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A Hybrid Approach for Predictive Modeling of KPIs in CNC Machining Operations

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Abstract

In a CNC machining operation, key performance indicators (KPIs) of process, such as machining time, quality, and energy consumption, vary with cutting parameters. This paper explains a methodology for building physics-guided data-driven models for predicting these process KPIs in CNC machining operations from the planning, machining, and quality data. These physics-guided data-driven models are developed by combining data-driven and physics-based models of machining operations. Using hybrid physics-ML method, predictive modelling of energy consumption and surface roughness in CNC milling operation is also explained by conducting experiments. Finally, accuracies obtained by these models are compared with respective physics-based and data-driven models.

Keywords: CNC machining; Physics-guided data-driven modeling; Data analytics

1. Introduction

The rapid technological advancements in sensor technologies, communication systems and intelligent data-driven techniques make the CNC machines and their processes more intelligent. These new-generation CNC machines can yield machining data faster from the in-built machine sensors. As a result, these data can be used to build predictive models that would guide better process planning as well as machine maintenance activities. Typically, data-driven methods such as machine learning (ML) techniques are directly applied to these machining data and build the required data-driven models [1]. Moreover, there is a growing practice of connecting the theory behind the physical phenomena and data-driven techniques for better model performance and thereby address data insufficiency [2]. Hence, these physics-guided data-driven techniques can be extended to build predictive models for evaluating the performance of CNC machining process by fusing the reported theories behind the corresponding machining outputs and data-driven techniques.

1.1. Key performance indicators (KPIs) of CNC machining operations

Generally, industries assess the effectiveness of their selection of cutting parameters on output by calculating the key performance indicators (KPIs) of machining process [3]. Therefore, their machining objectives can be optimized by appropriately choosing the machining parameters at the process level [4]. The primary categories of process KPIs in CNC machining processes are productivity, quality, and sustainability factors [5]. Fig. 1. shows the list of KPI categories and its major indicators of the CNC machining process that are impacted by selection of cutting parameters.

Machining time, which is an indicator for productivity assessment, depends upon the material removal rate. That can be improved by better combination of feed rate, width of cut and depth of cut [6]. Similarly machining quality parameters such as surface quality and accuracy can also be improved by properly selecting cutting parameters [7]. Nowadays, organizations are implementing sustainable practices to

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reduce their energy consumption. Controlling the cutting parameters during process planning stage can improve the energy efficiency of machining process [8]. Therefore, accurate predictive models of these performance indicators can be used to predict the machining outputs and thereby optimize the machining operations.

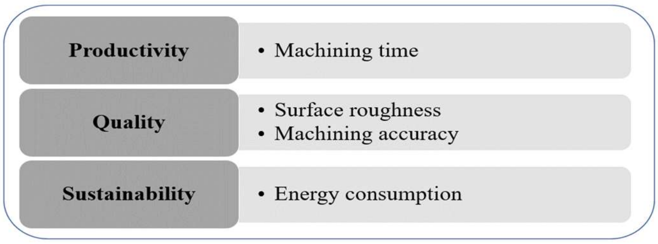

Fig. 1. Major process KPIs in CNC machining.

1.2. Model building methods of process KPIs in CNC machining

The classical methods of calculating the machining KPIs were calculating them from the physics-based equations with cutting parameters data. However, these modeling methods are made generic in theory because of the difficulties involved in building relationship between cutting parameters of complex machining phenomena [9]. Alternatively, empirical modeling techniques are predominantly used for building the predictive models of performance indicators. In that technique, experiments are conducted, and empirical methods draw the relationships between the cutting parameters and machining outputs [10]. With the large amount of machining data from the sensors and process planning systems, data-driven models such as ML algorithms derive better accurate models for predicting the performance indicators [11]. Among those techniques, Gaussian process regression (GPR) is used for building predictive models of energy consumption with NC level data preparation with its cutting parameters [12]. Deep neural networks (DNNs) are used for building predictive models for machining time in the cases where the feed fluctuation leads to increased machining time [13]. Artificial neural networks (ANNs) and support vector machines (SVM) have been used for building surface roughness prediction models [14, 15]. These data-driven models provide accurate results within the specified limit of collected data without the inclusion of theory behind the machining processes.

2. Physics-guided data-driven approaches in predictive modeling

The scientific community has started applying the theoretical knowledge along with data-driven techniques to generalise the models. This leads to include the scientific findings in the process to the learning mechanism of data-driven techniques. There are several methods reported to include the physical phenomena in the data-driven techniques. Fig. 2. explains the list of methodologies reported to combine the theoretical knowledge and the data-driven techniques [16].

In the manufacturing process as well, these techniques can be extended to apply with physics of metal cutting. With physics-guided data-driven techniques, tool wear prediction of machining can be made to avoid the physical inconsistencies in the conventional data-driven methods to predict the tool wear [17]. Similarly, a physics-guided neural network was introduced for predicting tool wear, which shows that its results are better than the accuracy of a data-driven model [18]. A physics-guided logistic classification technique is reported, and it needs a lower data set to optimise the machining conditions in the production environment than a data-driven method [19]. A self-machining system with a physics-guided data-driven method is proposed for improved accuracy by fusing the decades of knowledge gained with the experimental data with data-driven methods [20]. Similarly, a growing practice to use these physics-guided data-driven techniques are there in operations of cyber-physical systems (CPSs), where sensor data and scientific knowledge of process can be fused together with data-driven methods [21]. New generation CNC machines are considered as a CPS system that can be extended to work with physics-guided data-driven methods for predictive modelling of KPIs.

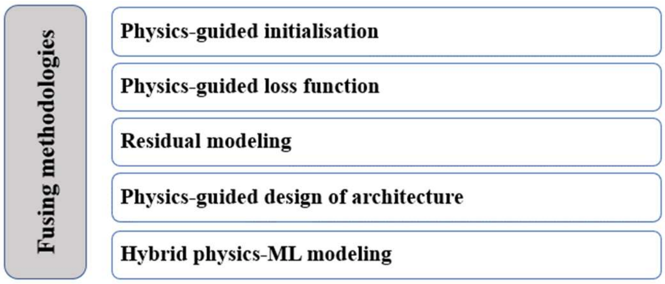

Fig. 2. Physics-guided data-driven methods.

For the prediction of KPIs of machining process the physics-guided data-driven methods can be applied with existing scientific knowledge in the machining process. The method used in this work is the hybrid physics-ML method, in which the output from the physics equations is supplied as a feature in the data-driven method as illustrated in Fig. 3.

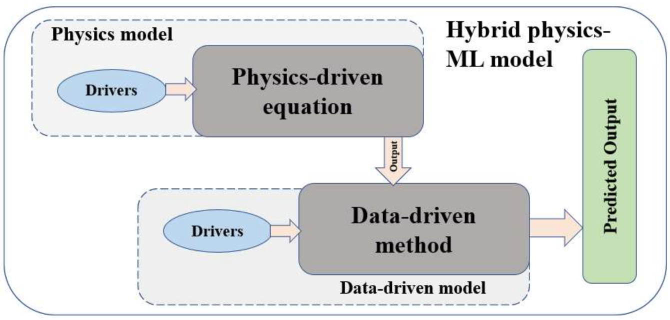

Fig. 3. Architecture of hybrid physics-ML model.

Therefore, the derived scientific knowledge that are available for the prediction of performance indicators can be made use with hybrid-physics ML method for better model accuracy. To check the feasibility of hybrid physics– ML method for predicting machining KPIs, predictive models of energy consumption and surface roughness with the experimental data is built in this work.

3. Data preparation model building

Data required for the model building was prepared by conducting machining experiments in a milling machine. The experiment was planned, and the process planning data was also included for building the models. The output of the machining experiments was captured from the execution and quality measurement system.

3.1. Data generation

Initially, a contoured surface was modelled in the NX software modelling environment. After that, a 3-axis contour machining strategy was applied over the surface to generate a toolpath. Fig. 4. shows the generated CAD surface and the toolpath on the NX software platform. Sixteen samples were made to apply the combination of cutting parameters with different levels of variables, as given in Table 1. The NC code was generated for all the 16 toolpaths, and it was executed in the CNC milling machine. The chosen material was aluminium and 16 mm diameter ball end mill was used for machining. The data generated from the CNC machine was collected through the TRACE function of the SIEMENS controller. Power data of the axes was collected with a sample rate of 4 milliseconds. At the end of the machining, the surface roughness value (Ra value) of all samples was measured with a profilometer. Finally, these collected data processed for building the models.

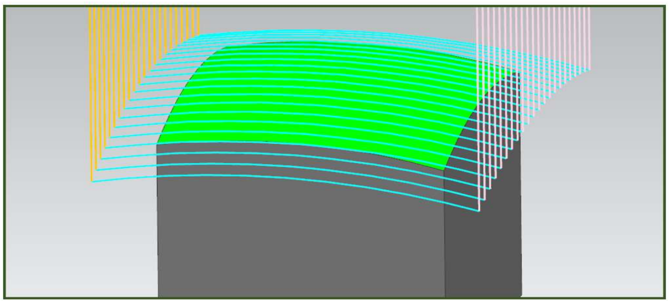

Fig. 4. Toolpath generation on contour surface.

Table 1. Levels of variables used for the experiments.

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

3.2. Data cleaning

The dataset for building the hybrid model is prepared according to the executed NC block in the machine. That is, each NC block is taken as a dataset. Against each data set, all the input parameters and output are mentioned by cleaning the sensor and process planning data. The energy consumption value is calculated from the power data of all axes motors and the spindle motor of the CNC machine. The total power is summed and multiplied by the machining time of the NC block to get the energy consumption per NC block in Joules. Similarly, the Ra value of the dataset is considered at the NC block level. Therefore, the Ra value is taken as the same for all the NC blocks for a particular experiment. Fig. 5. shows a sample of cleaned datasets. After the datasets were prepared similarly across all the 16 experiments, three variants of models were built for Ra value and energy consumption prediction models. Those were physics-based models, data-driven models, and hybrid physics-ML models. Total 3161 datasets from 16 experiments were prepared at the NC block level to build these models. Among these datasets, 2012 datasets of 10 experiments were used for training all the models and 504 datasets of 3 experiments were used to validate the models. The remaining 645 datasets of 3 experiments are kept for testing the built models.

Spindle speed	Feed rate	Depth of cut	Width of cut	Coolant condition	Direction of cut	Cut length	Energy Consumption	Ra value
1000	800	1.5	0.6	1	1	1.11964	2.851520792	1.92
1000	800	1.5	0.6	1	1	2.39874	4.930639988	1.92
1000	800	1.5	0.6	1	1	1.02457	3.546456276	1.92
3000	2000	1.5	0.2	0	0	3.21767	21.7067662	0.5694
3000	2000	1.5	0.2	0	0	2.2647	12.30694405	0.5694
3000	2000	1.5	0.2	0	0	2.26472	11.85035849	0.5694

Fig. 5. Sample cleaned data blocks.

3.3. Preparation of hybrid physics-ML model for energy prediction

The major contributors to the energy consumption for the machining operation, such as feed rate, spindle speed, depth of cut, width of cut and the cut length, are considered for building the data-driven model of energy consumption. Fig. 6. shows the data-driven model building method for predicting energy with cutting parameters as input by the deep neural network.

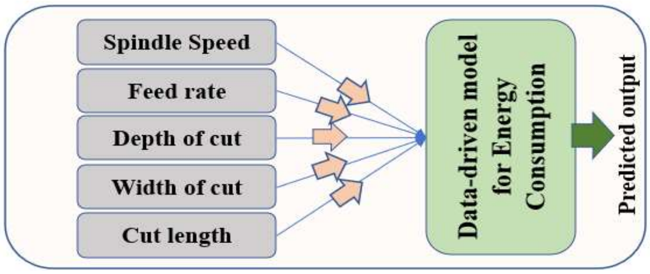

Fig. 6. Data-driven framework of energy prediction.

For the physics-based energy prediction model, the classic method of calculating the energy consumption for the milling machine process is applied. The physics-based calculation of the energy is prepared from the method discussed in the literature [22]. The equation is as follows.

$$P = \frac{a_p \times a_e \times v_f \times k_c}{60 \times 1000} \tag{1}$$

In the equation (1) P is cutting power in watts, a_p is the depth of cut in mm, a_e is width of cut in mm, v_f is feed rate in mm per minute and k_c is specific cutting force for the material. Here the material for milling was used aluminium. So specific cutting force value is taken as 700 N/mm^2 from the tool databook [23]. After calculating the power, the energy per NC block is calculated by multiplying the machining time with the calculated power. These modelling techniques are made tested separately, and their accuracy is compared with the hybrid physics-ML model's accuracy.

3.4. Preparation of hybrid physics-ML model for surface roughness prediction

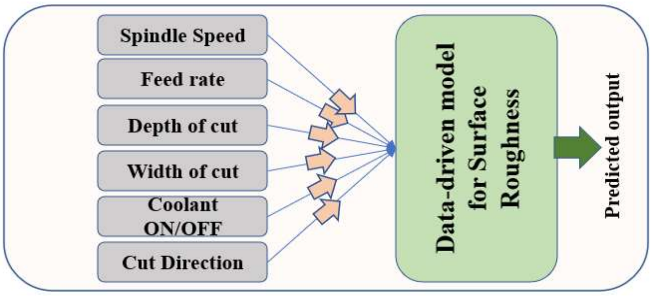

Fig. 7. Data-driven framework of surface roughness prediction.

Surface roughness is a complex phenomenon which are affected by cutting parameters and machining environment. The data driven formulation of surface roughness prediction is formed as discussed in Fig. 7. with the cutting parameters. The used variables for the surface roughness building are feed rate, spindle speed, depth of cut, and width of cut, cut direction and coolant status.

Empirical and geometrical research findings are reported for calculation of roughness value in milling operation using ball end mill. In this work a geometry-based calculation of surface roughness is that was reported is considered as physics input for the hybrid model. The calculation is as follows [24].

$$R_a = \frac{2}{A_e} \times \left[R^2 \times \cos^{-1}\left(\frac{R-y}{R}\right) - \left[(R-y) \times \sqrt{(2R \times y) - y^2} \right] \right] \tag{2}$$

Value y is given from equation (3).

$$y = \frac{h}{2} + \frac{R}{2} - \left(\frac{R^2}{A_e} \times \sin^{-1}\left(\frac{A_e}{2R}\right) \right) \tag{3}$$

Value h is given from equation (4).

$$h = \left(1 - \frac{\sqrt{4 - \left(\frac{A_e}{R}\right)^2}}{2} \right) \times R \tag{4}$$

Here value R is the radius of the ball end mill used for the experiment. That is 8 mm since the diameter was 16 mm. Ae is the width of cut which is varied as per the experiments. After obtaining the Ra value from this equation it is converted to micrometres by multiplying by factor of 1000 since the equation output is in mm. These data-driven model and physics-based models are used for predicting the surface roughness values for comparing with the hybrid physics-ML model.

4. Model building and result discussion

The models are developed with a deep neural network and its hyper parameters were kept the same for all the models for the comparison purpose. The hyper parameters of the model are explained in Table 2. For building the hybrid model for predicting energy consumption, initially the energy is calculated with physics equation, and its output is given as a feature input to the data driven model as an additional feature. Fig. 8. explains the methodology of fusing the theory of energy calculation with the data-driven techniques. The prediction output is tested with the test data samples and its accuracy is plotted in Fig. 9. For comparing the accuracy with physics and data-driven methods, MSE and RMSE of all the three models are discussed in Table 3. The results show that the addition of physics-based calculation as an input to the data-driven modelling is improving the model performance.

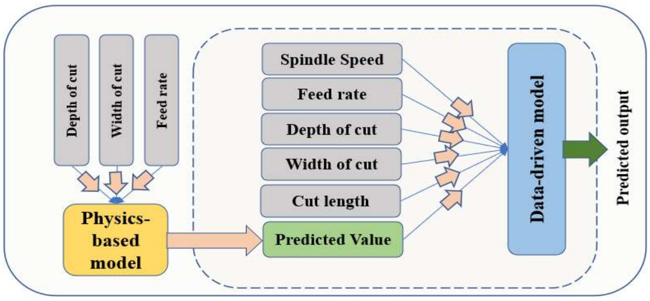

Fig. 8. Hybrid physics-ML architecture of energy prediction.

Similarly for the surface roughness prediction, the geometry-based calculation is used to calculate the physical value of the surface roughness and it is fed into the data-driven framework as a new feature. Fig. 10. explains the methodology of fusing the theory of surface roughness geometry with the data-driven techniques. Fig. 11. shows the prediction accuracy of the surface roughness models after testing. Table 4. shows the comparison of all three models of surface roughness prediction.

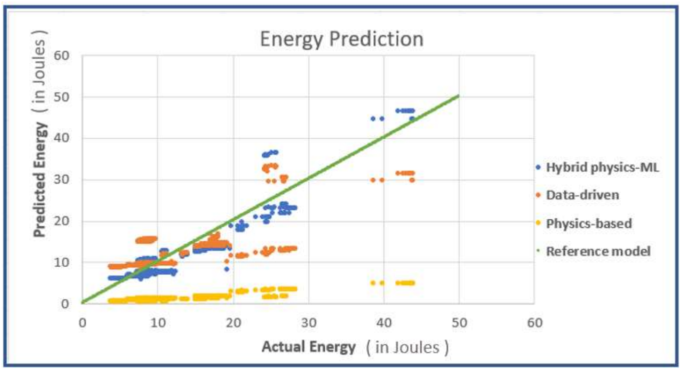

Fig. 9. Testing result of energy prediction with models.

Similar to hybrid method of energy prediction model, the surface roughness hybrid model accuracy also getting improved by fusing the theoretical knowledge. Therefore, the results show that the accuracy of both surface roughness prediction and energy consumption prediction is getting improved by adding theory behind those phenomena, in the hybrid physics-ML method.

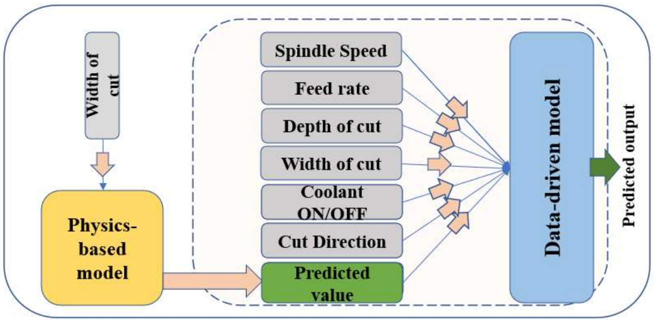

Fig. 10. Hybrid physics-ML architecture of surface roughness prediction.

Table 2. 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	0.4
Batch size	10
Epoch	100

Table 3. Accuracy comparison: energy prediction models.

Model	MAE(Joules)	RMSE(Joules)
Physics-based	10.68	12.56
Data-driven	3.73	5.01
Hybrid physics-ML	2.44	3.04

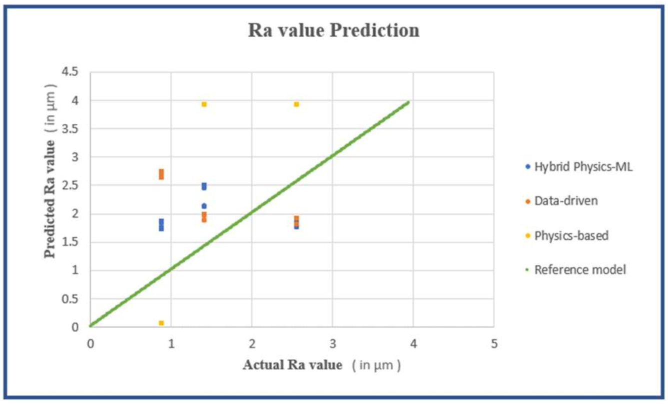

Fig. 11. Testing result of surface roughness prediction with models.

Table 4. Accuracy comparison: surface roughness prediction models.

Model	MAE (µm)	RMSE (µm)
Physics-based	1.02	1.15
Data-driven	1.61	1.68
Hybrid physics-ML	0.95	0.96

5. Conclusion

The data-driven techniques are widely used for predictive modelling applications in manufacturing with the plentiful data collected from the manufacturing systems. Similarly, years of research in the theoretical and empirical findings are also functional to make use for manufacturing applications. This scientific information in manufacturing and data-driven methods can make the predictive models more robust by integrating them. This growing practice of developing physics-guided data-driven models would generalise the model with better accuracy, and thereby it can address the data insufficiency in data-driven modelling applications.

This paper uses the hybrid physics-ML method to build the predictive models for KPIs in the CNC machining process for better accuracy. Subsequently, the accuracy obtained for the hybrid physics-ML model of the surface roughness and the energy consumption is compared with a physics-based and data-driven model. This work can also be extended to predict other KPIs of the CNC machining process, with the respective theoretical findings in predictive modelling. This work uses a deep neural network to compare the hybrid physics-ML model with the physics-based and the data-driven models. Similarly, other ML methods can also be applied to build hybrid data-driven models. Also, additional theories and empirical models of surface roughness and energy calculations can be added to this hybrid physics-ML models for better results. Other than hybrid physics-ML method, techniques reported to build physics-guided data-driven techniques, can be applied to build predictive models of machining process KPIs. Finally, the models which are derived by the hybrid physics-ML method can be utilised for the real-time predictions in the digital twin of CNC machining processes, in future work.

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