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A Data-driven Digital Twin of CNC Machining Processes for Predicting Surface Roughness

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Abstract

Digital Twin of a CNC machining process can enhance process optimisation at process planning stage and machining stage. Quality of a machined product depends upon machining accuracy and surface at the end of the machining stage. In this paper, a Digital Twin framework for CNC machining processes is proposed that allows simulation, prediction, and optimisation of key performance indicators (surface finish in this instance) during process planning stage and machining stage with historical and real-time machining data, respectively. This paper describes the development of data-driven models for surface roughness prediction at process planning stage and machining stage of a milling process. These models constitute the digital twin. Three different data driven models are evaluated for building the surface roughness prediction models.

*Keywords:*Digital Twin; Computer-aided process planning; CNC machining; Data-driven modelling; Quality

1. Introduction

The concept of Digital Twin (DT) is being introduced in several sectors where it has a huge potential for improving decision-making capability [1]. Even though it is being modified according to the nature of applications, a DT needs to ensure that it holds the same characteristics as that in the physical space. It should also be realised by real-time simulation and prediction. Thereby, better decisions can be made to optimise the performance of the physical system [2,3]. In a DT, bi-directional dataflow between the virtual and the physical space ensures the status update of the virtual space and control of the physical space whereas predictive and optimisation models help in better decision-making. Research trends show that, now the concept of DT is starting to be applied to prototypes, instances, and environments other than products [4]. One of the sectors where application of DT has promising advantages is manufacturing [5].

1.1. Digital-Twins for manufacturing application

Manufacturing assets and processes are becoming smart with the adoption of technologies such as cloud, IoT, cybersecurity, latest communication protocols and advanced sensors [6]. These improvements in the manufacturing systems make these assets as cyber-physical systems which are capable of handling bi-directional dataflow during its operation. Thereby its processes can be digitally twinned for better decision-making to improve aspects like quality, productivity, and sustainability [7,8]. Sensor updates data of these manufacturing systems can be used for building data-driven models for prediction and optimization of manufacturing process parameters and its outputs. In manufacturing, these data-driven methods can model complex machining processes [9,10]. In this paper a data-driven DT framework is proposed for CNC machining processes which can simulate, predict, and optimize quality of a machined product at process planning

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stage and machining stage. Experiments were conducted for building data-driven models to predict surface roughness value, which is a quality measurement for surfaces, at process planning stage and machining stage in the proposed DT framework.

1.2. Surface quality prediction

Quality of a machined product depends upon the machining accuracy and the surface quality obtained after the machining stage [11]. These quality measurement values are the outcome of defined process planning parameters and the machining variables at the machining stage. In the process planning stage, a process planner defines cutting parameters such as feed rate, depth and width of cut, spindle speed and these parameters have an impact on surface quality [12]. Factors such as tool wear and cutting force occurring at machining stage affect surface quality [13]. Machine kinematic errors, machine vibration and the factors such as acceleration and jerk also affect machining accuracy and surface quality [14]. Predictive models for machining accuracy and surface quality can be built with the data from process planning and machining stage [15]. Once the quality is predicted, it can be taken as an input for optimizing the machining parameters for required machining quality. The data-driven models which are explained as a part of DT framework, predicts & optimizes machining quality, and provides feedback to maintain the required quality in process planning and machining stage by adjusting the machining parameters.

2. Digital Twin for CNC machining processes

CNC machining processes, in practice, are planned with a CAM software in process planning stage and processes are carried out in execution stage with the generated NC code. In process planning stage, a process planner generates toolpaths, defines cutting parameters, simulates machining setup in a G-code machine simulator module and converts toolpaths as NC codes [16]. Quality evaluation in the simulator considers CAD geometry of the product, generated toolpath, and machine kinematics information. But the effect of defined cutting parameters such as feed rate, spindle speed and the effect of parameters such as machine vibration, kinematics errors in actual machining conditions are not considered in this simulation for evaluating expected quality of machining.

In the execution stage, initially, machine operator sets the job ready for machining with proper fixturing method and update cutting tools status such as tool wear and tool runout in the CNC machine. If required, operator can update cutting parameters such as feed rate and spindle speed in NC code for better machining quality after the initial machining setup, according to heuristic knowledge. But quality visualization and feedback on expected machining quality is not available to the operator. During the machining process executing on the CNC machine, effects of factors such as tool wear and machine vibration on machining quality are also not available to operator even though, a few cutting parameters can be controlled from the machine controller by the operator. Fig. 1 shows the activity flow of CNC machining processes from process planning to execution.

Latest CNC machines are cyber-physical machine tools equipped with communication protocols such as OPC U/A and MTConnect, by which real-time information from CNC machines can be accessed during machining operation [17]. This real-time machining information collected through the standard communication protocols along with external sensors data can be used to model the behavior of CNC machines [18]. In this proposed DT framework, data-driven models are required for predicting machining quality by considering the factors affecting machining quality from internal and external sensors data of CNC machine. These predictive models are data driven models and built using machine learning (ML) techniques. There are many types of models that can be used, and the method used is selected based on the accuracy of prediction. Once the predictive values of machining quality are available to DT, it optimizes the parameters which can be controlled to maintain the required quality and sends feedback for controlling the machining process at process planning stage and machining stage.

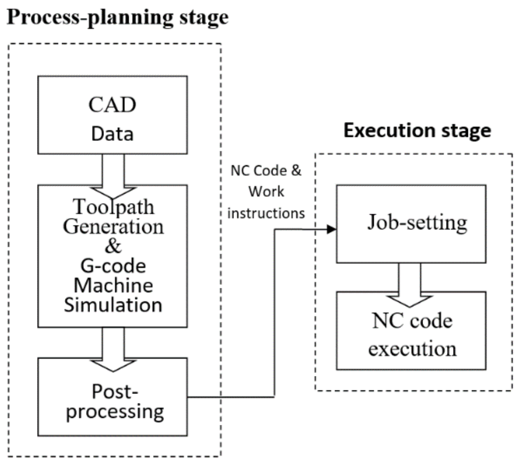

Fig. 1. CNC process planning & execution stages

This quality optimisation and prediction are done at process planning and machining stage by interfacing CAM software and CNC machine with the DT which is a digital representation with predictive and optimisation modules. For use at the process planning stage, CAM software can be interfaced with proposed DT by using an API which can enable bi-directional data communication between CAM software and DT. At machining stage, CNC machine is interfaced with DT by one of the communication protocols such as OPC U/A or MTConnect to channelise data from CNC machine to DT. Fig. 2 shows the schema of proposed DT framework for machining quality.

2.1. Use of proposed DT in Process planning stage

Choice of CNC machine, cutting tools and cutting parameters selected by a process planner during process planning stage have an impact on machining quality. Here, the predictive models which are updated with historical machining information predict the machining quality with the selection made by the process planner and the optimisation module provide optimised choice of parameters to be controlled to get the required quality. Some of the parameters will have variations when it comes to actual machining such as tool wear and these variations need to be predicted first at process planning stage, before predicting machining quality, since it is one of the variables affecting machining quality. The decision-parameters chosen at machining stage by the machine operator, which are affecting machining quality such as fixture clamping pressure, cannot be included for machining quality consideration in this stage.

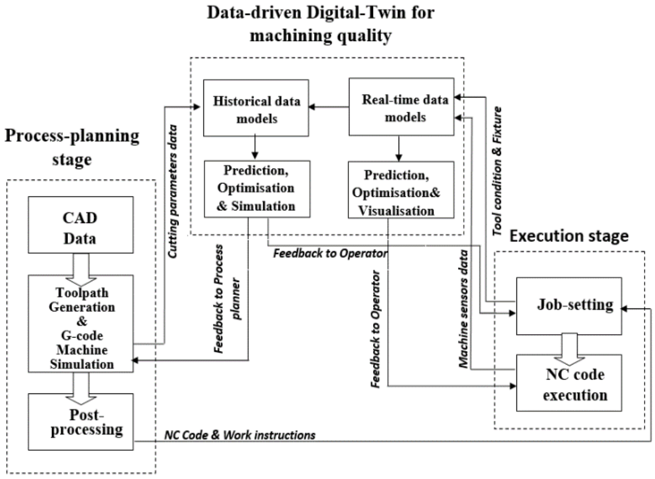

Fig. 2. Proposed Digital Twin framework

2.2. Use of proposed DT in machining stage

During the setting up of the work piece at the selected CNC machine, machine operator can update the cutting tool condition and fixture information which affects the machining quality with the DT. Here, DT considers process planning information available in the NC code and the job-setting updates for the quality consideration. Once the DT optimises the parameters for maintaining the required quality, the operator can update parameters such as feed rate and spindle speed in the NC code accordingly.

During the machining operation, the DT works with the real-time machining data from the CNC machine. The sensor data on variables which affect the machining quality become the inputs for quality prediction here. Further to this, real-time optimisation provides feedback to operator to control the cutting parameters such as feed rate and spindle speed in the machine controller to meet and maintain the required machining quality.

2.3. Model building

Predictive models in the proposed DT need to be built with the historical data from the process planning stage and machining stage and individual models are required for each stage and its activities. Model preparation and update of models can be made separately for all the three predictive models which are used in the DT framework. Since separate models are needed in the different stages, choice of prediction techniques such as ML can be made according to the accuracy of prediction. Similarly, methods used for optimising the parameters for maintaining quality can also be different in both the machining stages. The variables whose data are not available in the process planning stage and job setting activity of machining stage can be either predicted first and use for predicting quality, or it can be excluded in the prediction model. Fig. 3 lists the different parameters which are considered from process planning and machining stage for building predictive models for machining quality consideration in the DT framework.

Once the model is trained for a fixed machining conditions it can give good prediction results for the same fixed machining conditions. If the machining conditions are distinctly different, there will be errors in the prediction results. Implementing continual learning methods help reduce the number of experiments required to obtain data required to build the learning model. Using the continual learning methods, models can adapt a model learnt with one type of data to new information as data from operations with new machining conditions become available. The data driven model therefore becomes better over a period with increase in the availability of varied data from different machining conditions [19,20].

2.4. Feedback control

The feedback to control and maintain the quality of machining at each process stage is given by the DT. The control of parameters is done by humans in loop of the DT framework. Here process planner and machine operator control the physical system at process planning stage and machining stage, respectively, to obtain and maintain the required quality of machining. In process planning stage, planner can change the defined cutting parameters as per the feedback given by DT. In execution stage, machine operator can change the parameters in the NC code as per the feedback received from DT during job setting and adjust the controller parameters such as feed rate and spindle during the actual machining process occurring at CNC machine.

Process planning stage	**Machining stage**	
	Job setting activity	**NC code execution**
Feed rate	Tool runout	Trajectory variation
Spindle	Tool wear	Acceleration
Depth of cut	Tool height	Jerk
Width of cut	Clamping force	Tool wear rate
Direction of cut	Job location	Vibration
Tool material		Spindle power
Tool geometry		
Coolant (M8/M9)		

Fig. 3. Parameters for predictive model building

3. Building of surface roughness predictive models

Surface roughness value is one of the surface quality measurement for a machined surface. Three models are created by an experiment which would be the part of proposed DT framework. Fig. 4 shows the set of parameters used for building these prediction models.

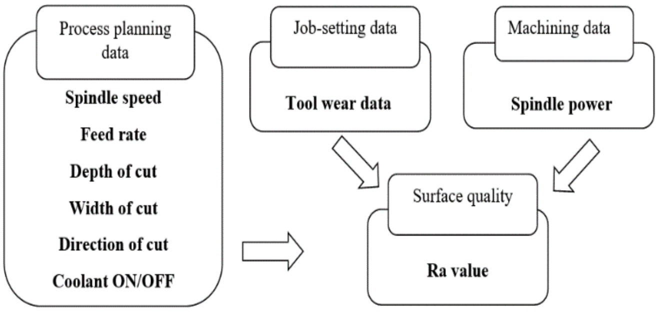

Fig. 4. Parameters for predictive model building

3.1. Toolpath generation

A form surface is created in NX CAD software & a contour machining toolpath is generated by NX CAM software. Fig. 5(a) shows the CAD geometry and Fig. 5(b) shows generated tool path. The same strategy is applied for a Taguchi L16 design of experiments with different process planning parameters. Table 1 shows the levels parameters used for generating 16 experiments. Table 2 lists the parameters for each of the 16 experiments conducted. The machining is performed on the work piece that has been rough cut. This ensures uniform finishing stock equal to the depth of cut value for the finishing operation.

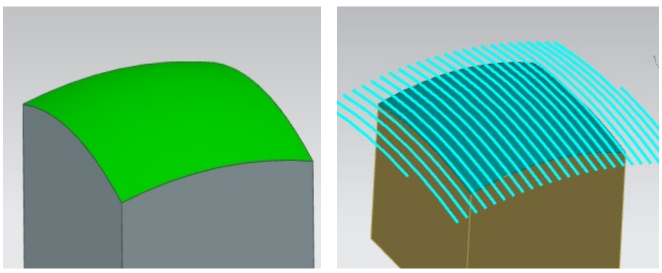

Fig. 5. (a) CAD geometry; (b) Generated toolpath

Table 1. Taguchi experimental levels

Feed (mm/min)	Spindle speed (rpm)	Depth of cut (mm)	Width of cut (mm)	Cutting direction	Coolant
200	1000	0.5	0.2	Up	On
800	2000	1.5	0.6	Down	Off
1400	3000	2.5	1.0	-	-
2000	4000	3.5	1.4	-	-

3.2. Execution

Experiments with each of the 16 set of process parameters in the table2 were executed with 4 different tool wear values. During execution of these experiments, spindle power consumption of spindle was recorded with a sampling frequency of 4 milliseconds from the machine controller. Surface roughness values obtained after the machining of 64 samples were inspected by a profilometer and its values were recorded. Table 3 shows the machining and inspection set-up used for conducting the experiments.

Table 2. Parameter sets for experiments

Exp No	Feed rate (mm/min)	Spindle speed (rpm)	Depth of cut (mm)	Width of cut (mm)	Cutting direction	Coolant
1	1400	3000	0.5	0.6	Down	Off
2	2000	4000	0.5	1.0	Down	On
3	800	2000	0.5	1.4	Up	Off
4	200	1000	0.5	0.2	Up	On
5	200	2000	1.5	1.0	Down	Off
6	800	1000	1.5	0.6	Down	On
7	2000	3000	1.5	0.2	Up	Off
8	1400	4000	1.5	1.4	Up	On
9	800	4000	2.5	0.2	Down	Off
10	200	3000	2.5	1.4	Down	On
11	1400	1000	2.5	1.0	Up	Off
12	2000	2000	2.5	0.6	Up	On
13	2000	1000	3.5	1.4	Down	Off
14	1400	2000	3.5	0.2	Down	On
15	200	4000	3.5	0.6	Up	Off
16	800	3000	3.5	1.0	Up	On

3.3. Data preparation & predictive models building

After completing the experiments, datasets were prepared for building three predictive models. From the prepared dataset, correlation matrix is generated for surface roughness value against all the parameters considered in the experiment. This can help for choosing the useful features for building models. Fig. 6 shows the derived correlation matrix. Cutting speed and material removal rates which can be derived from the parameters specified in each set are added as features in the dataset.

Table 3. Machining & inspection conditions/methods

Condition/software/hardware	Specification/type
Machine make & model	Jyoti K2X8 Five
Controller make	Siemens 840 D sl
Work piece material	Aluminum
Tool diameter	16 mm
Tool type	Indexable ball end mill
Tool make	Seco
Tool wear(flank) values(mm)	0,0.04,0.08,0.12
Profilometer	Taylor Hobson- Form Talysurf 50

As outlined in the DT framework in figure 2 and 4, three predictive models are constructed. Model-1 would be used in process planning stage with process planning data. Model-2 is used during job setting prior to machining stage for predicting surface roughness. This model is built using both process planning data and tool wear data. Model-3 is built from actual machining data which consists of process planning parameters and spindle power consumption. Three data modelling techniques, Support Vector Machine (SVM), Gaussian Process (GPR) and Fully connected deep neural network (FCDNN) were considered for building the models. Based on the validation accuracy and size of data available, SVM was selected for building Model-1 and Model-2, whereas FCDNN was selected for Model-3. Table 4 shows the performance of the predictive models by the respective method chose and reports its accuracies obtained after testing the models with test datasets.

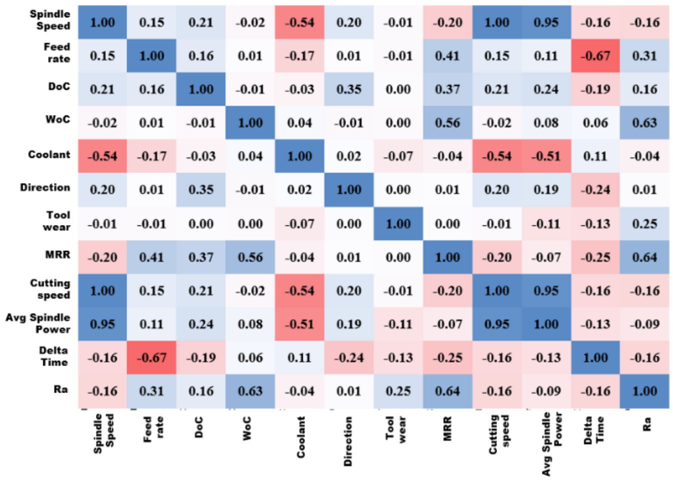

Fig. 6. Correlation matrix

Table 4. Predictive models information

Model	No of dataset	Method used	Platform	RMSE	MAE
Model-1	16	SVM	MATLAB	0.9814	0.7606
Model-2	64	SVM	MATLAB	1.081	0.9231
Model-3	12559	Fully connected DNN	Python	0.9693	0.8989

In Model-3, dataset is subdivided per NC block so that it can be used during executing NC code in machine. Thus, the number of datasets is more compared to other model datasets, deep learning is chosen for building the predictive model. But roughness value is taken as common for all the NC block in each experiment since, NC block wise surface roughness value was not able consider here. Model parameters used for SVM is given in Table 5. Table 6 shows the hyper parameter details of deep learning method used for building Model-3.

Table 5. SVM Model parameters

Model	Box constraint	Kernel scale	Kernel function
Model-1	200	60	Gaussian
Model-2	200	65	Gaussian

3.4. Prediction of surface quality on a test data sets

A new 16 set of experiments with different process planning parameters and tool wear were used to test the three predictive models. Table 7 shows the testing dataset and Table 8 shows results comparison with measured surface roughness value.

Table 6. Hyperparameters of Fully connected deep neural network

Parameter	Value/Method
No: of Hidden layers	4
No: of units per hidden layer	{32,512,128,32}
Activation function	ReLU
Loss function	Mean Square error
Optimizer	Adam
Dropout	0.5
Batch size	20
Epoch	100

Table 7. Testing datasets

Test	Feed rate (mm/min)	Spindle speed (rpm)	Doc (mm)	Woc (mm)	Cut Dir.	Coolant	Tool wear (mm)	Avg. Power (W)
1	1300	3300	0.6	0.7	Down	Off	0.09	177.8
2	1800	3800	0.6	1.1	Down	On	0.09	222.9
3	900	2400	0.6	1.3	Up	Off	0.09	117.2
4	300	1200	0.6	0.3	Up	On	0.09	41.3
5	300	2400	1.2	1.1	Down	Off	0.09	120.1
6	900	1200	1.2	0.7	Down	On	0.09	52.1
7	1800	3300	1.2	0.3	Up	Off	0.05	197.1
8	1300	3800	1.2	1.3	Up	On	0.05	256.3
9	900	3800	2.3	0.3	Down	Off	0.05	248.9
10	300	3300	2.3	1.3	Down	On	0.05	207.1
11	1300	1200	2.3	1.1	Up	Off	0.05	62
12	1800	2400	2.3	0.7	Up	On	0.05	140.2
13	1800	1200	3.2	1.3	Down	Off	0.08	84.1
14	1300	2400	3.2	0.3	Down	On	0.08	130.8
15	300	3800	3.2	0.7	Up	Off	0.08	234.5
16	900	3300	3.2	1.1	Up	On	0.08	215.3

Table 8. Testing results

Test data	Measured Ra	Model-1 (SVM)	Model-2 (SVM)	Model-3 (FCDNN)
1	3.64	1.88	2.15	2.67
2	2.11	2.105	2.6	2.18
3	3.65	2.29	2.8	2.54
4	1.19	1.07	1.49	1.06
5	3.03	2.44	2.48	2.4
6	1.65	2.02	2.48	2.53
7	0.57	1.35	1.74	1.51
8	1.59	2.09	2.43	1.77
9	0.99	1.72	1.46	1.51
10	1.46	2.57	2.37	1.71
11	1.96	2.67	3.2	3.19
12	1.26	1.94	2.52	2.59
13	3.02	3.46	4.07	4.02
14	1.55	1.95	2.18	1.23
15	4.42	1.98	1.84	1.99
16	2.51	2.34	2.61	2.24

For increasing the accuracy of prediction, more data sets that have enhanced coverage of the range of each parameter affecting the surface roughness is required. These three different models can be tuned with more datasets along with different combinations of parameters forming the features set to improve the model accuracy. The three predictive models are not compared with each other here since all the three models are created with different model parameters.

4. Conclusion

In this work we are proposing a DT framework for CNC machining process which allows simulation, prediction, and optimization of the machining quality both at process planning stage and machining stage. This DT enhances the decision-making making capability of process planner and machine operator for controlling the machining parameters for quality consideration at process planning stage and machining stage. Predictive models are built for predicting surface roughness values at both the stages and its results are reported in this work. This framework needs a digital representation of machining process along with complete machining setup in a CNC machine and which needs to be interfaced with CAM software and CNC machine. To make this DT as a high-fidelity representation, it requires accurate predictive models and optimization modules for machining quality and its challenging. Other drawback with this DT is operator can control only few parameters such as feed rate and spindle speed for controlling machining quality at machining stage. The predictive models developed for predicting surface roughness value at both stages, requires more data to improve model accuracies and suitable method needs to be selected for better predictive results. Developing suitable optimization techniques for this DT framework is one of the future scopes of this work. Other than machining quality consideration, performance parameters of machining such as productivity and sustainability, would be considered in the future work along with realizing this proposed DT framework.

References

[1] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, "Characterising the Digital Twin: A systematic literature review," CIRP J. Manuf. Sci. Technol., 2020.

[2] C. Cimino, E. Negri, and L. Fumagalli, "Review of digital twin applications in manufacturing," Comput. Ind., vol. 113, p. 103130, 2019.

[3] M. Dr. Grieves, "Digital Twin : Manufacturing Excellence through Virtual Factory Replication This paper introduces the concept of a A Whitepaper by Dr . Michael Grieves," White Pap., no. March, 2015.

[4] Grieves M, Vickers J (2017) "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems" in F. J. Kahlen, S. Flumerfelt, and A. Alves, Transdisciplinary perspectives on complex systems: New findings and approaches, no. August 2017. 2016.

[5] M. Macchi, I. Roda, E. Negri, and L. Fumagalli, "Exploring the role of Digital Twin for Asset Lifecycle Management," IFAC-PapersOnLine, vol. 51, no. 11, pp. 790–795, 2018.

[6] Y. Lu, C. Liu, K. I. K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," Robot. Comput. Integr. Manuf., vol. 61, no. April 2019, p. 101837, 2020.

[7] Q. Qi et al., "Enabling technologies and tools for digital twin," J. Manuf. Syst., no. August, pp. 0–1, 2019.

[8] E. Negri, L. Fumagalli, and M. Macchi, "A Review of the Roles of Digital Twin in CPS-based Production Systems," Procedia Manuf., vol. 11, no. June, pp. 939–948, 2017.

[9] Q. Qi and F. Tao, "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," IEEE Access, vol. 6, pp. 3585–3593, 2018.

[10] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," J. Manuf. Syst., vol. 48, pp. 157–169, 2018.

[11] H. W. Chiu and C. H. Lee, "Prediction of machining accuracy and surface quality for CNC machine tools using data driven approach," Adv. Eng. Softw., vol. 114, pp. 246–257, 2017.

[12] A. M. Zain, H. Haron, and S. Sharif, "Prediction of surface roughness in the end milling machining using Artificial Neural Network," Expert Syst. Appl., vol. 37, no. 2, pp. 1755–1768, 2010.

[13] P. G. Benardos and G. C. Vosniakos, "Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments," Robot. Comput. Integr. Manuf., vol. 18, no. 5–6, pp. 343–354, 2002.

[14] Z. Li, Y. Wang, and K. Wang, "A data-driven method based on deep belief networks for backlash error prediction in machining centers," J. Intell. Manuf., no. 2008, pp. 1–13, 2017.

[15] S. Schorr, M. Möller, J. Heib, and D. Bähre, "Quality Prediction of Drilled and Reamed Bores Based on Torque Measurements and the Machine Learning Method of Random Forest," Procedia Manuf., vol. 48, pp. 894–901, 2020.

[16] R. Dubovska, J. Jambor, and J. Majerik, "Implementation of CAD/CAM system CATIA V5 in simulation of CNC machining process," Procedia Eng., vol. 69, pp. 638–645, 2014.

[17] C. Liu, H. Vengayil, Y. Lu, and X. Xu, "A Cyber-Physical Machine Tools Platform using OPC UA and MTConnect," J. Manuf. Syst., vol. 51, no. June 2018, pp. 61–74, 2019.

[18] Y. Cai, B. Starly, P. Cohen, and Y. S. Lee, "Sensor Data and Information Fusion to Construct Digital-twins Virtual Machine Tools for Cyber-physical Manufacturing," Procedia Manuf., vol. 10, pp. 1031–1042, 2017.

[19] G. I. Parisi, R. Kemker, J. L. Part, C. Kanan, and S. Wermter, "Continual lifelong learning with neural networks: A review," Neural Networks, vol. 113, pp. 54–71, 2019.

[20] H. Tercan, P. Deibert, and T. Meisen, "Continual learning of neural networks for quality prediction in production using memory aware synapses and weight transfer," J. Intell. Manuf., 2021.