system, ii) adapting data from a similar machine where sufficient data is available, or iii) artificially generating the data. The physics-based approach requires to accurately model degradation caused by wear, tear, and other processes in the robot arm. This approach requires creating a model describing both the operation and degradation process. It is time consuming, and the results are not likely to be accurate because of many assumptions that must be made. It is, therefore, not practicable. Data on similar robots covering various modes of degradation and failure are not available since robots are normally operated in a healthy state. Artificially generating data would require building a virtual representation of the system that runs on real-time from the real system. This virtual world representing the evolution of the real robot or robot workcell in real-time is called the digital twin. In this paper, a digital twin of a real robot workcell is built to support monitoring, simulating, and optimizing PHM operation.

A digital twin is an integrated virtual representation of a system that connects and synchronizes a part of or the whole manufacturing system, enabled by historical and real-time data. A major difference between the digital twin and traditional simulation is that the digital twin is updated with the real system. Shao et al [6] discuss the role and state of the art of the digital twin for manufacturing research from the perspective of the simulation community and it argued that a digital twin should be tailored for a specific application. As such, the digital twin for the workcell in this paper is built using the physical modeling method. The factors and data that link the real system with the digital twin have been specified. The main data captured includes joint positions, joint velocities, joint accelerations, joint torque, joint current, TCP pose, TCP velocity, TCP force, joint temperatures, execution time, tool acceleration, main voltage, and main robot current. However, in this initial effort, data relevant to mechanical motion and degradation, i.e., position, velocity, acceleration, and torque at the joints, is used as input. Robot degradations will be incorporated in the digital twin for the components identified as being more prone to failure but are crucial for the robot's proper functioning. The initial focus is on failures at the joints, particularly the effects of increased bearing friction and gear backlash. The roadmap for using a digital twin to support PHM is summarized in Figure 1.

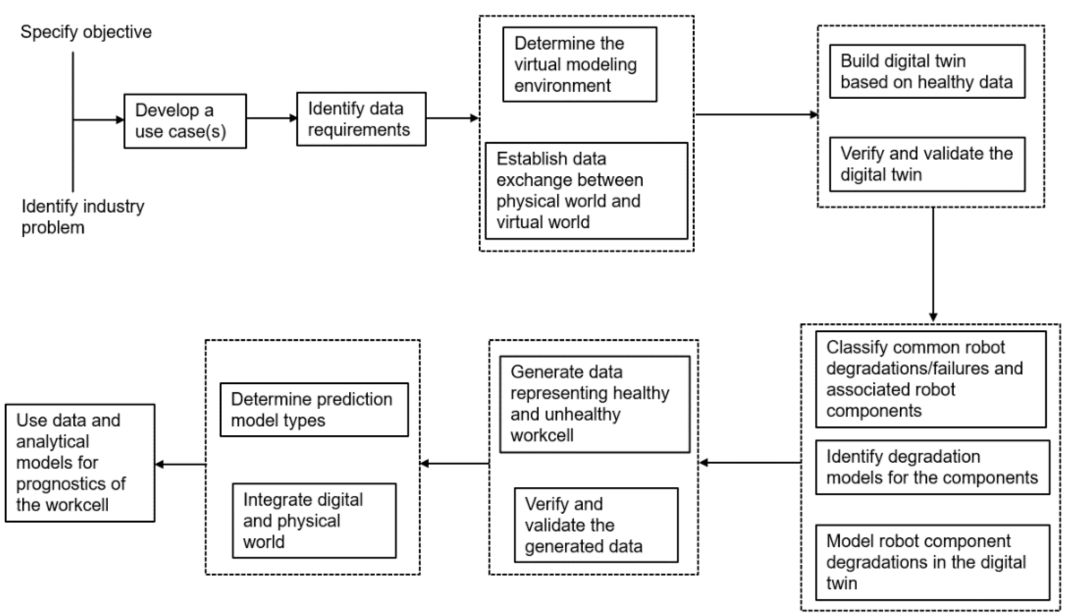

FIGURE 1: ROADMAP FOR THE ROBOT WORKCELL DIGITAL TWIN

The scope of this paper is to generate degraded state data and comparing it with a base healthy state data. How to develop prediction models, integrating the real world with virtual world in real-time, and using data analytical models for prognostics will be the work of our future efforts. The rest of the paper is organized as follows. The next section describes the workcell and use case scenario. Section 3 describes the method for building a digital twin. Section 4 shows how degradations are introduced into the robot components within the digital twin. In Section 5 comparisons are made between the healthy and degraded data. Section 6 is the discussion and way forward.

2. THE ROBOT WORKCELL USE CASE SCENARIOS

Robot workcells produce a family of products with high repeatability in product quality. Several use cases of the workcell may be needed for a digital twin to generate data for a prediction model that would be valid for a range of robot tasks. Recognizing this situation, the National Institute of Standards and Technology (NIST) researchers undertook efforts to identify industrial arm robot system use cases that are currently active in industry [7]. Among these use cases is a workcell with two robot arms, end effectors, safety systems, and other requirements for a workcell. One of the robots performs pick and place operations, including moving parts from an input area to in-process work fixtures while the other performs a precision operation on a part. When the operation is completed, the material handling robot will then move the completed part to an output. This robot workcell has been installed at NIST.

Figure 2 is the top view of the workcell as adopted from [8]. The material handling robot is a UR5 (to the right in the picture) and equipped with a RG2 gripper. The precision operation robot is a UR3 (left) equipped with a spring-loaded pen gripper and a pen to leave a trace on a part. Our previous work has built and validated a digital twin for a healthy state of the workcell [9]. The digital twin representing a healthy state is the base upon which to model the degradations at the joints.

3. MODELING OF THE ROBOT WORKCELL

This section describes the procedure to model the real workcell in the virtual world. With the physical modeling used in this research, robot degradations can easily be incorporated at the component level as represented in the Simscape blocks [10]. The method used does not require sophisticated programming and can be easily transferred to industry.

3.1 Overview of the Robot Arm Modeling

The robot arm is a mechanical structure that consists of links connected at flexible joints. The links of the UR5 and UR3 robots are the base, upper arm, lower arm, link4, link5, and tool flange. The end effector is attached to the last link. Figure 3 shows the UR3 robot indicating the links and the connecting revolute joints. All the six joints contribute to the transformational and rotational movements of the end effector. The joints house the components such as drive motor, gearbox, encoder, controller, electronics, brakes, and bearings. The link motions are actuated by the drive motor following the robot instruction program.

The tool used for building the digital twin is Simscape Multibody [10]. Simscape uses blocks to represent links, joints, constraints, and force elements. The data collected from the real robots is saved to a database and input into the digital twin through the motion signal input feature of Simulink and used to actuate the joints. Data is collected from the twin by modeling sensors attached to the respective elements.

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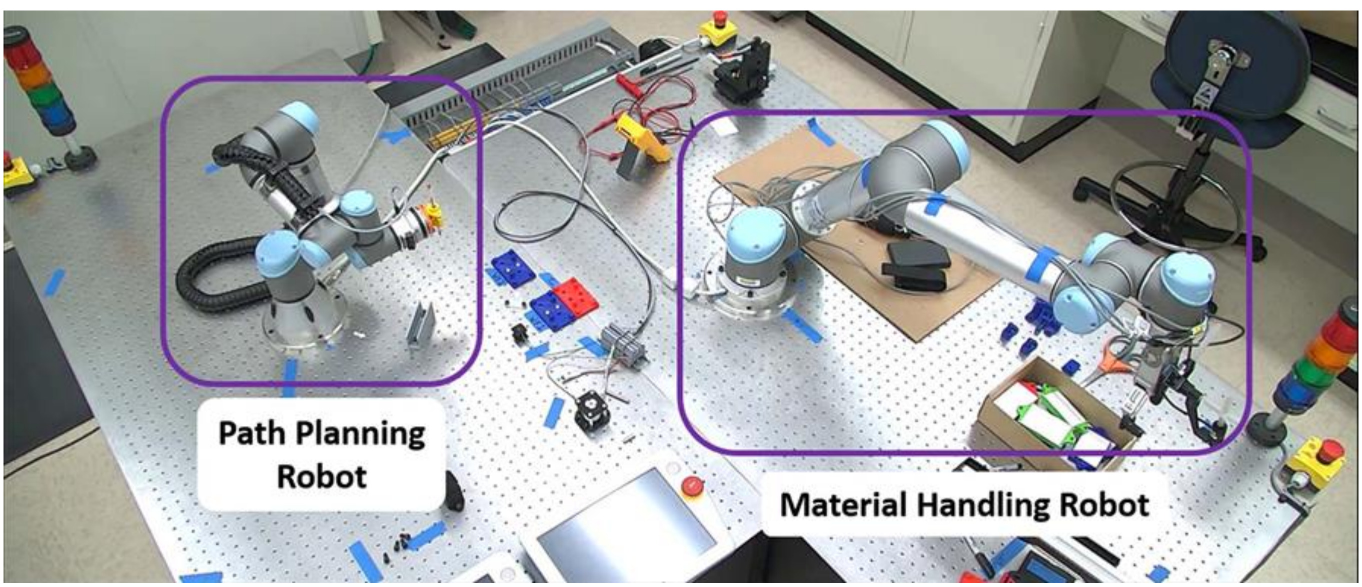

FIGURE 2: ROBOT WORKCELL FOR THE USE CASE SCENARIO [8]

The strength of this tool for PHM is that you can compute and analyze forces, torques, and stresses within the joints and links. The values of these dynamic effects depend on the state of health of the robot arm in addition to loading and environmental conditions. The left side of Figure 4 shows the building blocks of the model for the UR3 robot and the controller. UR5 model blocks in the digital twin are the same as those for the UR3 robot. The right side of Figure 4 shows the animation section of the model for the workcell. Our previous work describes the details of the blocks used in the digital twin [9]. In that work, the twin was verified and validated by comparing the motion and torque data that are computed by the controller in the real world with those that are predicted by the digital counterpart.

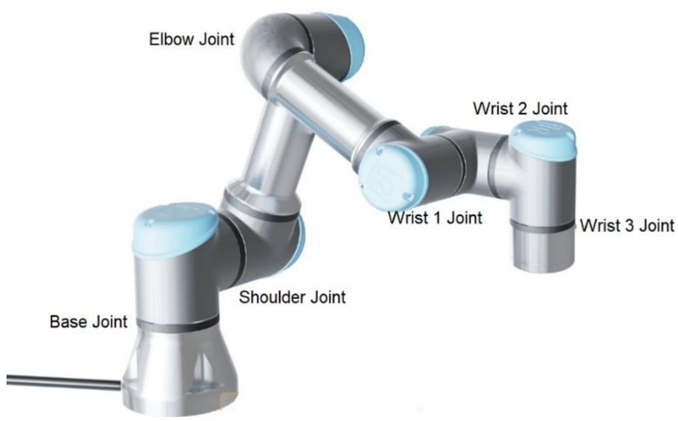

FIGURE 3: UR3 ROBOT [11]

4. DEGRADATION MODELING APPROACH

Robot degradations lead to poor product quality and reduction in efficiency. If left unrepaired, the machines eventually beak down and stop functioning. Research work at NIST is advancing technology to verify and validate methods and technologies for robot health assessment especially with regards to accuracy [12]. In addition, efforts are directed at building a digital twin to model robot degradations and generate data to be used for building a prediction model to support PHM. Robot degradations occur from different sources including environmental factors such as temperature, moisture, corrosion, or external abrasion. However, the focus of this research is on degradation resulting directly from operation.

The major causes of robot degradation during operation are mechanical wear, encoder slip, and thermal effects. This research investigates the effects of mechanical wear to determine how these degradations affect joint and robot performance through the digital twin. There are two main ways of modeling degradation of a robot or its components [13]. These are the physics-based approach and data-driven approach. In a physics-based approach, a mathematical model is developed to describe how the physics of the system is related to degradation and failure phenomena. Equations are developed specifying wear and tear in terms of contact loads and the relative sliding speeds which, in turn, depend on the forces and moments applied at the joints. This model is very difficult to produce without many simplifying assumptions. A data-driven approach uses collected data and machine learning or statistical methods to detect patterns and classify degradations. There are several challenges to acquiring run-to-failure data for machinery including robots, as discussed in [14]. It is also observed that machinery generally express a long-term degradation process from a healthy state to failure. In this paper, this data is obtained by modeling degradations within the digital twin.

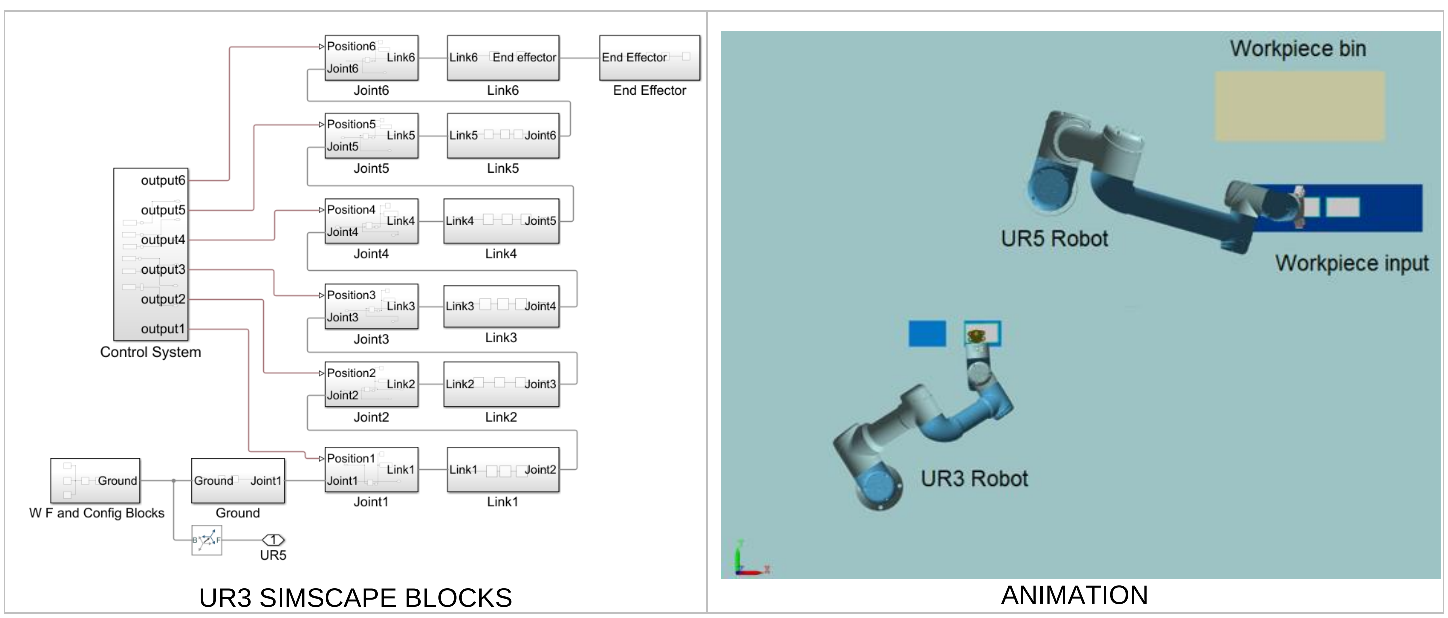

FIGURE 4: THE WORKCELL MODEL IN SIMSCAPE

4.1 Degradation Curves

The health state of a robot arm component can be expressed using a parameter. Examples of these parameters are root mean square (RMS) torque of a motor, friction of a bearing, and gear backlash. The degradation of the component with respect to the parameter can be expressed as a degradation curve. Since machine elements such as gears follow similar degradation profiles, degradation curves can be constructed for selected robot components. Experience in robotics maintenance with respect to motors, gears, and bearings can be exploited to develop these curves. A digital twin, with embedded degradation curves, is then used as a simulation to generate data that is exploited for degradation modeling and prediction.

A degradation curve can be expressed in terms of a system parameter change as a function of time, cycle, or another factor. In real life a robot operates under different payloads and velocity, which changes the rate of degradation. The profile of the curve may remain the same because degradation is caused by the same mechanical processes. It has been determined that bearing life is inversely proportional to the cube of the payload [15]. The digital twin simulates degradation curve changes due to different payloads and operation speeds. The degradation curve updates are realized by using real-life health state parameter data and mapping it to the appropriate point on the time scale. Updates are then made to the curve accordingly.

4.2 Procedure for Degradation Modeling

The procedure for degradation modeling in the digital twin is as follows:

- Identify the robot components more prone to failure but vital for the robot's proper functioning
- Model these components in detail in the digital twin
- Define modeling parameters, develop an initial degradation curve for each component and incorporate it in the model
- Simulate the digital twin to generate data including values of select parameters
- Update degradation curves based on a parameter value from the real system
- Generate data representing future health state of the system

The crucial components for robot functioning are the drive system and it is the one that is most prone to failure [16]. The drive system is located at the joints and comprises components such as motors, reducer, joint motor, stopper, drive, sensors, brakes, electronics, bearings, and harmonic drives. The most common robot failures stem from increased bearing friction and gear backlash [17]. Bearing friction increases because of wear as bearing surfaces move relative to each other. There is also fatigue, which leads to formation of bearing surface cracks and small pieces (spalls) breaking away, a process called spalling. Spalling, in turn, results in increased vibration and friction.

Regarding gear backlash, Universal robots are equipped with harmonic gears to achieve high speed reduction between the servo motor and the driven link. At their best, harmonic gears have minimal backlash. Some backlash is built into gears so that they can mesh without binding, allow for thermal expansion, and provide space for a film of lubricating oil. A robot is supplied with specified backlash, which should be kept within specified tolerances. However, the loads and velocity on the gear teeth result into wear leading to some backlash. Backlash can be detected by comparing the changes in position, velocity, and torque profiles for healthy state with the actual torques sensed at the joints.

4.3 Simscape modeling of degradations

We use the shoulder and elbow joints of the UR3 robot to model robot degradation due to joint friction and gear backlash respectively. The shoulder joint connects the base to the upper arm while the elbow joint connects the lower arm to the upper arm. See Figure 3.

4.3.1 Bearing friction degradation curve

Bearing friction takes the profile of the curve shown in Figure 5 [18]. The graph shows that for most of the bearing life, the friction values change only slightly up to a time when it increases exponentially as wear accumulates. Other studies of bearing through accelerated tests and other methods produced similar profiles of failure progression [19, 20]. It is observed that, for machines with intermittent operation but high dependability requirements, the bearing life is between 8000 and 12000 hours [21]. For the use case scenario of this paper, this is equivalent to 200000 - 300000 cycles. The plot of Figure 5 is used for the UR3 robot under light loading since its end effector comprises a spring-loaded pen gripper and a pen. It is a plot used in the digital twin and is the (initial) degradation curve of the robot, which is updated in real time during operation as parameter data is obtained from the real system. In the digital twin, a section of this graph that represents a transition from beginning of degraded state to a fully unhealthy state is selected for modeling. This time is between 250000 and 280000 cycles.

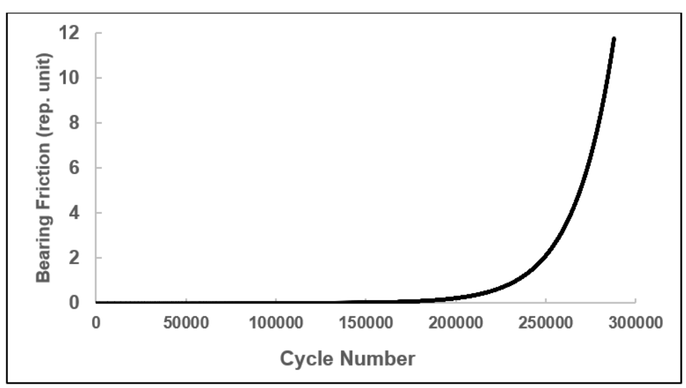

FIGURE 5: VARIATION OF BEARING FRICTION DUE TO DEGRADATION

4.3.2 Modeling bearing degradation

There are no built-in blocks to model bearing degradation, but custom blocks can be used to model this behavior. Parameters, such as friction in the revolute joint at the shoulder, are modeled in detail using Simscape networks. A rotational multibody interface block is used to establish bidirectional connections between the Simscape Multibody joint and the Simscape networks. The Rotational Multibody Interface block matches the torque and relative angular velocity across the interface. This section of the model is shown in Figure 6.

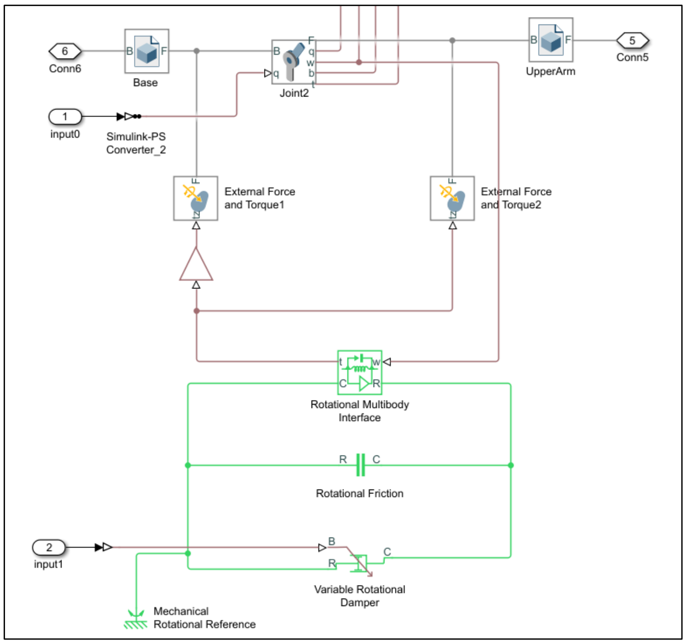

FIGURE 6: BEARING FRICTION MODELING FOR THE SHOULDER JOINT

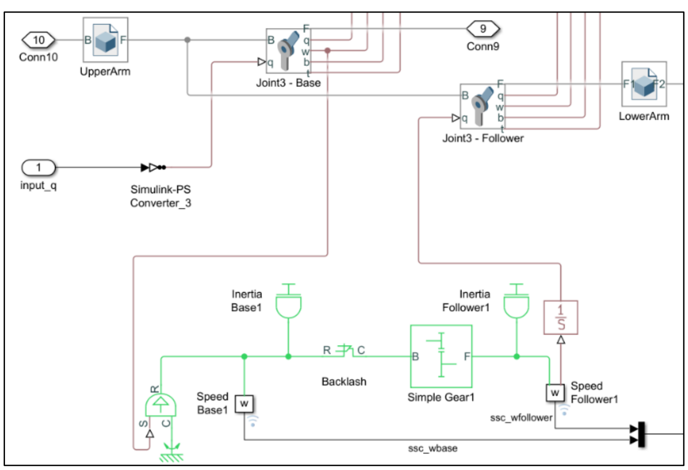

FIGURE 7: GEAR BACKLASH MODELING FOR THE ELBOW JOINT

4.3.3 Gear backlash

The approach to modeling backlash in Simscape is different from that used for the bearing friction. Two parallel revolute joints are created. One joint is labelled “Joint3 - Base” while the other is labelled “Joint3 - Follower”. The “Base” joint is motion actuated with the desired joint position while the velocity is input to the backlash model, as shown in Figure 7. A simple gear block is used to model the effect of backlash thorough a rotational hard stop block, which enables specifying the free movement of the drive gear before it fully engages the driven gear. This free movement is the input backlash. A PS Integrator block derives the motion from the velocity output of the gear, which is input into the follower revolute joint. The follower motion then incorporates the effects of backlash. Use of a simple gear block rather than a harmonic gear block helps to simplify the model but still introduces backlash effects in the joint accurately.

5. ROBOT DATA FOR A DEGRADED STATE

During this initial research work, the robot workcell is still operating in a healthy state. Therefore, there was no real data from the workcell representing an unhealthy state that can be used to update the degradation curve. Therefore, the scope of this section is limited to comparing degradation parameter data for the initial degradation curve with a reference (healthy state). Even without additional data analytics being deployed, the patterns observed in the plots can be used to identify the type of fault.

5.1 Procedure and setup

The gear backlash was set to 0.2 degrees. The digital twin was executed, and virtual sensors are used to collect data for a gradual increase in the bearing friction. During the case scenario, the UR3 robot undergoes a cycle where the same sequence of motions is repeated. Each cycle starts by moving the end effector into a position near the part, putting a trace on a part, moving into position close to a second part, putting a trace on the second part, and back to a staging position. Joint torques, positions, and velocities are the data used to illustrate the effects of bearing friction and backlash.

5.1.1 Bearing friction

The peak torque during each cycle is identified and plotted. Figure 8 shows a section of the peak torque data when the graph for increasing bearing friction is compared with reference data. The higher the friction, the higher the needed actuating torque. The peak torque matches for both cases when the bearing friction is low because the dominant contributors to the joint torque are the mass and inertia of the links and end effector that the shoulder joint supports. As the bearing friction increases, so does the component of the torque attributed to it.

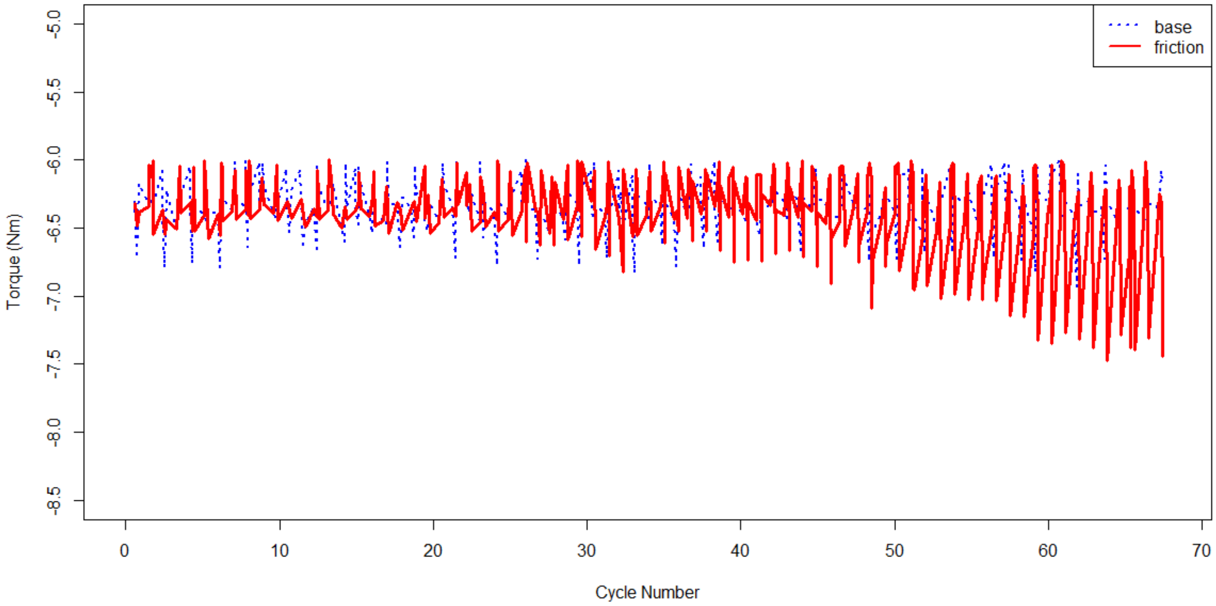

FIGURE 8: PEAK TORQUE VARIATION FOR HEALTHY AND DEGRADED STATES

5.1.2 Gear backlash

The effects of gear backlash on output (driven) gear position are plotted in Figure 9 and Figure 10. The discontinuous physical effects of backlash require a small step size to capture the behavior accurately, especially for visualization. Hence, the backlash plots for Figure 10, Figure 11, and Figure 12 are for a duration of only 40 seconds. Secondly, the motion data requires a detailed view at the plots. Thus, the plot of Figure 10 is an isolated section of the plot of Figure 9. The motion output lags the input because there is deadband before the gears engage. On a change in the direction of rotation, the gears initially disengage, and the output remains the same until the gears reengage.

Figure 11 and Figure 12 show comparison of the plots of output velocity and torque respectively. Figure 11 shows that when there is a change in the direction of rotation, backlash leads to the driven gear being out of contact with the driving gear. However, because of inertia, the driven gear keeps rotating in the original direction until contact is reestablished. The driven gear then starts rotating in reverse along with the driving gear. The result is a more jagged graph than the case of zero backlash. For those sections of the curve where there is a sustained rotation in one direction, the plots of velocity are coincident. The torque data plot with backlash (Figure 12) shows spikes when there is a change in the direction of rotation. The torque increases because the driven gear was rotating in opposite direction at the point of contact. The effects of backlash are more noticeable in the plots of velocity and torque than for position data.

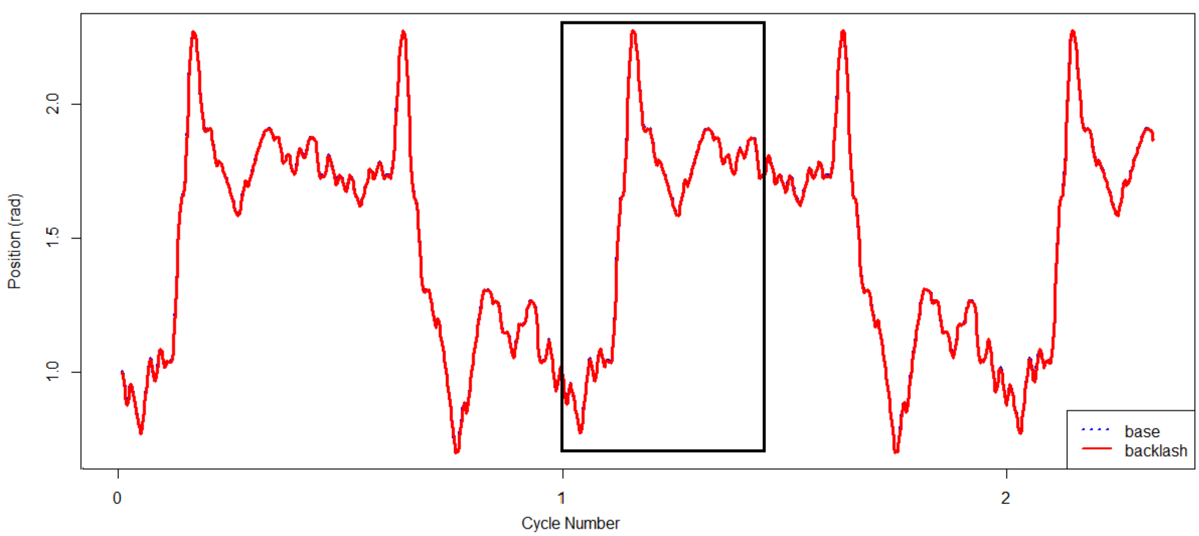

FIGURE 9: POSITION DATA INDICATING THE ROBOT CYCLES (BOUNDING BOX IS THE ISOLATED SECTION FOR FIGURE 10)

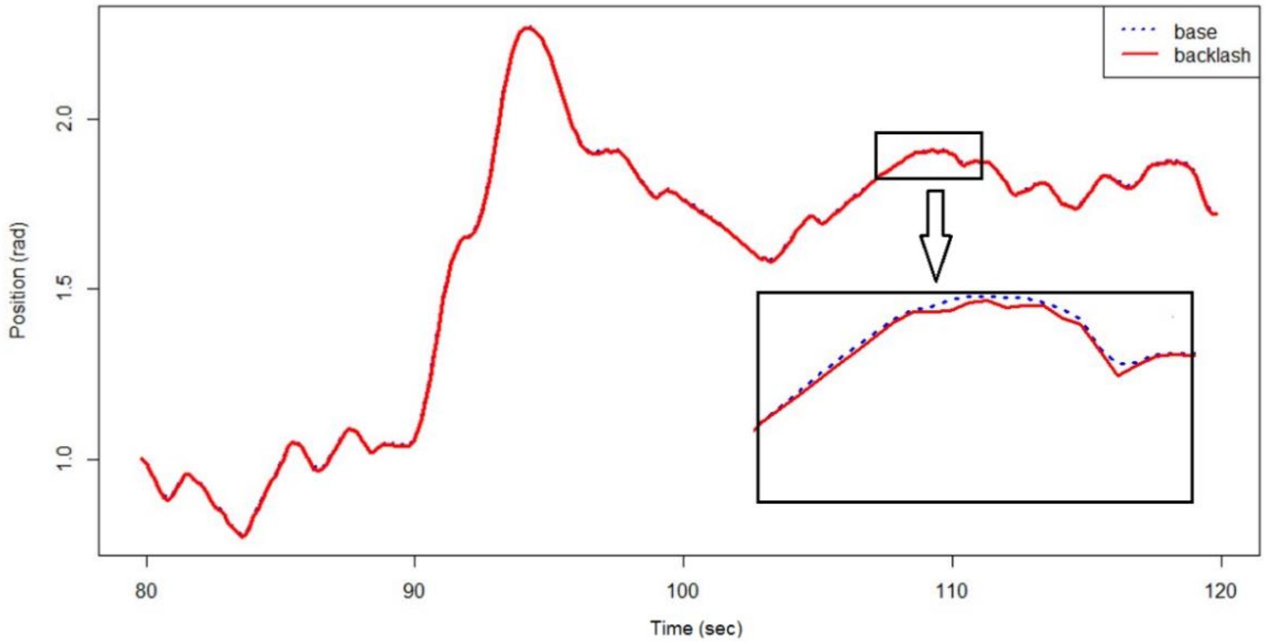

FIGURE 10: POSITION DATA FOR HEALTHY AND DEGRADED BACKLASH STATE

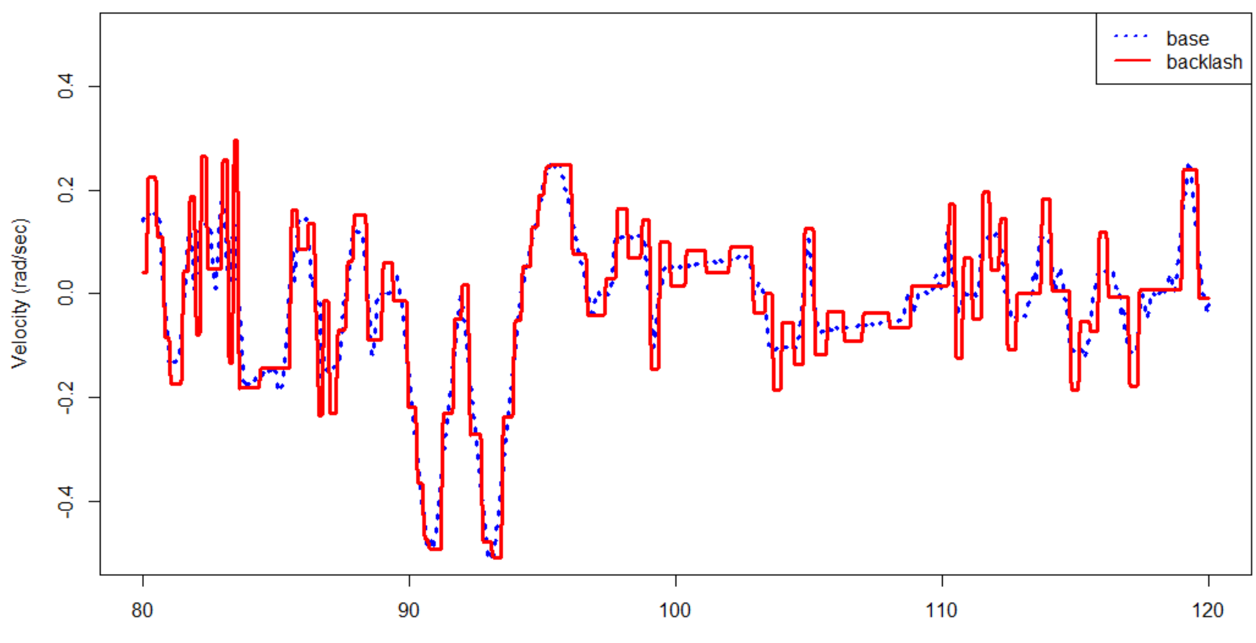

FIGURE 11: COMPARING VELOCITY PROFILE OF THE HEALTHY AND DEGRADED BACKLASH STATES

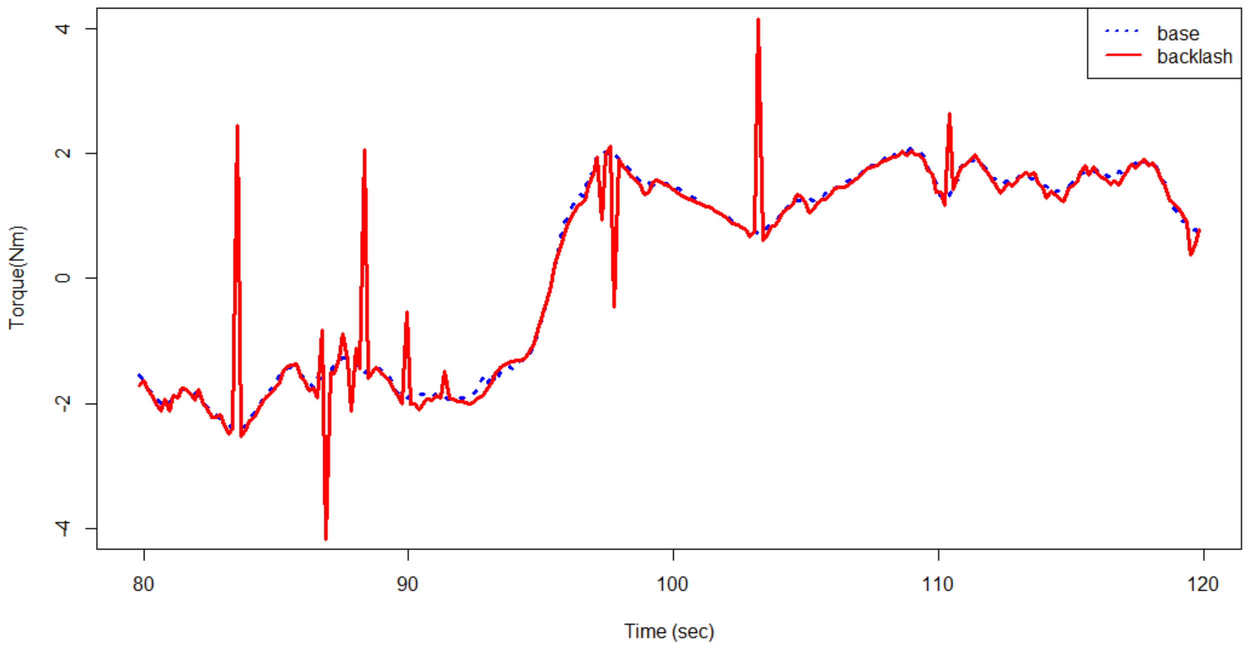

FIGURE 12: COMPARING TORQUE FOR A HEALTHY WITH A DEGRADED BACKLASH STATE

5. DISCUSSION AND WAY FORWARD

The paper has developed and demonstrated an approach to generate data that represents a degraded state of the robot workcell. This approach replaces the need to physically introduce faults in the real robots to generate this data. In many cases, physically generated data relies on accelerated conditions, leading to unnatural degradations of the robot component under study. Two types of mechanical degradations, i.e., bearing friction and gear backlash, are introduced into two robot joints. These degradations are introduced because most robot faults are attributed to drive failure. The examples in the paper are based on literature review of the degradation of the modeled components. Other forms of mechanical degradations such as motor failure can also be incorporated using this method.

One of the major challenges is constructing accurate degradation curves of robot components that are required or estimating the progression of gear backlash with time. More information is needed from robot manufactures, industry robot users, and the research community to provide information on repair, replacement history, and duration of robot components.

The twin developed can also aid to generate degraded data to help to advance verification and validation prognostic solutions. The digital twin contributes to addressing the lack of valid data representing healthy and degraded state stemming from various causes for robot systems. One of the approaches is to compare the performance of PHM algorithms with the predictions by digital twin generated data. Further, in case of multiple robots, physical sensors on real robots can be used to capture data on key physical factors of individual robots. The digital twin would reflect the real physical conditions, which may be different because of different operating conditions resulting in different generated data sets.

Research in robot PHM using the digital twin is a relatively new area of research without significant published case studies. The digital twin work at NIST is continuing. A way forward for this work will be to integrate the digital twin with the real system. The digital twin will then be updated with data from the real workcell in real time. This data includes the health state parameter such as motor torque or joint current which will update the initial degradation curve. The point at which the curve is updated becomes the starting point for generating data indicating future state of the robot through simulation of the digital twin. This data would be input into analytics and the results used for repair and maintenance planning.

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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