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Digital Twin Framework for Lathe Tool Condition Monitoring in Machining of Aluminium 5052

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ABSTRACT

Digital Twin (DT) is a virtual representation of a product system that exhibits the properties and analyzes the system's functions. The significant impact of DT extends to several fields, which increases productivity and reduces wastage. This article focuses on developing a Digital twin model of a Lathe machine for Tool Condition Monitoring (TCM). DT implementation in industries is challenging due to simulating online cutting forces and wear. Even though several pieces of research have been carried out in the prediction of tool conditions using machine learning, Artificial Neural network models, only a few pieces of research have been made in digital twins for TCM. This article provides the technique for implementing the DT model of a lathe tool. The feasibility of the DT Model framework is verified by a case study of the turning process with a CNC Lathe machine while machining of Aluminium 5052 workpiece using Titanium Nitride coated tool inserts. The sensor's data are acquired and fed to the microcontroller for real-time data acquisition. The real-time dataset is processed in the DT model for monitoring and predicting the tool conditions. The tool wear classification using the DT model is achieved. Developing the Digital Twin model in machining increases productivity and assists in predictive maintenance.

Keywords: Digital twin; Machine learning; Tool wear; Cutting forces; CNC

1. INTRODUCTION

In manufacturing industries, cutting tools are vital components in metal removal operations. Owing to the fast growth of material science, it isn't accessible to machine alloys, especially in the defense and aerospace industries. It led to the development of modern cutting tools and tool monitoring systems for manufacturing precise and accurate machined products. In continuous machining, tool wear happens due to the high temperature, heavy cutting forces, and hard abrasion[1-5]. Many research scholars have blended manufacturing technologies, especially, artificial intelligence, machine learning, Machine vision, signals, and systems for tool condition monitoring and prediction systems. After the development of modern machine learning algorithms, the prediction of tool characteristics in machining is feasible with more accuracy. However, real-time data processing data needs high processing capability processors. The obstacle is cleared by modern fast computing processors, which enriches the Digital Twin (DT) technology more feasible for industries. In the digital twin process, end-to-end factory simulations are made, live machine data can be acquired using sensors and signals, and transparency in inventory and operational performance can be monitored. Preventive asset maintenance also can be achieved in the digital twin process. Changing machine layouts and sequence of operations can be simulated in process digital twin models[6-8].

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The CNC Machine is modelled in PTC Creo Elements, and the control systems are developed using python. The DT framework's development into three phases, as illustrated in Fig. 1.

- Data acquisition systems acquire sensors and signals from the physical machine
- The data received are interfaced with the cloud or local system for prediction and condition monitoring
- The virtual machine visualises the results obtained from the prediction
- The machine learning technique is adopted for regression
- The real-time physical machine acquires the data and is used for training the machine learning model in the digital twin framework.

The schematic representation of data flow in the DT framework is illustrated in Fig. 2.

The scope of the DT Model in the CNC machine is to simulate the tool behavior and predictive maintenance, as illustrated in Fig. 3. Therefore, the derived DT model is symmetric with the physical and virtual models[9-15].

2. DEVELOPMENT OF DIGITAL TWIN FRAMEWORK

This research paper focuses on developing a digital framework using sensors and signal data acquisition systems. DT model is experimented with turning of Aluminium 5052 workpiece in CNC Lathe Machine in dry condition. In the initial stage, the data acquisition system is developed using sensors. Monitoring the data from the machine and building the model

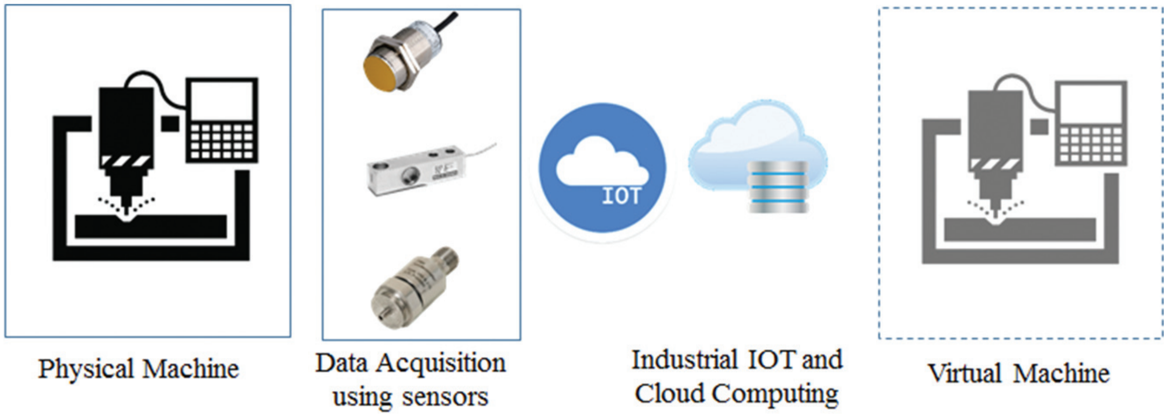


Figure 1. Stages of digital twin development.

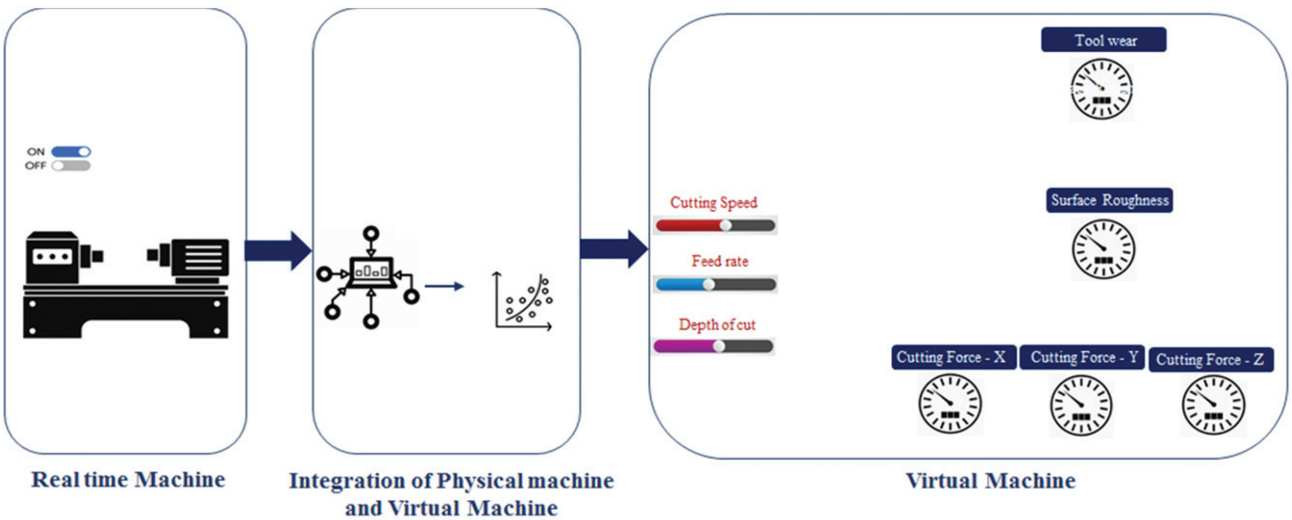


Figure 2. Real-time machine and virtual machine.

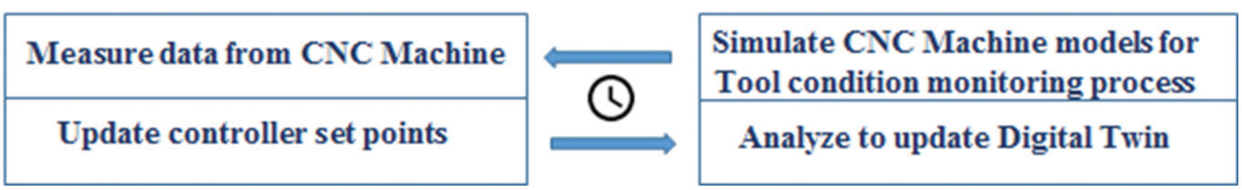


Figure 3. Scope of digital twin model.

is an initial step of DT model development. The thermocouple is used to acquire the temperature while machining. The tool dynamometer and vibration sensors are used to receive the cutting force and vibration signals, respectively[16-19]. Several types of research have been carried out for indirect measurement of cutting tool characteristics while machining, such as acoustics, vibration, and image processing. Based on the outcomes of the literature study, the DT framework is developed by integrating acoustic sensors, thermocouples, speed sensors, tool wear measurement, and cutting force measurement systems. The surface roughness of the workpiece is monitored in an indirect measurement technique based on the cutting forces. The sensor is connected to the workstation in this data acquisition system. The real-time data set is fed to the KNN machine learning algorithm in regression analysis. The tool wear behavior and fracture characteristics are time-variant. Hence the data is recorded concerning the machining time[20-26].

The signals from the Lathe tool dynamometer, vibration sensor, and speed sensor are interfaced with the ATMEGA microcontroller.

The Arduino platform is interfaced with python to receive the data. The Lathe tool dynamometer was developed with three axes load cell, which uses a Wheatstone bridge circuit. The smart lathe tool holder acquires the tangential, feed, and radial force signals[27-34].The cutting force given by the operator is converted into electrical signals and amplified. The pre-processed electrical signals are interfaced with the ATMEGA microcontroller integrated development environment (IDE). The LM393 Infrared optocoupler senses the speed of the lathe machine. The disc attached to the lathe machine enables it to hold the optocoupler, which reads the revolutions of the

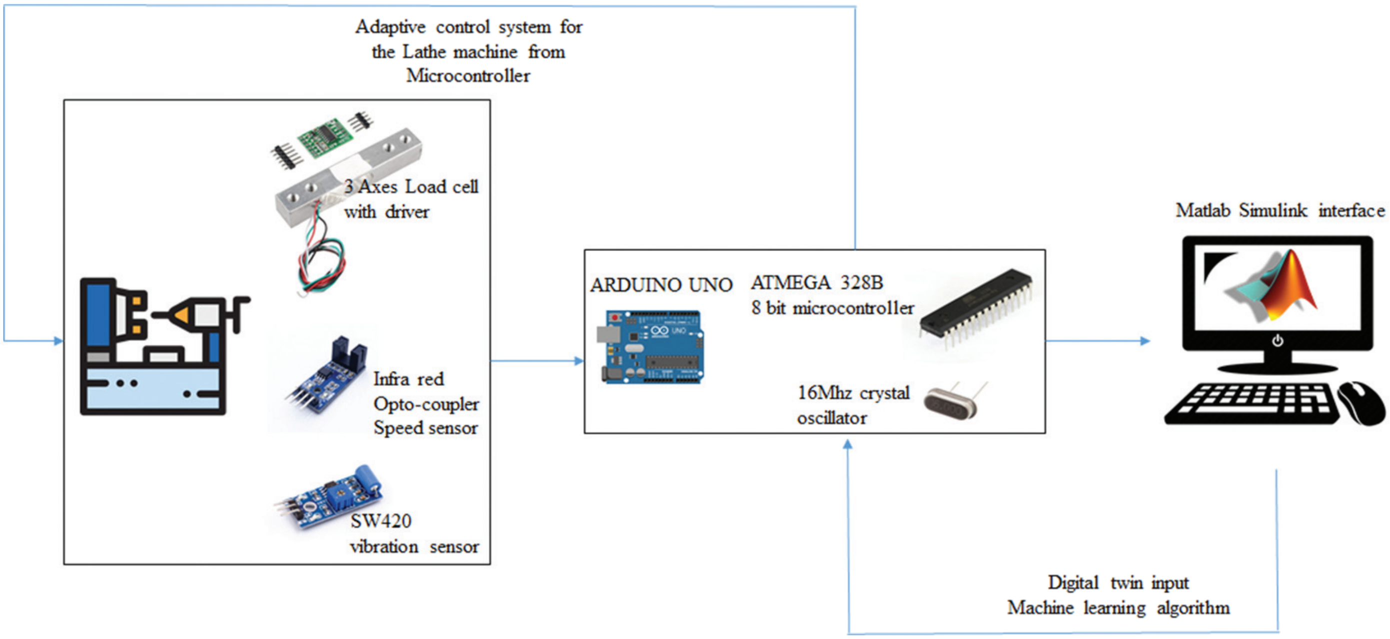


Figure 4. Sensors for digital twin of lathe machine.

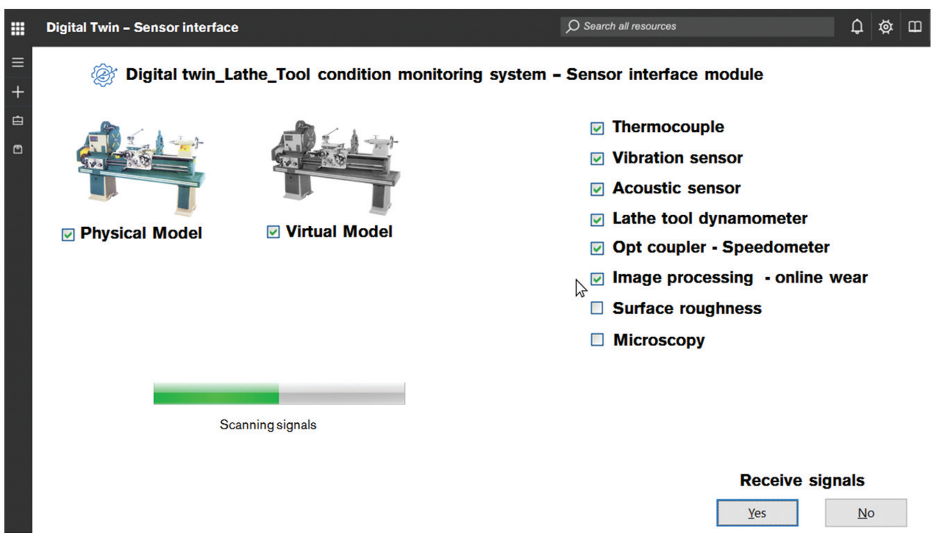


Figure 5. Sensor interface and data acquisition system.

chuck. An SW420 Non-contact type vibration sensor senses the vibrations of the machine[35-38].

The components used in sensors systems, and controllers, are exhibited in Fig. 4. The real-time machining data is stored in the workstation as data set and consistently updated in a python machine learning environment. Python 3.10.6 and the machine learning libraries used in regression analysis are used. The real-time machining data acquired in the workstation is interfaced with the python environment using a graphical user interface (GUI), as shown in the Fig. 5.

The hyperparameter tuning of regression equations is accomplished in the DT model during the turning operation. The DT model is verified by an MTAB CNC machine (Physical Model) in which an Aluminium 5052 workpiece is machined. A 25.4 mm diameter of the aluminium rod is held in three jaw chucks, aligned to avoid runout errors. The belt drive transmits the power from the motor to the lathe spindle. Power transmission efficiency is taken as 90 % from belt to spindle. Since the tool wear phenomenon is consistent concerning time, the DT model is validated for time. The Aluminium 5052 workpiece is machined up to 200 mm in length with varied feed rates, depth of cut, and spindle speed. The real-time indirect tool wear measurement is compared with predicted values, which shows the performance of the DT model prediction efficiency. The prediction performance of the DT model is illustrated in the results section. The actual system response is compared with the simulation results. The parameter tuning of the model improves the DT model's prediction accuracy. The continuously calibrated DT model results in high prediction accuracy. To develop the digital replica of the CNC Machine, machining features such as cutting speed, feed, and depth of cut are injected to calculate the cutting forces[39-40]. The features of the digital twin are to predict, control and optimize the process, as shown in Fig. 6.

The predictive maintenance is performed by selecting algorithms such as KNN, support vector machine (SVM),

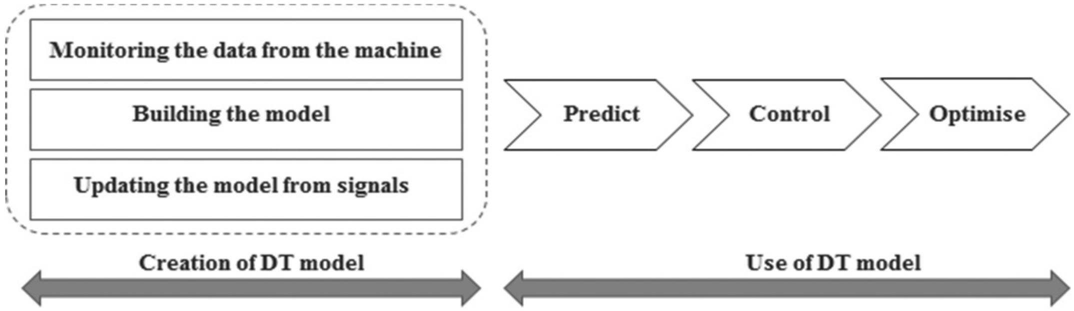


Figure 6. Features of DT model.

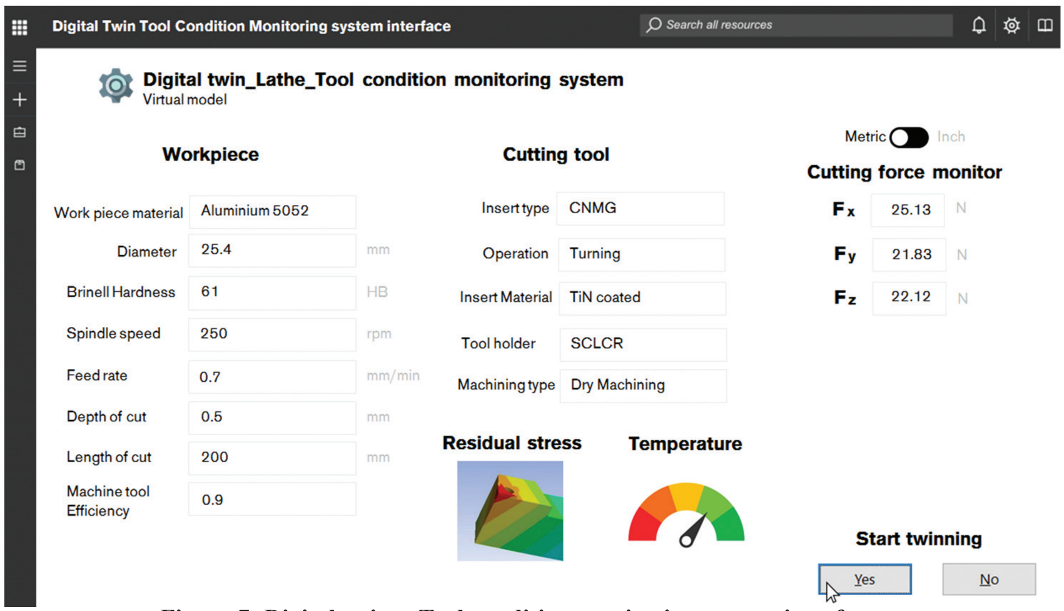


Figure 7. Digital twin – Tool condition monitoring system interface.

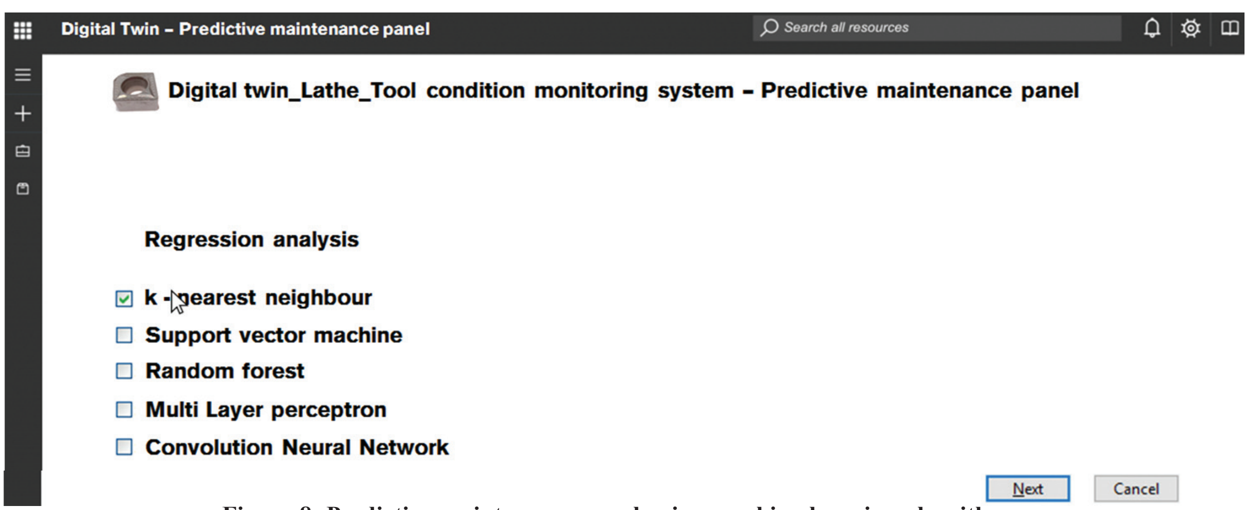


Figure 8. Predictive maintenance panel using machine learning algorithm.

Random forest, Multilayer perceptron, and convolution neural network. The stress, cutting forces, and temperature monitoring GUI is shown in Fig. 7. The tool wear classification and optimization of machining parameters are carried out in the regression phase. The GUI was developed for linking the python environment, and the dataset is illustrated in Fig. 8. Finally, the performance of the Digital twin framework is evaluated. At the same time, the machining of the Aluminium workpiece with Titanium nitride-coated tool inserts is summarised in the results and discussion section.

The development of a DT framework for lathe tool condition monitoring in machining of aluminum 5052 involves the integration of vibration sensors, temperature sensors, cutting force sensors and image capturing devices. Data from these sensors is used to generate a real-time model of the lathe tool condition and performance. This model is then used to analyse and detect any changes in the tool condition or performance which indicates the need for maintenance or repair. The DT model also identifies any changes in the machining process, such as changes in cutting parameters, which leads to tool failure or poor quality parts. The Digital Twin framework also enables the generation of predictive models that anticipate the future condition of the lathe tool based on current and historical data.

Table 1. Average real time data set vs DT model prediction for 200 turning tests

Machining parameters	Units	Real time dataset	DT model prediction
Length of cut (C_L)	mm	200	200
Feed (F)	mm/rev	0.1	0.1
Cutting speed (V_c)	mm/min	40	40
Depth (D_p)	mm	0.5	0.5
Tangential force (f_t)	N	870	776
Feed force (f_f)	N	424.47	564.5
Radial force (f_f)	N	268.15	290.6
Resultant (R)	N	1004.48	1350
Cutting time (C_t)	min	3.99	4.65
Metal removal rate (M_{RR})	cm^3/min	2	2.85
Spindle speed (S)	1/min	501.3	550.6
Machining tool efficiency factor (η_t)	(No units)	0.9	0.9
Ps Horsepower at the cutting tool (CT_{HP})	KW	0.58	0.59
Pm Horsepower at the motor M_{HP}	KW	0.64	0.69
Torque (T)	N-m	11.05	13.64

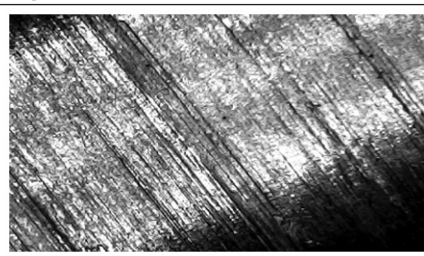
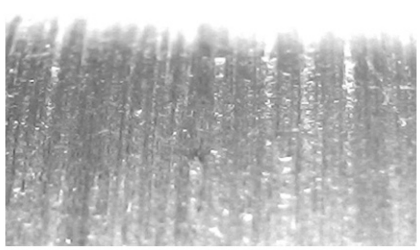
This predictive capability can be used to optimize machining operations and reduce the need for unexpected downtime due to tool failure. Machine learning algorithms, such as Support Vector Machine (SVM), KNN, Random forest, multilayer perceptron, and convolution neural network are deployed to build the models and to monitor the tool condition.

Optimising tool wear monitoring using digital twin technology involves utilizing the data generated by the digital twin to identify patterns and trends in tool wear. The data can be used to develop predictive models that can be used to anticipate tool wear before it becomes a problem. Additionally, the data can be used to identify routes to reduce tool wear, such as changing cutting parameters or using different cutting tools. The parameter tuning of the DT model is used to improve its prediction accuracy by optimising the parameters of the model to best fit the data. This is done by adjusting parameters such as the learning rate, the number of nodes in the neural network, the number of layers, the regularization technique, and the activation functions to achieve the best possible performance. The DT model is also continuously calibrated to enhance its prediction accuracy. This is done by using a validation set which is used to evaluate the performance of the model and identify which parameters need to be adjusted. The model is then adjusted to improve its accuracy and reduce its errors.

3. RESULT AND DISCUSSIONS

The performance of the digital twin model is evaluated using the data set obtained from the machining of the Aluminium 5052 workpiece using titanium nitride-coated tool inserts. The tool wear obtained under each cutting condition after turning of Aluminium 5052 workpiece using TiN-coated inserts is recorded. To validate the proposed DT model, the real-time cutting forces, flank wear, and surface finish of the workpiece are compared with the prediction made by the DT model. The nose radius of TiN-coated tool inserts at the initial stage is measured as 1.6 mm, and after machining, the nose radius changed to 2.5 mm. This may happen due to the cutting tool

Table 2. Comparison of surface roughness of Aluminium 5052 work piece with Digital Twin model predictions using machine learning

Description	Surface roughness – Digital microscopic images	Physical model	Digital Twin model prediction
Surface finish after turning at 250 rpm, feed rate 0.5mm per rev, 0.5 depth of cut		Actual surface roughness of work piece 2.675 µm	Predicted surface roughness of work piece 3.064 µm
Surface finish after turning at 750 rpm, feed rate 1 mm per rev, 0.5 depth of cut		Actual surface roughness of work piece 1.264 µm	Predicted surface roughness of work piece 2.031 µm

material's frictional force and wear behavior. The DT model predicted the change in nose radius of 3.2 mm. A variation of 0.7 mm is observed between the actual and predicted results. Flank wear after machining at a feed rate of 0.2 mm per rev, spindle speed of 750 rpm, and depth of cut 1 mm are measured as 3mm, whereas in DT model prediction, 5 mm is obtained through the KNN regression technique. Similarly, the chip formation and metal removal rate are compared between the real-time and DT model predictions, as illustrated in Annexure I. Surface finish after turning at 250 rpm, feed rate 0.5 mm per rev, 0.5 depth of cut is measured as 1.264 µm, and DT model predicted Surface roughness of workpiece 2.031 µm the surface roughness behavior is compared in Table 2.

The wear behavior of cutting tool inserts is time-dependent. The consistent machining of workpieces and intermittent machining vary the wear behavior. The comparison of Actual flank wear and Digital twin predicted value is illustrated in Fig. 9.

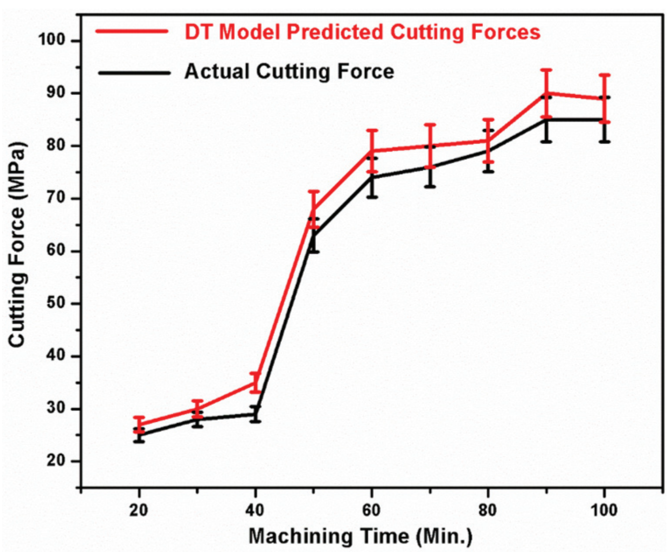


Figure 9. Variation of Flank wear with real time CNC machine and DT predicted model.

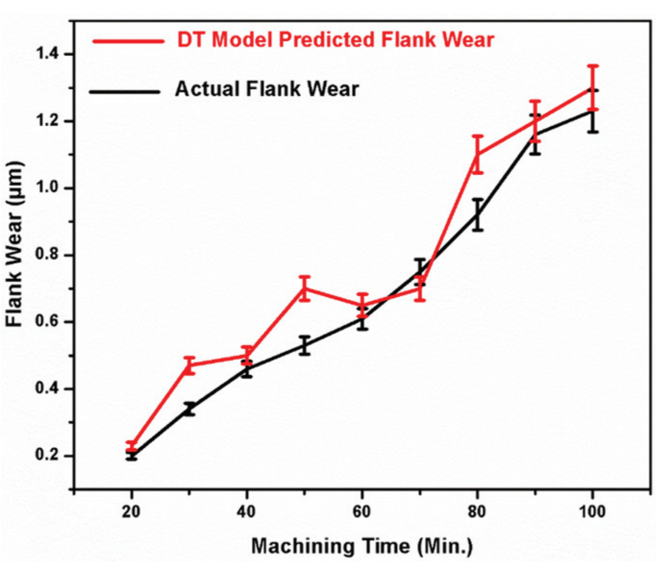


Figure 10. Variation of resultant force with real time CNC machine and DT predicted model.

The resultant cutting forces concerning time are plotted for Actual and Digital model prediction in Fig. 10. The average deviation for 100 turning tests is found to be 10 %. Hence it can be concluded that the Digital twin model works with 90 % accuracy[41-46].

The Coincidence of predicted and actual values of cutting force values takes 100 seconds, as shown in the figure. The cutting forces from X, Y, and Z directions are taken from the strain gauges, and resultant forces are calculated using embedded C, which is programmed in an ATMEGA processor. The chip formation while turning the aluminium workpiece with various cutting speeds shows the variation in chip length. The average chip length of 50 mm is observed at a cutting speed of 250 rpm. The chip length reduces concerning increased cutting speed. At a speed of 1000 rpm, the average chip length decreases to 4 mm.

4. CONCLUSIONS

Future machine tools require the Digital Twin model for troubleshooting and optimizing processes. These Digital twins need to be customized for specific tasks or operations. In the Digital twin model, the physical behavior is updated in the virtual system, and the data is used to forecast the cutting tool wear behavior. It assists in the decision-making process for giving speed, depth of cut, and feed rate to the workpiece.

- The results show the time taken for the coincidence of experimental results and predicted results strongly influenced by the frequency of the sensors, processors, and selection of algorithms.
- In this article, an aluminium specimen is turned using a lathe machine. Similarly, the DT model can be customized for general machine tools and processes.
- The DT model can be extended to quality control, resource planning, and design. The integration of processes. Further research can be conducted in this direction[47-48].

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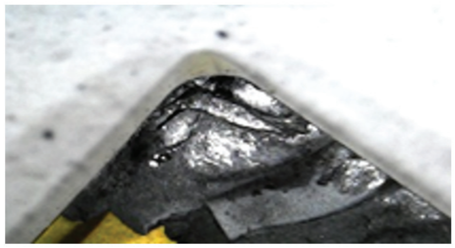
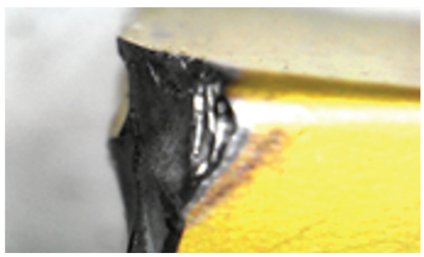
Annexure I

Comparison of tool wear and chip formation for real time with Digital Twin Model predictions using machine learning

Description	Tool insert and chip formation	Physical model	Digital Twin model
Titanium Nitride coated turning tool insert (Layer thickness - 5µm) Coating method – Physical Vapour deposition)		Material properties such as hardness, friction resistance, toughness, and wear resistance are given as input for the Digital twin model	
Change in Nose Radius Wear of TiN tool insert after machining of Al 5052 work piece.		Change of Nose radius from 1.6mm to 2.5 mm	Change of Nose radius from 1.6 mm to 3.2 mm
Flank wear Flank wear after machining at feed rate 0.2 mm per rev, spindle speed of 750 rpm and depth of cut 1 mm		Actual flank wear after machining 3 mm	Predicted flank wear 5mm
Chip formation and metal removal rate at 250 rpm, depth of cut 1 mm, feed rate 1 mm per rev		Actual metal removal rate 2 cm^3/min	Predicted metal removal rate 3.32 cm^3/min
Chip formation at 250 rpm, feed rate 0.5mm per rev, 0.5 depth of cut		Actual metal removal rate 0.5 cm^3/min	Predicted metal removal rate 0.85 cm^3/min
Chip formation at 750 rpm, feed rate 1 mm per rev, and 0.5 depth of cut		Actual metal removal rate 3 cm^3/min	Predicted metal removal rate 3.65 cm^3/min