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A Digital Twin Design for Maintenance Optimization

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DT model to determine the optimum service. The user interface is developed within the MATLAB app designer platform. A three-axis milling machine is selected to test the validity of the DT design.

Abstract

Digital Twin (DT) is being regarded as a suite of innovative technologies within the Industry 4.0 revolution. DT brings so much excitement to the industries pursuing digitalization. DT, as a real-time representation of a physical object supports manufacturers to enhance the yield from their operations. In particular, it offers a unique and advantageous outlook on the predictive maintenance of complex engineering assets. Along with DT, advanced systems simulation techniques enable industries to efficiently model and analyze real-world problems. In this study, a simulation-based DT design for the operation of a complex engineering asset is developed, in which the virtual model of the critical components is integrated with their degradation model. The DT design aims to understand the components' degradation status and suggest a suitable maintenance intervention. The mathematical algorithm for the components' remaining useful life and the related maintenance strategies is integrated with the DT model to determine the optimum service. The user interface is developed within the MATLAB app designer platform. A three-axis milling machine is selected to test the validity of the DT design.

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1. Introduction

In recent years, advancements in computer processing have increased modern-day manufacturing systems' dependency on data. As a result, the current evolution of manufacturing, Industry 4.0, is built on computer processing and data science. One of the specific branches of this revolution is the emergence of Digital Twins (DT). Digital Twin is “an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history to mirror the life of its corresponding flying twin” [1]. DT technologies are studied and deployed in different areas, including product design [2], decision support systems [3], smart cities [4], manufacturing processes [5], warehousing [6], cost estimation [7] and asset management [8–10].

In the context of asset management, DT expresses an engineering asset as a virtual model capable of understanding its operational degradation, which is more commonly

associated with the overhaul and upkeep of the engineering asset. DT technologies can be deployed to predict the failure of components based on multiple data sources. The related knowledge-based and DT systems need to be devised to collect such data, including a method that will amalgamate this data to produce an accurate forecast. Due to the nature of the DT system, the input data is continuous and real-time; hence it can be labelled as a living entity. This characteristic means that when the machine updates itself based on the physical asset's current operating conditions, the maintenance solutions are accurate and tailored specifically to the machine. DT technologies offer a unique advantageous outlook to the maintenance planning of machines to such an extent that research on this field has exponentially increased since 2016 [11]. The technology provides a look into the future of the performance of a machine by fusing sensory information about real-time data from the physical asset and previous data trends.

Although DT and its application in maintenance planning have been explored in the existing research, insufficient

scientific works are focused on developing a simulation-based DT system that allows modelling of the degradation presented in critical components of a complex engineering asset. Such a DT system will effectively suggest suitable maintenance interventions based on the outcome from the degradation model and the estimated remaining useful life (RUL).

This research proposes a DT system architecture for maintenance optimization of complex engineering assets with multiple critical components. The DT architecture integrated simulated degradation data with components degradation model, remaining useful life and maintenance intervention. The DT system is tested on a set of simulated deterioration data for three critical components of a CNC milling machine. A set of mathematical based simulated data for the components' degradation model are used as an input to the DT system. Simulated sensors are integrated into the DT to monitor the critical components' degradation mechanism: spindle, servo motor, and linear axis. An integrated degradation analysis in the DT system evaluates the level of degradation and the remaining useful life of the critical components. This research work proposed a DT solution for maintenance optimization, intending to identify suitable maintenance interventions when using multiple data sources during operation for several critical components within an asset.

The remainder of this paper is structured as follows: In Section 2, a literature review on the topics of digital twin and maintenance strategies are presented. The proposed DT system architecture is outlined in Section 3. A demonstrative example of DT system application is described and discussed in Section 4. Finally, Section 5 presents conclusions and future work.

2. Literature Review

Predictive maintenance is crucial in the lifecycle operation of complex equipment. Muchiri et al. [12] presented a generic conceptual framework for developing maintenance performance measures with the flexibility in customization of maintenance strategies. Errandonea et al. study [11] reviewed literature in DT applications for maintenance. They found that scientific research around DT and maintenance has significantly increased since 2018. Moreover, they concluded that manufacturing sectors with a higher cost of maintenance are more attracted to investing in DT technologies. Their research identified three main upcoming challenges in implementing DT technologies: lack of data, data security and a well-detailed maintenance procedure.

A DT conceptual framework for the degradation assessment process of a complex engineering asset is presented by D'Amico et al. [9]. Their proposed DT framework aims to enhance decision-making in maintenance operations. Magargle et al. [13] presented a model-driven approach, including a DT system and numerical modelling to support heat monitoring and predictive maintenance of an automotive braking system. The Modelica models in the ANSYS Simplorer are developed to leverage existing modelling work and connections with finite element models. Aivaliotis et al. [14] presented a methodology to estimate the equipment Remaining Useful Life (RUL) using physics-based simulation models and the DT concept. They suggested that the modelling should mimic the physical systems whilst considering the kinematic and dynamic

behaviours. Additionally, the input from the physical asset should be established in which to allow for updating. In a more recent study, Ariansyah et al. [15] expand this approach by including qualitative steps such as defining the intended DT's scope and proof checking the model. This approach allows for detecting and avoiding issues within DT.

Guo et al. [16] presented a simulation-based DT for a rail power system. They analyzed the characteristics of various components in the traction power supply AC-DC hybrid network using MATLAB/Simulink environment. Kochunas and Huan [18] investigated the applicability of DT technology in nuclear power systems. They suggested that DT development should rely on mechanistic model-based methods. Their research concluded that integrating uncertainty quantification techniques to DT system enhances data exchange between the asset and its digital representations.

Machine tools have an immense application in high-value manufacturing. Using DT technologies to improve the availability of machine tools with minimum maintenance costs have always been of interest to researchers in this area. Thoppil et al. [19] proposed a fuzzy-based methodology to identify the critical subsystems of a CNC machine that must be considered for predictive maintenance. Their approach aims to prioritize the critical subsystems of a machine tool for predictive maintenance. A DT modelling method for CM machines is presented by Luo et al. [20]. Their modelling approach includes a multi-domain unified modelling method, a mapping method and an autonomous strategy. Later, the authors integrated predictive maintenance techniques into the DT architecture to be used for RUL prediction model [21]. Qiao et al. [17] presents a data-driven DT model. Their proposed model is composed of a prediction method using deep learning techniques. The approach aims to enhance machining tool condition prediction.

There has been a growing interest in adopting DT technologies in asset management due to the recent developments in digitalization and Industry 4.0 technologies [13,22,23]. However, DT technologies are currently constrained by the need for physical-based entities in the system. Historical data are vital for integrating DT systems into predictive modelling. This requires long-term data collection during operation to enhance the accuracy of predictive models.

This paper aims to demonstrate the capacity of using simulation-based DT models in maintenance optimization considering the recent advancement in simulation techniques. This research attempts to produce a fully virtual system capable of mimicking a physical asset and still utilizing the DT technology. This research argued the possible benefits of reduced complexity due to physical sensors' constraints. Such constraints include limited space to fit sensors and sensing any kind of parameters that some sensors may not be able to accurately measure. An additional benefit includes the possibility to supersede the manufacturing process of the physical asset, allowing suggestive maintenance plans for a future asset to be devised as the physical asset will not be required. This paper investigates a novel concept of a simulated DT to provide strategic insight into an asset's maintenance activity without the dependency on a physical asset by developing a dashboard model of the system in MATLAB.

3. Digital Twin Design

The existing literature highlighted that within the design of a DT system, three main aspects cover the entire system, the asset, the digital representation, and the communication links between the physical and digital spaces. In a simulation-based DT system, the simulated physical part of the system is a model-based representation of a physical asset that will produce output signals reflecting the operational use of the device. The generic architecture for a simulation-based DT of a complex engineering asset with many critical components is presented in Fig 1.

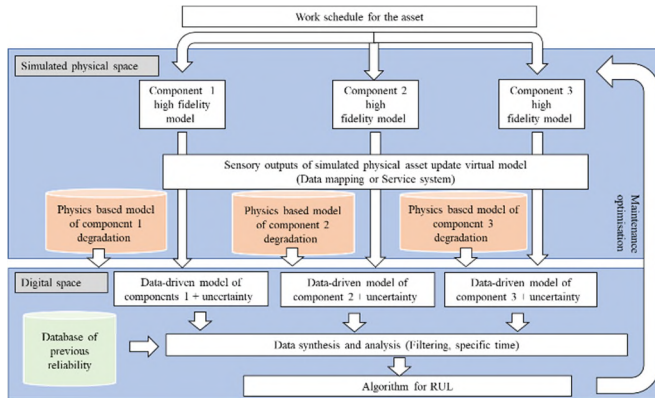


Fig 1. Simulation-based DT architecture

The proposed system architecture has two main parts namely simulated physical space and digital space. The simulated physical space includes the simulated operational data, and the sensory data for several critical components. The operational data mimics the real-world operational condition for an asset. The sensory data represents the simulated data from the installed physical sensors for different deterioration correlated parameters such as speed, head, temperature, etc. The digital space is composed of simulated real-time data from the sensors and the degradation model of the components under uncertainty. The digital space also allows the integration of real-time data with historical reliability data to estimate the components' RUL.

The communication links between these two spaces include the data mapping and maintenance optimization functions. The data mapping is an important function of the system as it will ensure that the system is dynamic, in turn promoting the accuracy of maintenance suggestions. The mapping function transmits the data between the sensor database into the virtual machine, producing an estimate for each component's life. The second communication link is maintenance optimization. The RUL algorithm fuses information from multiple sources within the simulated asset to produce an accurate estimation for maintenance intervention [14].

After the maintenance intervention, the updates on the operational condition are fed back to the simulated physical space. In this proposed design, the modelling of the components within the DT system has been completed favouring a mathematical approach rather than a physics-based approach. This means that the degradation of the components within the DT system of the machine tool is oriented towards data trends

rather than detailed modelling of the components of the system. This method has been selected as it provides insight into the functionality of the dashboard-based model rather than expending energies on generating a model of extreme accuracy, which can commonly be found in the literature [13,16].

4. Case Study: Results and Discussion

In this paper, three critical components of a milling machine tool, namely, the spindle system, servo motor and a linear axis, are considered for the simulated physical part of the DT system. In a milling machine, servo motors driving ball screws provide the means for axis motion. Milling machines are composed of three linear axes, called 3-axis mill, or more rotational axes, called 5-axis mill, for complex tools. The spindle is the motor assembly that rotates the workpiece. The simulated data from virtual sensors collect real-time health conditions of these critical components. The three components were selected on their criticality ratings of a Failure Mode Effects Analysis (FMEA) study by Thoppil et al. [19]. The DT system demonstrates the degradation model and the RUL estimation for these components based on a mathematical algorithm. Existing research determined that each of the three main components have a weaker critical part that degrades at an accelerated rate, often causing component failure. For the purposes of this research, they have been modelled and account for the primary component failure. Specifically, the ball screw and bearings contribute to the linear axis's failings and the servo motor and the spindle system. For spindle and servo motor, the fatigue life of bearings due to a dynamic vibration load is calculated as follows:

$$L_b = 10^6 \times (C/P)^\rho \quad (1)$$

Where, L_b is the rating fatigue life of bearing in hours, C is dynamic load rating, and P is the equivalent dynamic bearing load in Newton, ρ is Exponent which is equal to 3 for ball bearings. The dynamic load of the bearing is calculated by the sum of the radial and axial forces exerted upon the bearings in a specific operating condition. Therefore, the spindle and the servo motor have the defect trend in the form of $P = X.F_r + Y.F_a$. Equation 1 provides the remaining fatigue life for a given running condition and will not record the operation the bearing has encountered to this point. Recording this data is possible with the use of an additional formula where the bearing RUL_t given at an instant will deduct a percentage from a variable that represents 100% of the bearing's useful life, as thus:

$$\dot{U} = U + (\alpha \times n)/(L_b \times f_s) \quad (2)$$

$$RUL_b = L_b \times (1 - \dot{U})/n \quad (3)$$

Where $\dot{U}$ is accumulated used rate, U is history used rate, α is Bathtub factor, n is the rotation speed in revolution per minute (rpm), and f_s is sample frequency. The ball screw is chosen as the critical part for the linear axis. The ball screw's useful life varies based on load and speed. Functional life should be determined by approximating equivalent rotational speed and loading force over typical performance cycles.

The mathematical model of RUL for a ball screw is the flaking effect caused by rolling contact fatigue. The basic dynamic load rating is the axial load that allows 90% of a group of the same ball screws to rotate one million times (106 rev) under the same conditions without flaking occurring due to rolling contact fatigue. The rated fatigue life of a ball screw can be estimated by a basic dynamic load rating.

$$L_{bs} = (C_a/F_a)^3 \times 10^6 \quad (4)$$

Where, L_{bs} is rated fatigue life of a ball screw in revolutions, C_a is basic dynamic rating and F_a is the axial loads in Newton. Considering that the axial force is variable during machine operation, the rated fatigue life would change accordingly. Therefore, A dimensionless value D is used to characterize the progress of degradation and the RUL_{bs} is calculated as follows:

$$RUL_{bs} = \frac{L_{bs} \times (1 - D)}{60 \times n_{bs}} \quad (5)$$

Where, n_{bs} is the rotational speed in min^{-1} and $D = D + n_t/L_{bs} \times 100$, and n_t is the number of turns for ball screw. The modelling has been carried out in MATLAB code along with the production of a dashboard model. Verification is performed by comparing the output of DT simulation and theoretical calculations to check if DT imitates the behaviour of the simulation-based asset. Constant sensor data (Table 1) is used to simplify the calculation.

Table 1. Case study: assumptions for critical components

Running parameters	Values
Linear Axis axial load (N)	90000
Linear Axis speed (rpm)	400
Servo Motor radial load(N)	5000
Servo Motor axial load (N)	1000
Servo Motor speed (rpm)	4800
Spindle radial load (N)	14000
Spindle axial load (N)	2000
Spindle speed (rpm)	6000

The results of the RUL calculation for the three critical components are presented in Table 2 to Table 4. The theoretical RUL and the simulated runcount are calculated and compared.

Table 2. Spindle RUL and Runcount comparison

	$t=$	90%	50%	10%	avg.
Theoretical RUL (min)		223.91	124.39	24.88	
Simulation RUL (min)		224	125	26	
RUL error (%)		0.0417	0.4883	4.5078	1.68
Theoretical Runcount		9.95	109.47	208.98	
Simulation Runcount		10	109	209	
Runcount error (%)		0.4883	0.4252	0.0098	0.31

Table 3. Servo Motor RUL and Runcount comparison

	$t=$	90%	50%	10%	avg.
Theoretical RUL (min)		725.60	403.11	80.62	
Simulation RUL (min)		726	403	80	
RUL error (%)		0.0544	0.0282	0.7725	0.29
Theoretical Runcount		32.25	354.74	677.23	

Simulation Runcount	32	353	676	
Runcount error (%)	0.7725	0.4906	0.1818	0.48

Table 4. Linear Axis RUL and Runcount comparison

	90%	50%	10%	avg.
Theoretical RUL (min)	903.56	501.98	100.40	
Simulation RUL (min)	903	502	100	
RUL error (%)	0.0625	0.0039	0.3945	0.15
Theoretical Runcount	40.16	441.74	843.33	
Simulation Runcount	40	441	843	
Runcount error (%)	0.3945	0.1681	0.0388	0.20

As it is shown in the Tables above, the maximum RUL and Runcount error is 1.68%. The error mainly comes from data storage format and the difference between discrete and continuous running. In practice, the data detected by the sensor usually fluctuates within an appropriate range; accordingly, random numbers are used to introduce the fluctuation. The simulated runcount results for operational conditions and the RUL for spindle, servo motor, and linear axis are presented in Fig 2-Fig 4. The results show that the deterioration rate for the spindle is higher than the servo motor. The deterioration rate for the servo motor is higher than the linear axis.

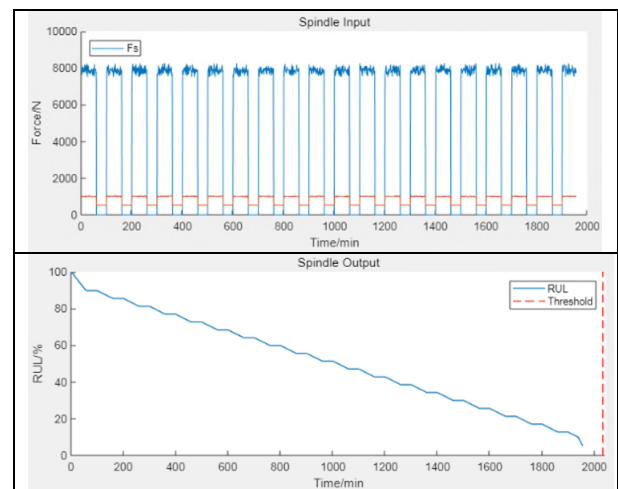


Fig 2. Operation condition and RUL for spindle at the time of failure

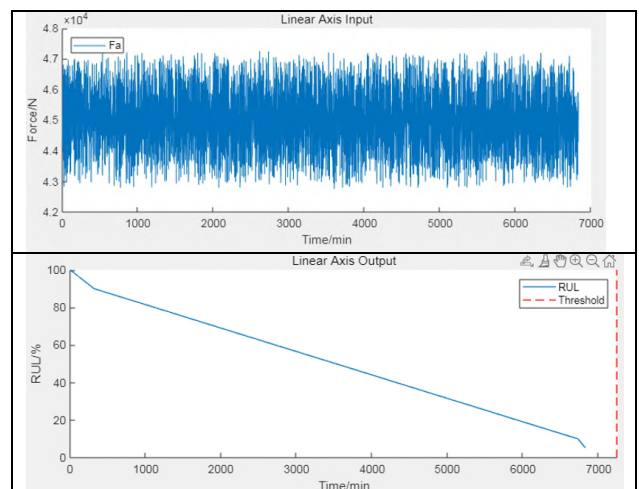


Fig 3. Operation condition and RUL for linear axis at the time of failure

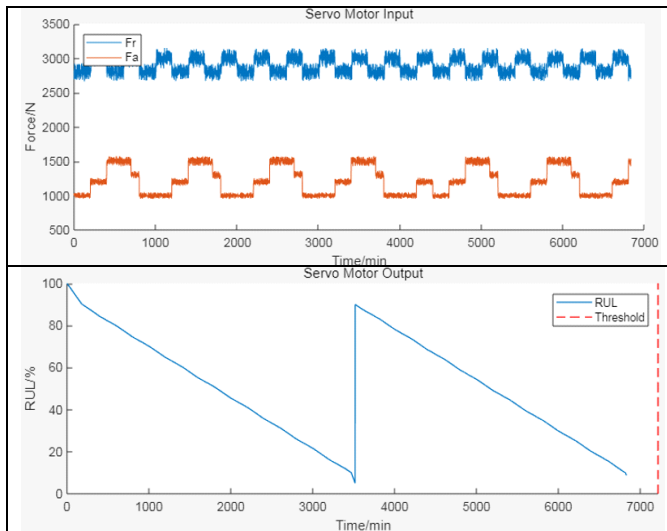


Fig 4. Operation condition and RUL for servo motor at the time of failure

The dashboard is linked to the sensory data replicating the likely characteristics of the environments. The sensory data is simulated in Excel. The interface the user can interact with is displayed in Fig 5. The dashboard provides information to the user about the RUL based on the information received from the sensory database via the call back function.

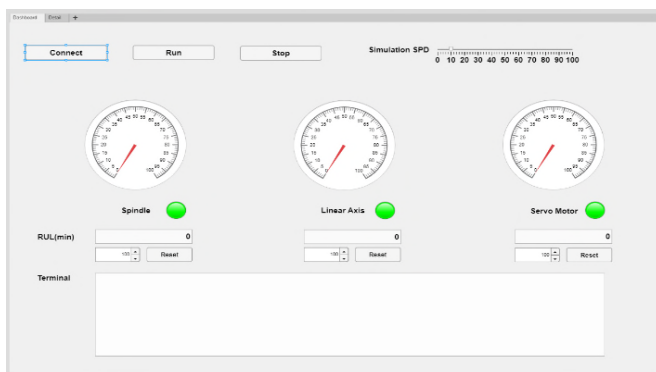


Fig 5. User interface dashboard for DT system in MATLAB

The call back function contains the code and the specific characteristics for each of the three components; it is not something that is readily changed unless the components-specific parameters (size, weight, geometry, etc.) are altered. The three buttons and the speed slider on the top are the control panel of the whole digital twin which are used to set the initial parameters and control the simulation.

The dashboard has a gauge and lamp system for each component's, in this case, three lamps. This system creates direct interaction with users. The function of the gauge is to display the RUL percentage from 0 to 100%. The lamp has three colours (green, yellow, and red), which indicates the recommended maintenance measures. The output plot for the servo motor is taken as an example to analyze the trend of the results. Suppose the recommended repair time is set at 50% of RUL. The yellow lamp will be ON at the threshold, and the system suggests the repair maintenance (see Fig 6).

Terminal	Simulation started
	Please repair Spindle component
	Please replace Linear Axis component
	Please replace Servo Motor component
	Linear axis component failed, please make replacement
	90% Linear axis component replaced/repared
	Simulation started
	Servo motor component failed, please make replacement
	81% Servo motor component replaced/repared
	Simulation started

Fig 6. A user interface for information summary

The system also has a failure cushion for the component. So, when the RUL prediction reaches 10%, the red lamp will be ON, and a suggestion will be shown in the Terminal; e.g. 'Please replace the component'. The RUL in minutes is displayed in the box to show how much remaining time can the component keep working. The repair/replace box and the reset button are used to indicate the new status of the new component. When the component is repaired/replaced to a certain degree of RUL, the system updates and subsequently runs on a rejuvenated basis.

In addition, the dashboard can produce trend information and track the history of each of the components through their usage (see Fig 5). The degradation rate at the beginning and the end of a life process corresponds to early failure and wear-out failure, respectively. This rate is faster with respect to the constant failure rate, which is reasonable since the bathtub model is used in the algorithm. The RUL would recover to a value after maintenance. How much exactly it recovers depends on the type of maintenance operation and the component itself. After failure, the component needs to be replaced, and then the simulation continues until the linear axis also fails. At this time, the simulation ran for a total of 6834 minutes.

5. Conclusion

This research demonstrates the applicability of a simulation-based digital twin (DT) for maintenance optimization. The DT system is developed in MATLAB and tested with a CNC milling machine case study. The mathematical degradation model of critical components, the spindle, servo motor, and a linear axis, are integrated with the DT system to predict the remaining useful life (RUL). In addition, the DT system enables real-time tracking of the components' degradation and their RUL. This capability allows remote and continuous monitoring and analysis of components performance. Moreover, the DT system benefits manufacturers by efficiently monitoring and assessing the impact of maintenance strategies on assets' performance.

This work developed a dashboard in MATLAB as the user interface to effectively communicate the two-way link between the DT system and the simulated degradation data. The dashboard provides detailed information about the components' degradation trends and the likelihood of failure. The availability of such information offers engineers to plan the maintenance interventions effectively. The plethora of available information is vital for a successful DT system that relies on the asset's transparency and control [12]. Engineers can go beyond the real-time data envisioned by the simulated DT, experimenting with the system without affecting the

physical asset to derive breakdown information in a speculative scenario [14].

There are a number of limitations within this research work. There were no generic component operational and failure data to validate the DT system. Further research is required to implement and test the DT system architecture using a real case study. The degradation and RUL algorithms were based on mathematical parameters, which provide a starting point for future research. The user interface can be customized based on several data sources and the manufacturers' requirements. Moreover, it is vital to assess the accuracy of the DT model [24]. This enhances the level of confidence in decision making for maintenance planning and interventions strategies.

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