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Energy Prediction in Process Planning of Five-axis Machining by Data-driven Modelling

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Abstract

Process planning for a computer numerical control (CNC) machining is a multi-objective decision-making activity. A process planner defines machining set-up along with operation-sequencing at macro-level and decides toolpath strategies with its cutting parameters at micro-level. This paper proposes a data driven model that enables consideration of energy consumption also as a decision-making criterion during process planning for five-axis machining. A two-stage predictive energy model with an intermediate stage of exact feed prediction is proposed for machining on a five-axis machine. A process planner can use this model to choose optimal machining conditions that minimizes energy consumption during five-axis machining.

*Keywords:*Smart manufacturing; Predictive modelling; Energy; Five-axis machining; Computer-aided process planning

1. Introduction

Process-planning for machining a component consists of macro and micro levels of decision-making. In macro process planning stage, a process planner decides the sequence of machining set-ups a component must undergo starting from the machining stock [1]. Cutting parameters are chosen and cutting tools are selected during the micro-level of process planning [2]. In industries, computer numerical control (CNC) machining is being increasingly chosen during the macro-level planning of components, to increase productivity and to machine complex geometries. Here, micro-level process planning is done in a computer aided manufacturing (CAM) software environment resulting in a path for the cutting tool to follow. A commercial CAM software offers various strategies for toolpath generation and its simulation module helps in verifying the expected quality after the machining. A process planner optimizes quality and machining time by choosing proper toolpath strategies and corresponding cutting parameters. The choice of toolpath strategies depends upon the geometry of the component and the type of CNC machine selected for those operations. The toolpath strategies available in a CAM software are based on the number of axes or degrees of freedom required or available to locate the tool with respect to the part on the machine.

Machining of complex surfaces, such as those encountered in a turbine blade are only possible with five-axis machines. Process planner selects suitable five-axis machining strategies for machining this type of components. Point milling and flank milling are the widely used five-axis machining strategies in which toolpaths are generated as segmented cutter location (CL) data [3]. Strategies such as non-uniform rational B-spline (NURBS) and B-Spline toolpaths are rarely used in industries [4]. With increasing emphasis on costs and sustainable manufacturing, the energy consumed in a machining process is gaining importance as a performance indicator for the machining process. This paper proposes an energy model for a five-axis machine that predicts energy consumption given the

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toolpath and the corresponding process parameters. This enables energy to be also considered as a decision-making parameter along with machining time and quality to arrive at optimal parameters and toolpath in the process planning stage itself.

2. Energy modeling for CNC machines

Energy consumed by a CNC machine during its operation is electrical energy and it is categorized under two types: constant and variable consumption [5]. Constant energy is consumed when the machine is idle which includes energy requirement of the controller unit and other accessories such as lighting unit, cooling fan etc. During machining, the energy consumption varies according to the process parameters for a fixed machining conditions such as workpiece material, cutting tool material, cutting tool parameters and toolpath strategy. This variable energy consumption is categorized into cutting and non-cutting motions. Non-cutting motions are the rapid feed movements for positioning the cutting tools in which energy consumption varies linearly with distance moved by each servo motors. Cutting parameters, which are decided during process planning, control the energy consumption during the cutting motions [6,7]. Physics-based energy models are not suitable for this sophisticated machining environment because of the complex relationship between these cutting parameters and the energy required or used. Empirical energy models, as an approximation to physics-based models, for energy prediction require large number of experiments [8]. Data-based energy models that use data on process parameters and the corresponding energy consumed, give better energy prediction results [9,10]. However, these models need data gathered in real-time from either sensors or the machine controller, during the machining operation. This precludes the use of these models to predict energy given only the data in the process plan. This is a critical requirement for the process planner in the quest to optimize energy consumption along with surface quality and time of machining by choosing suitable toolpath strategy and cutting parameters. Major cutting parameters that need to be specified in the process plan and that affect energy consumption are feed rate, spindle speed, depth of cut and width of cut. The problem in using the planned values of these parameters in any prediction model is that some of these parameters vary during the actual machining process. Such variations affect the accuracy of prediction of the energy model that uses only data available in the process plan.

The source of variation between the parameters prescribed in the plan and that prevalent during machining is the initial parameters set in the controllers to limit the acceleration and jerk (derivative of acceleration).These parameters affect the feed rate when the controller ramps up and then ramps down to achieve the desired feed rate in a segment of the tool path. This results in a variation in the feed rate achieved in the segment. This variation from the planned values causes deviation of machining time from the planned value during actual machining [11]. But, for a long toolpath segment, this variation is negligible because the average feed rate is quite close to the planned feed rate. This variation due to the controller parameters is therefore not predominant in the three-axis machining strategies where the toolpath segment is usually long enough to reach the planned feed rate while machining. A predictive energy model that uses only data available in the process plan in five axes machining may not be accurate because of this feed variation since the pattern of the actual feed fluctuation during machining is not captured in the energy model.

In this work an energy model that works in two stages, is proposed to accommodate the feed variation from the planned values. The model is built by analyzing data from the process plan and data collected in real-time during machining. The first stage is a feed prediction module developed for predicting average feed in each segment of block (NC block) of the tool path. In the second stage, energy prediction module is developed with the predicted feed rate and other cutting parameters. This energy model is compared with energy model which works only with the planning data and the results are discussed. Since there is a significant variation in the feed rate from the planned value, the time of machining is changed accordingly. Therefore, time prediction is also included as part of feed prediction module. The predicted energy can be used for process planning optimization with various decision-making parameters. The energy model developed is verified with another freeform surface and the results are compared.

3. Experiment on a five-axis contour machining

Five–axis machining of a freeform surface was conducted to study the variations of planned feed rate and for building the energy model using process planning and monitored energy data.

3.1. CAD geometry with a freeform surface

Free-form surfaces are usually a part of die, mold and sculpture geometries [12]. A free-form surface is generated by NX modeling software. It is made to be a part of a rectangular block for easy holding in the machining fixture. Fig. 1 shows the 3-D model of the generated free-form surface with block.

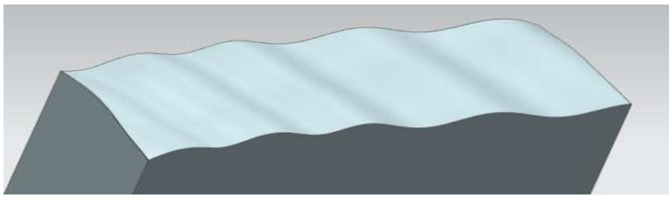

Fig. 1. CAD geometry with freeform surface.

3.2. Process planning and toolpath generation

Process planning for machining this freeform surface in a five-axis machine was done in NX CAM™ software. A five-axis machining strategy in which tool axis is always normal to the surface, was selected for final surface machining. Table 1 lists eight different combinations of machining parameters that were selected for the same toolpath strategy, using Taguchi level-2 design of experiments (DOE) method, suitable for the selected machining conditions.

The material stock and depth of cut for the final finishing was ensured by a roughing toolpath. The tool path for finish machining for each of the eight different combinations were generated using a post processor in the CAM module. Fig. 2 shows the strategy (tool axis always normal to surface) and the tool path obtained for one of the eight combination.

Table 1. Cutting parameters for five-axis toolpaths.

Toolpath number	Feed (mm/min)	Speed (rpm)	Depth of cut (mm)	Width of cut (mm)
01	1000	3000	0.5	1.0
02	1000	3000	1.0	2.0
03	1000	2000	0.5	2.0
04	1000	2000	1.0	1.0
05	600	3000	0.5	2.0
06	600	3000	1.0	1.0
07	600	2000	0.5	1.0
08	600	2000	1.0	2.0

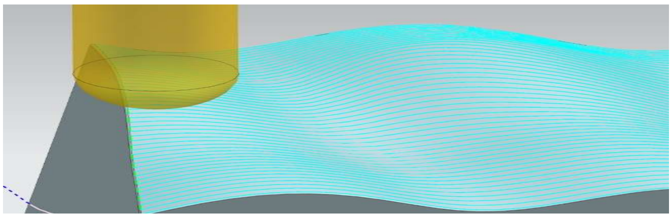

Fig. 2. Five-axis toolpath strategy (Tool axis normal to surface).

3.3. CNC machining

Toolpaths were executed on a five-axis and all the toolpaths were executed with the part fixtured in the same position as planned in the simulation module. This was to avoid any change in servo motor movement because of the change in location of the part [13]. Changes in the motor movement will result in changes in the energy consumption rendering the prediction model useless. Table 2 lists the hardware and software details of the machine and the machining conditions were used during the execution of toolpaths.

Table 2. Machining conditions & software and hardware details.

Condition/software/hardware	Specification/type
Machine make & model	Jyoti K2X8 Five
Controller make	Siemens 840 D sl
Five-axis functions used	Cycle 832, TRAORI
Workpiece material	Aluminum
Tool type	12 mm diameter ball end mill
Tool material	Coated carbide
Coolant supply	On

A separate set of experiments involving cutting in air were done to collect data for the feed prediction module. Table 3 lists with the five different feed rates used for collecting the data for feed prediction module. In this, the same five-axis toolpath was executed in the machine with different feed rates and, the actual feed rate data collected from the machine controller.

Table 3. Different feed rates used for feed prediction module (feed in mm/min).

Feed rate 1	Feed rate 2	Feed rate 3	Feed rate 4	Feed rate 5
1000	850	700	600	500

3.4. Monitoring and data collection

OPC UA™ standard is used for the data exchange between controller and human machine interface (HMI) [14]. The data is provided by an OPC server and consumed by an OPC client. OPC UA can be configured to directly collect data from the CNC machine controller [14]. An application can be developed over the HMI using OPC and the controller user can collect the data through that application [15]. In this experiment, the positions of the cutting tool, spindle speed, interpolation feed rate, and the power of each axis motors and spindle motor were collected from the data collection application of the controller by keeping a sampling period of 4 milli-seconds in both servo and IPO cycle.

4. Data analysis and energy modeling

The post-processor that generates the tool path, segments the overall path into segments of finite lengths referred to as cut-length or segment. The length of each segment depends upon the tolerance defined for the toolpath depending on the tolerances to be achieved. As tolerance decreases, the length of the toolpath segment also decreases in the point to point five-axis machining. The required tolerance is decided by the process planner according to the quality requirement of the component. For each segment the post-processor defines the target locations for each of the machine tool axes such that the desired tool position is achieved. This is referred to as NC block. Fig. 3 shows the NC blocks corresponding to five cut-lengths/segments.

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N390 X-78.39 Y53.901 Z-11.427 A-46.664 C-66.983
N400 X-79.52 Y53.931 Z-10.596 A-43.808 C-68.59
N410 X-80.705 Y53.962 Z-9.799 A-40.521 C-70.488
N420 X-81.936 Y53.994 Z-9.053 A-36.763 C-72.712
N430 X-83.13 Y54.026 Z-8.413 A-32.828 C-75.207
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Fig. 3. Sample of five-axis NC codes.

In Fig. 4, feed pattern of toolpaths (Toolpath set 1) with feed rate 1000 mm/min and toolpaths (Toolpath set 2) with feed rate 600 mm/min are shown. As mentioned earlier the feed rate accelerates at the start of the cut length or block to reach the target feed rate and decelerates at the end to zero. Therefore, when the feed rate data from the controller is analyzed it is observed that the feed rate is varying for different five-axis NC blocks and it is not same as the planned NC feed. This feed reduction from the planned value, leads to increase in execution time of five-axis NC code from the planned time. Planned time is the time calculated by the CAM software based on the length of the toolpath and the defined feed rate.

It is observed from the data that feed changes affects the power requirement of servo motors also. The power consumption decreases when interpolation feed decreases. This affects the energy consumption because of change in feed. In order to have a good predictive energy model, it is important to be able to first predict the actual feed in each NC block (given the planned feed) and then use the predicted feed in the prediction model of energy. The resulting model is therefore referred to as a two-stage energy prediction model. In the first stage average feed per NC block is predicted with length of cut in all the axes and planned feed. In the second stage, energy is predicted with length of cut in all axes, predicted average feed per block, spindle speed, depth of cut and width of cut. There are other possible cutting parameters which affects energy consumption such as up-milling and down-milling. These are not considered at present in this two-stage energy model.

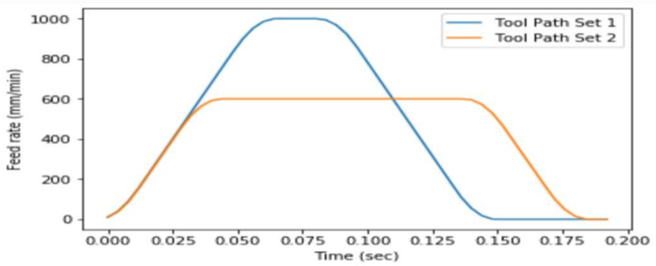

Fig. 4. Feed profile of five-axis NC codes.

Separate datasets are prepared for building feed prediction module and energy prediction module from the two different experimental data. Average feed of each NC block is calculated, and length of cut is calculated for each axis by taking the difference of values between the successive NC blocks. Total power in each sample is calculated by adding all the servo axis powers and spindle power. Energy consumed in the sampled period is calculated from power consumption and sampling rate. Total energy per NC block is calculated by adding the energy of all samples in that block. A total of 25954 datasets is used in the feed prediction module and a total of 31719 dataset is used for energy prediction module.

4.1. Deep Neural network

Deep learning methods are representation-learning methods which is suitable for advanced data analytics. It uses raw data to automatically discover representations at multiple levels, which the conventional machine-learning techniques lack. Since deep learning method is complex in nature; it is referred as black-box model [16].

Table 4. Deep neural network parameters.

Parameter	Value/Method
No: of Hidden layers	4
No: of units per hidden layer	{32,256,64,32}
Activation function	ReLU
Loss function	Mean Square error
Optimizer	Adam
Dropout	0.3
Batch size	20
Epoch	30

A fully connected deep neural network [17] is designed for building two-stage energy model in this work. The parameters for the fully connected deep neural network used for building feed prediction module and energy prediction module are shown in Table 4. Performance of the neural network used for the energy prediction module in the two-stage energy model, is set for the best value iteratively tuning its parameters. These tuned parameters are fixed for the energy prediction module for comparative study.

4.2. Energy Prediction from planned feed and other process parameters

The tuned energy prediction module is used in this paper for energy prediction. This energy model uses only process planning data as model inputs. The model input parameters for energy prediction and achieved accuracy in root mean square error (RMSE) are illustrated in Fig. 5.

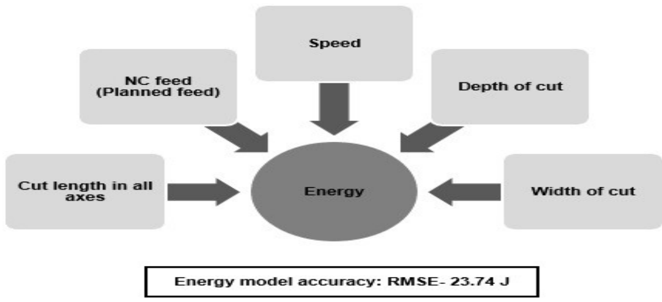

Fig. 5. Energy model from process planning data.

This direct energy model is suitable if there is only negligible variation from the planned cutting parameters, during actual machining. But for the five-axis machining, the accuracy of the direct energy prediction model is less because, even though feed variation is occurring during the actual machining, this model does not have any information about the actual feed rate that influences energy consumption.

4.3. Energy Prediction from monitored feed and other process parameters

This energy model uses the actual monitored feed values for the energy prediction. This model can give the best energy prediction results with the available parameters data since the measured feed is directly used for calculation. But this cannot be used for the process planning stage since this actual feed variation is not known. Fig. 6 illustrates the input parameters used for this energy prediction module and shows the accuracy achieved.

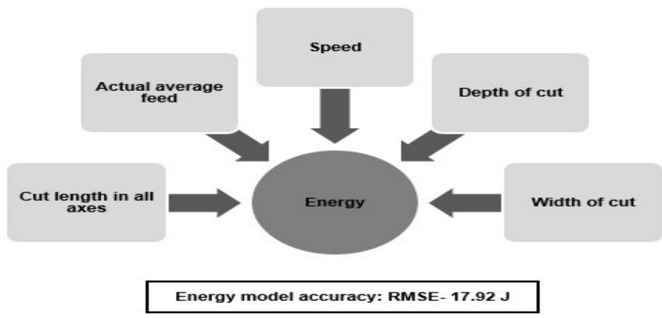

Fig. 6. Energy model from actual feed rate and other process planning data.

Result shows that accuracy of energy model with actual feed rate is better than the energy model with planned feed rate using the same model tuning parameters. If the actual feed rate is available for the energy models during the process planning, it makes better energy prediction results in five-axis machining. So, the proposed two-stage energy model aims for better prediction accuracy than the energy model with planned feed rate. The neural network's parameters are retained across the different models developed (with planned feed, measured feed and predicted feed respectively) so that the performance of the prediction can be compared across these models.

5. Two-stage energy modelling

In the two-stage energy model, two prediction modules are included. In the first module, feed rate is predicted for each NC block. In the second module, energy is predicted with predicted feed rate and other cutting parameters.

5.1. Average feed prediction module (First stage)

In this first stage of the proposed energy model, a feed prediction module is modelled using deep neural networks with planned feed and the length of cut in all five axes as inputs. This module predicts the average feed per block and the time of machining. The time required for machining is also predicted along with this module since factors affecting change in feed and machining time is same. Fig. 7 shows the input parameters and accuracy achieved for the feed prediction module and time prediction.

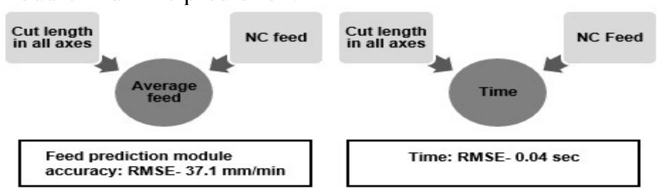

Fig. 7. Feed prediction module and time prediction from input parameters.

The predicted time and average feed per NC block, can be used by the planner to get feedback about the actual time of machining and the better selection of feed rates to reduce the feed fluctuation.

5.2. Energy Prediction from the predicted feed rate and other process parameters (Second stage)

In this stage, energy prediction module is modelled by the predicted average feed rate and other cutting parameters. The tuning parameters kept unchanged for this energy module. Result is illustrated in Fig. 8 and it shows that this two-stage energy model can predict the energy consumption better than the energy model with the planned feed rate since the two-stage energy model has the feed rate value which is nearer to the actual feed rate. The proposed two-stage energy model in the process planning system of five-axis machining is illustrated in Fig. 9. A kinematic transformation module is added to the proposed system to get actual motor movements even if the location of the part changes. This needs to be developed with the machine kinematics data. Since feed variation is predominant in five-axis tool path strategies, this proposed two-stage energy model can be used during process planning which provides feedback to the process planner about energy consumption of the selected five-axis machining strategy.

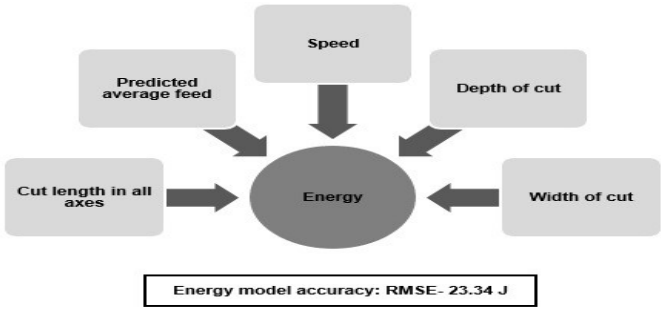

Fig. 8. Energy model combined with feed prediction module.

The machining time prediction of five-axis machining is another advantage of this two-stage energy model since there is a significant change in the actual machining time from the planned value.

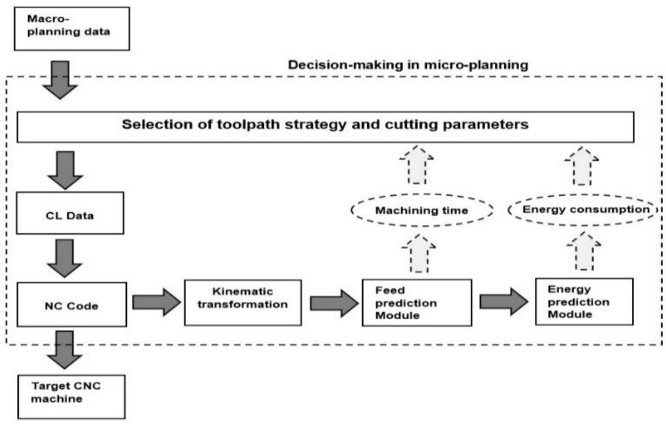

Fig. 9. Process planning with two-stage energy module in a five-axis toolpath.

6. Verification and prediction on a new freeform surface

The proposed two-stage energy model is verified on a different freeform surface. Fig. 10 (a) shows newly generated freeform surface and Fig. 10 (b) shows toolpath on this surface. The same five-axis machining strategy is generated for this new freeform surface machining with different cutting parameters by keeping the same machining conditions such as cutting tool, tool material and other machining parameters. The planning data and results are listed in Table 5.

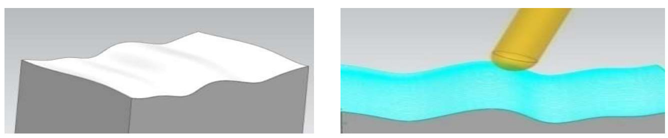

Fig. 10. (a) Freeform surface toolpath for verification; (b) Generated toolpath

Table 5. Cutting parameters and derived time from process planning.

Feed (mm/min)	Speed (rpm)	Depth of cut (mm)	Width of cut (mm)	Time (sec)
750	2500	0.75	1.5	296

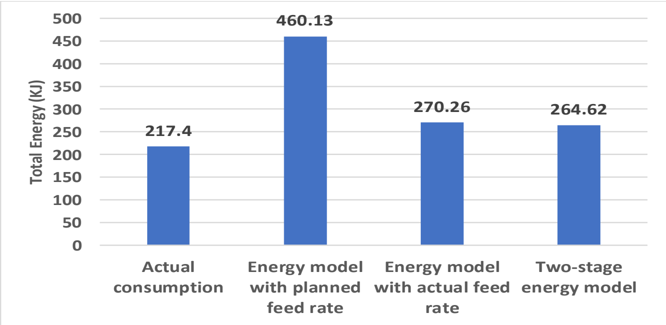

Fig. 11. Total energy comparison.

Table 6. Accuracy achieved with different energy models.

Energy Model with planned feed RMSE (J)	Energy Model with actual feed RMSE (J)	Two-stage energy model RMSE (J)
70.38	19.75	23.1

Fig. 11 compares total energy obtained by different prediction models and Table. 6 lists the accuracy of the different energy models obtained. The total energy is calculated by adding the energy consumed in individual NC blocks. The accuracy of the predicted values obtained in the different models shows that, in five-axis machining, because of change in feed rate from the planned value, the two-stage energy model can predict the energy consumption more accurately than the direct energy model with the planned feed rate. The final prediction results of the new freeform surface are plotted below. Machining time obtained from the prediction is compared with actual and planned time in Fig. 12.

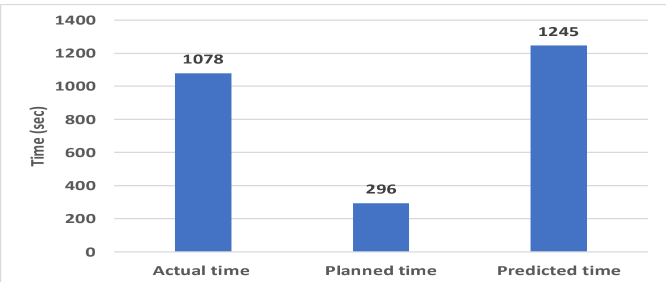

Fig. 12. Machining time comparison.

7. Conclusion

Energy models required for predicting the energy consumption during the process planning stage, use process planning data as input. Any significant variation from the planned data, which affects the energy, needs to be a part of the energy model. In this work, a two-stage energy model is proposed for the five-axis machining to accommodate the feed fluctuation from the planned value. The feed prediction module is modelled along with the energy prediction module and its accuracy is compared. Integration of this modules with the process planning system can provide instant feedback to the process planner about the time of machining and energy consumption thereby the decision-making objectives can be optimized iteratively by the process planner. The quality aspects such as surface finish and the tolerance for machining is not addressed in this work because it is considered that the process planner is optimizing these factors by choosing the proper cutting parameters and machining strategies. Since the cutting parameters which are chosen for modelling this two-stage energy model are incomplete cutting parameters list, there is a scope of improving this energy model by considering those parameters such as up-milling and down-milling. The experiment is conducted only for a certain fixed machining condition such as machine, material, cutting tool, machining strategy and coolant supply. This two-stage energy model can be made more generic by classifying these factors. In this energy model, deep neural network is selected for data-driven modelling. A comparative study with the other machine learning techniques are planned to be conducted in future work.

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