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An Experimental Study On Tool Wear Condition Monitoring Of CNC Milling Using Machine Learning Algorithms

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Due to the nonlinear nature of the cutting process, conventional regression models cannot provide reliable forecasts. In order to predict certain cutting parameters of CNC milling tool wear, this research presents a hybrid method that makes use of deep neural networks (DNN). We ran orthogonal cutting experiments and two-dimensional finite element model chip formation simulations over a range of cutting settings, tool geometries, and wear conditions to collect data for hybrid training. We used a DNN in conjunction with the tried-and-true linear regression technique to build our predictive models. The accuracy of the hybrid model that included machine learning methods was higher than that of traditional linear regression.

Keywords: *Regression, Machining, Wear, Optimization, Machine learning.*

1. Introduction

Machining process optimization and design relies heavily on accurate cutting force predictions. As a process signature, the thermal energy that is mostly transformed from mechanical energy that is generated by cutting forces is a critical factor in determining the surface integrity [1]. Cutting tools of CNC milling machine also have a direct correlation between mechanical loads and tool longevity. Both the geometry and surface roughness of the workpiece are impacted by the deformation and vibrations caused by these stresses. Thus, in order to optimize and refine cutting operations, it is crucial to precisely forecast cutting forces. Predicting cutting forces has been the subject of a great deal of research, with the Kienzle-force model among the most popular empirically-based regression models. Equation 1 shows that the particular forces and undeformed chip thickness are approximately exponentially related in this scenario.

$$F_c = K_c b h^{1-m_c} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (i)$$

To go deeper into this, König et al. [2] calculated the particular cutting forces Fc, K_c specific cutting force, b is the chip height (proportional to depth of cut), h is the chip width (proportional to feed rate) and m_c is a material constant. in turning processes involving various workpiece materials and tool geometries. Cutting speed and other process factors affect the cutting pressures, and extrapolation in the area of thin undeformed chips is not possible. It is time-consuming and expensive to develop such regression models from experimental data, particularly when trying to account for a broad variety of process circumstances. Analytical methods like shear plane theory and regression models have also been investigated. By supposing that deformation happens along a single shear plane, this theory enables the calculation of cutting forces using plasticity theory [3; 4]. Due to their oversimplification and idealized assumptions, analytical models have limited practical utility, despite their time benefit. Machine tool simulations have relied on numerical approaches, most notably the finite element method (FEM), for decades. The modelling of material and friction behaviors has been much improved by these approaches [5-8]. A number of variables, such as targeted cutting pressures, chip development, tool wear, and surface integrity, may be anticipated by finite element modelling of chip formation. Unfortunately, real-time analysis of cutting forces is not feasible with 3D FEM simulations because to their high computing requirements. Turning and milling CAD/CAM systems still can't handle 3D FEM simulations. An alternate, more efficient and economical method of forecasting individual cutting forces is a verified 2D FEM model. The intricacy of nonlinear cutting processes, which are affected by material characteristics, tool geometries, and cutting parameters, cannot be adequately managed by any of the existing experimental, analytical, or numerical approaches. Such complex challenges are beyond the capabilities of traditional regression methods. The use of data-driven models has been on the rise as a potential solution to these problems, particularly in the area of machining process prediction [9–11]. For example, Wu et al. [12] compared ANNs, SVR, and RF using experimental data to look at machine learning methods for milling tool wear prediction. Cutting forces, vibrations, and acoustic emission (AE) signals were all input variables. When pitted against ANNs and SVRs, RF proved to be the most accurate. Their research, however, failed to take tool geometries and other important cutting characteristics into consideration, and the artificial neural networks (ANNs) they used to have only one hidden layer, which is inadequate for complicated modelling. Predicting specific cutting energy from end milling experimental data is made possible by a strategy provided by Liu and Guo [13] that combines data-driven methods with process mechanics. Using a decision tree instead of more traditional artificial neural networks (ANNs) or support vector machines (SVRs), they conducted trials using a single end mill type and different cutting settings.

2. The idea behind the combined method and the machine learning plan

The CNC milling machine setup along with tool mounted is shown in in fig. 1. The hybrid method that makes use of ML algorithms is shown in Figure 2 as its architecture. This method tackles the problem of restricted data volume by integrating experimental and numerical data, which is the main novelty.

Fig. 1 CNC milling machine (a) New and worn tool (b) Magnetic mounting plate

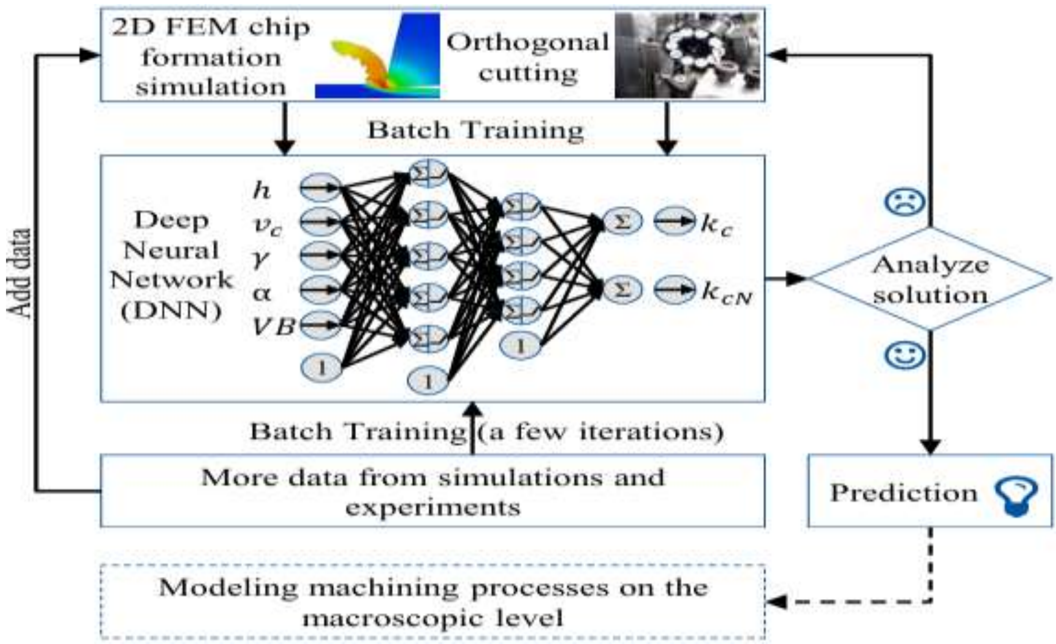

Fig. 2 Architecture of machine learning used in the current study

The ML model constantly gets updated as fresh data sets are made available since it uses a batch-supervised learning technique. A 2D finite element model and an orthogonal cutting test setup are used to calculate the specific cutting forces, kc and k_cN, which are affected by parameters of cutting, geometry of tool and its wear (V_B). To understand and anticipate these cutting forces, an Artificial Neural Network (ANN) more especially a Deep Neural Network

(DNN) with several hidden layers is developed. Through a series of rounds, the network in this research is able to autonomously adapt to new data sets, whether they derived from experiments or simulations, thanks to the batch learning technique. By following this procedure, you can be certain that the network is always reflecting the most recent data. To guarantee accuracy in forecasting the exact cutting forces. This trained ML model will be used in future work to do multiscale modelling on macroscopic-scale machining operations like milling and turning.

3. Experimentation

3.1. Inputs of experimental data

Here, we ran orthogonal cutting experiments on a workpiece made of Direct Aged 718 (DA718) also known as INCONEL alloy 718, is a nickel-chromium alloy that is used in many industries due to its high strength and resistance to corrosion and a cutting tool made of EMT 815 (WC-15Co). The measurements of the workpiece were 45 mm x 40 mm x 30 mm. Direct ageing heat treatment increases DA 718's tensile strength and resilience to cyclic fatigue [14, 15], but the chemical composition is identical to that of regular Inconel 718. A finer grain structure may have formed as a result of direct ageing, which might explain this improvement. In order to conduct the orthogonal cutting experiments, a vertical milling machine was used, as shown in Figure 2. The workpiece was held firmly in place using a specialized device. According to the findings, the dry cutting condition produced results that were either on par with or marginally better than the wet cutting condition. Nonetheless, the scope of the tool wear investigation went beyond VB, which is macroscopic. In the dry cutting condition, micro chipping was discovered by SEM examination. In order to feed the machine learning model, further tool life tests were carried out, as shown in Table 1.

Table 1. Cutting parameters

Cutting speed	10, 30
Undeformed thickness of chip	0.02, 0.05
Rake angle	-12, -6, 0, 5, 10
Clearance angle	3
Cutting edge radius	20, 35, sharp
Flank wear	0 - 200

By analyzing the relationship between undeformed chip thickness (h), cutting speed (Vc), and flank wear (V_B), which were evaluated using a Keyence optical microscope, these experiments helped calculate the cutting forces (F_c and F_cN). At the start, middle, and end of the tool's lifetime, Figure 3 illustrates the measured signals of flank wear (VB), Fc, and F_cN. A VHX-5000 digital microscope was used to validate the uniform distribution of flank wear, and SEM was used to analyse the tool wear processes, namely adhesion and abrasion.

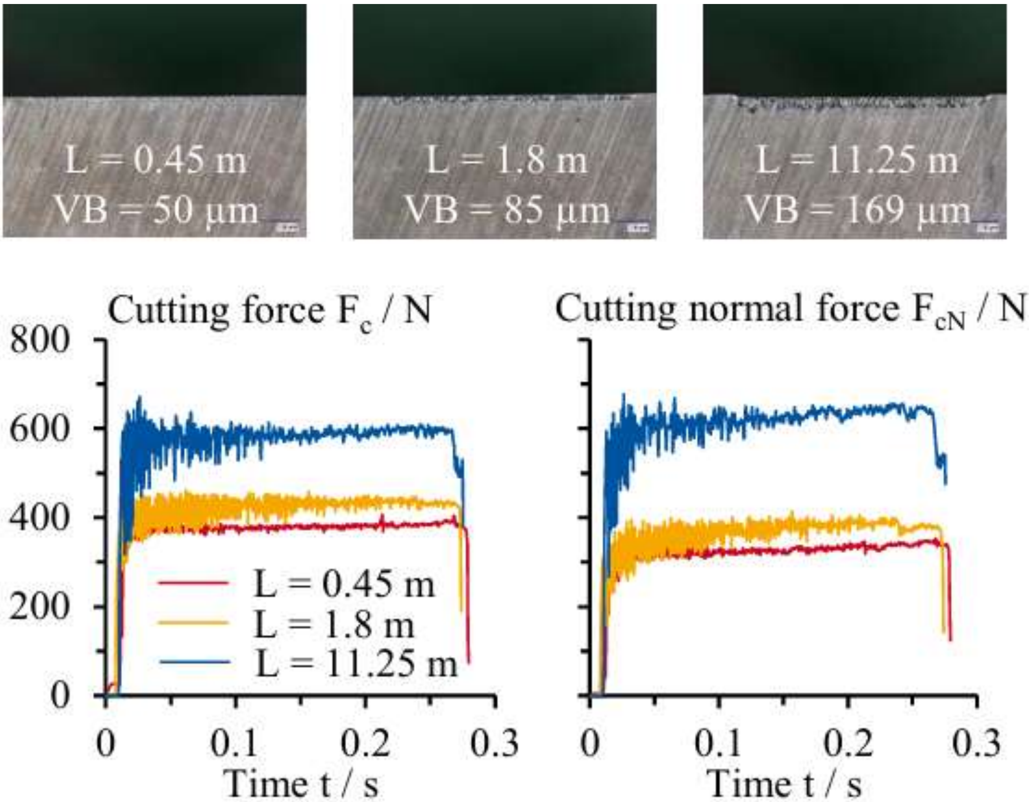

Fig. 3 Flank wear and corresponding cutting forces

The cutting forces, as expected, rose as flank wear (VB) increased because the worn surface was subjected to more mechanical strain. At steady state, the particular cutting forces kc and kcN were determined by plotting Fc and FcN against VB. Space limitations necessitate the publication of a separate work to address the in-depth analysis of the evolution of tool wear.

3.2. Numeric inputs

With a chip thickness of h = 0.02 mm and a cutting speed Vc = 10 m/min, Figure 4 shows the development of particular cutting forces and flank wear (VB) in relation to cutting length (L) under finishing circumstances.

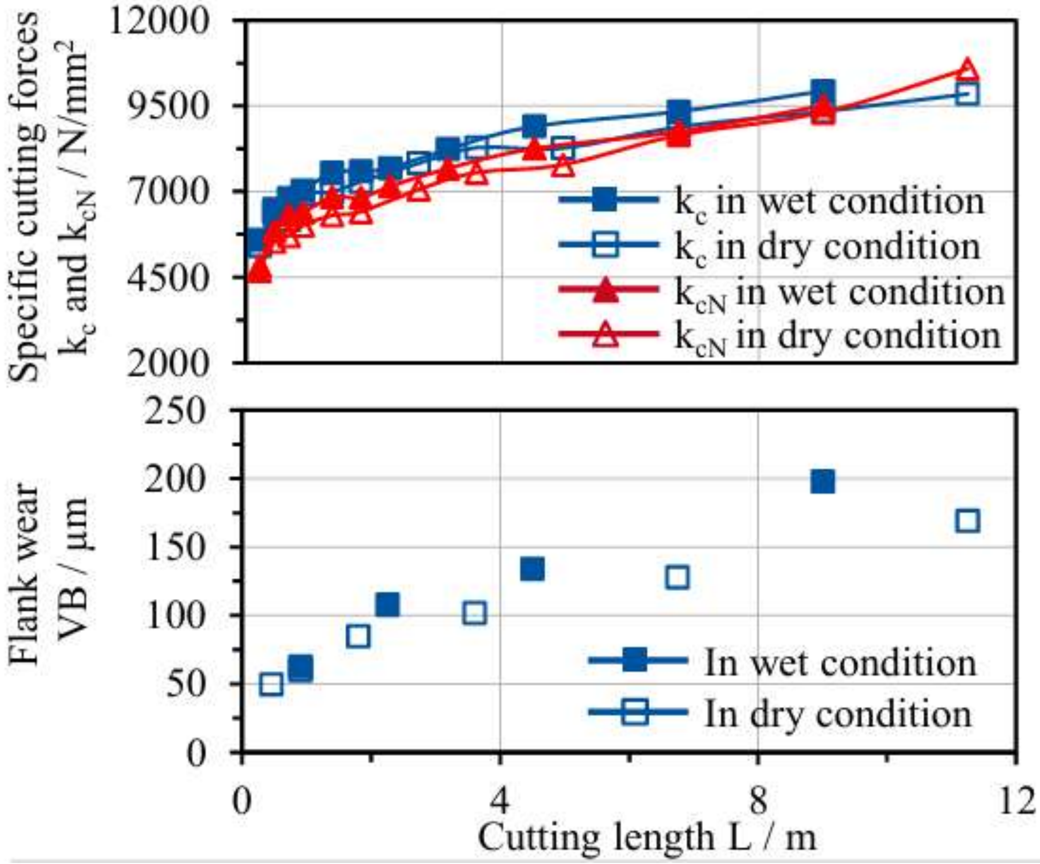

Fig. 4 Forces due to cutting action and corresponding wear

Specific cutting forces were proportional to VB. This work used a coupled Eulerian-Lagrangian (CEL) formulation in the finite element (FE) model, as shown in Figure 5, to improve the accuracy of chip formation simulations.

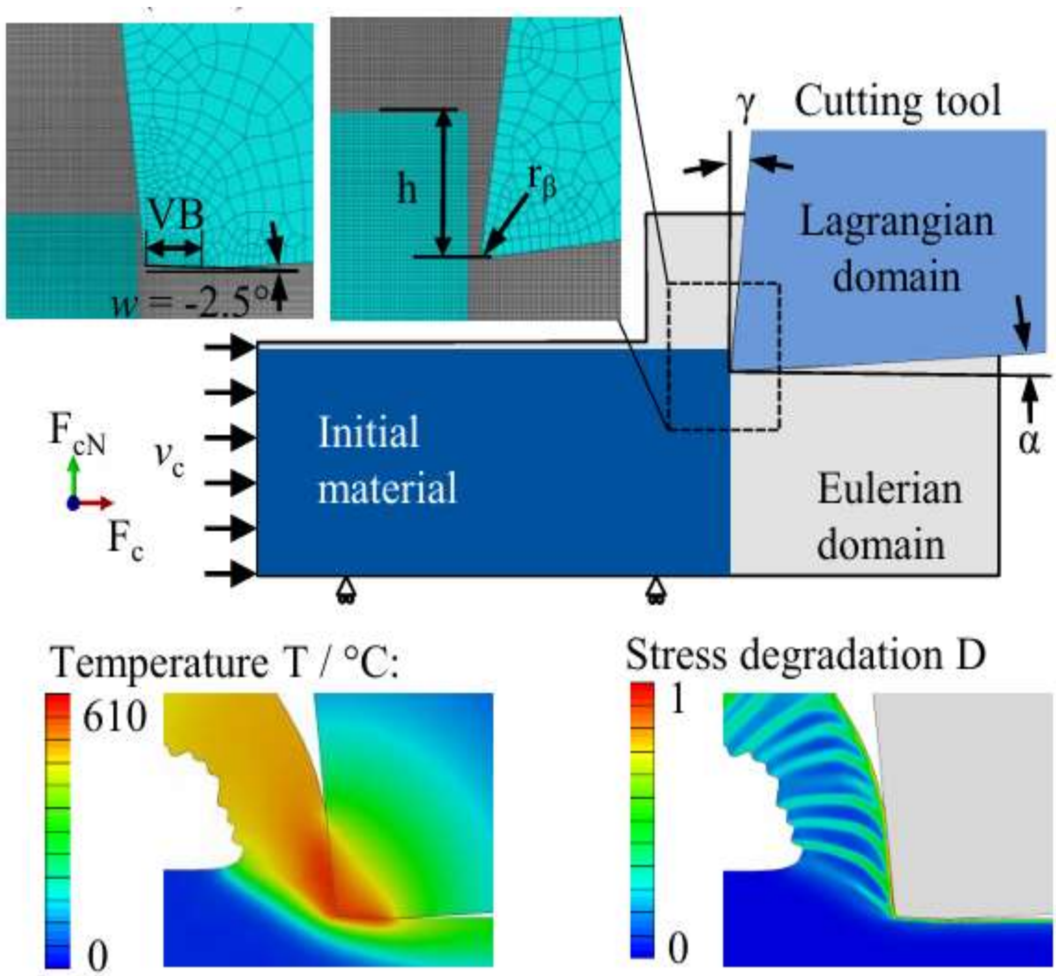

Fig. 5 Simulation of chip formation

This formulation varies from typical Lagrangian-based models. A workpiece mesh was created and maintained in the Eulerian domain. The material points were tracked as they flowed through the mesh using the volume-of-fluid approach, which was determined by their Eulerian volume fraction (EVF) inside each element. Accurate estimates of certain cutting forces in relation to tool wear were shown by the FE model.
With the help of ABAQUS/Explicit 6.14, the FE model was created. The use of the Eulerian element type EC3D8RT made thermo-mechanical analysis easier by allowing for the existence of numerous materials inside a single element. The specific shape of the cutting tool was defined by its rake angle (γ), clearance angle (α), and cutting-edge radius (rβ). The C3D8RT element type was used to model the cutting tool. In the Lagrangian formulation, it was considered a rigid body that behaved as an obstruction, forcing the workpiece to split into chips and the machined surface. The tool-chip interface was equipped with a friction model that depends on temperature, which allowed the Lagrangian and Eulerian components to

interact. The addition of flank wear to the FE model is also seen in Figure 5. A Keyence VK-X150 laser scanning microscope was used for 3D imaging and surface profiling in order to analyse the topography of the worn tool. The flank wear profile was determined using a MATLAB script. It is defined by the wear land width (VB) and a negative clearance angle (w). Other investigations have also shown that the cutting contact region experiences non-uniform wear, which led to the negative clearance angle, w = -2.5° [16]. Incorporating this negative clearance angle into the FE model was as simple as adjusting the tool geometry to guarantee a constant contact between the flank face of the tool and the machined workpiece.

4. Machine learning used for predictions

4.1. Deep Neural Network (DNN)

Designing intelligent devices influenced by the architecture of the brain led to the adoption of artificial neural networks (ANNs) [17] to control complicated nonlinear systems like the cutting process. To compensate for the network's mistakes, a variation of the training rules is used to train the perceptron. The model adjusts the connection weights from the inputs that should have contributed to the right prediction for each wrong output prediction. The stability and speed of the learning process are dictated by the learning rate (η). The production of serrated chips in DA 718 was mimicked using a damage model. Additional information on the material models, the friction model that is affected by temperature, and the finite element (FE) model validation may be found in earlier publications [8]. The effects of several cutting forces, as measured experimentally and in simulation, are compared in Figure 5.

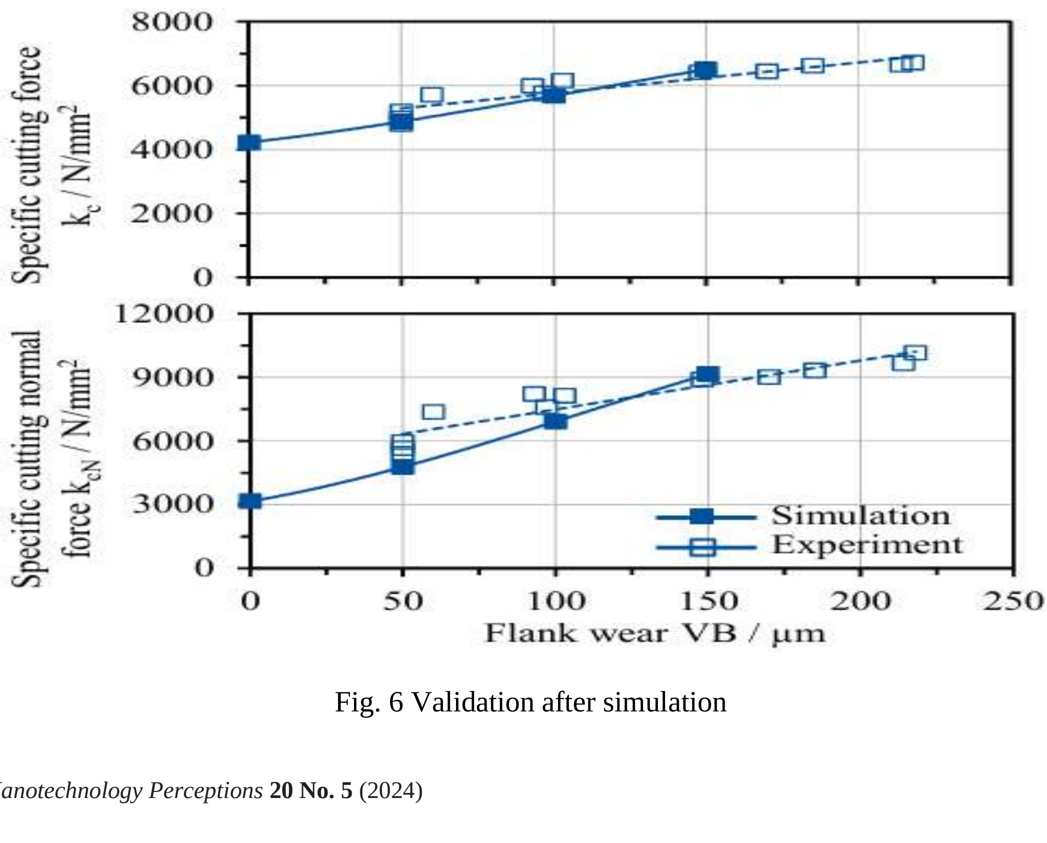

Fig. 6 Validation after simulation

To train the MLP, we used the backpropagation method, which assesses the output error and records the contribution of each hidden layer neurone to the final prediction error. Gradient Descent with reverse-mode is another name for this technique. This loop repeats itself until the network reaches the input layer, at which point the error gradient is propagated backwards. This work employed the Rectified Linear Unit (ReLU) activation function, with the exception of z=0, to guarantee correct error gradient propagation, which is especially important in nonlinear situations. The model was put into action using TensorFlow, a Google-developed framework for machine learning. When it comes to building and training neural networks, TensorFlow has you covered with both low-level and high-level Python APIs. Figure 7 shows the results of training a deep neural network (DNN) utilizing hybrid data sources; 15% of the total was set aside for assessment. The hidden layers of the network comprise 10, 8, and 6 neurons, respectively. A conventional scaler was used to pre-process the input data before to training. Ten thousand training iterations were applied to the model.

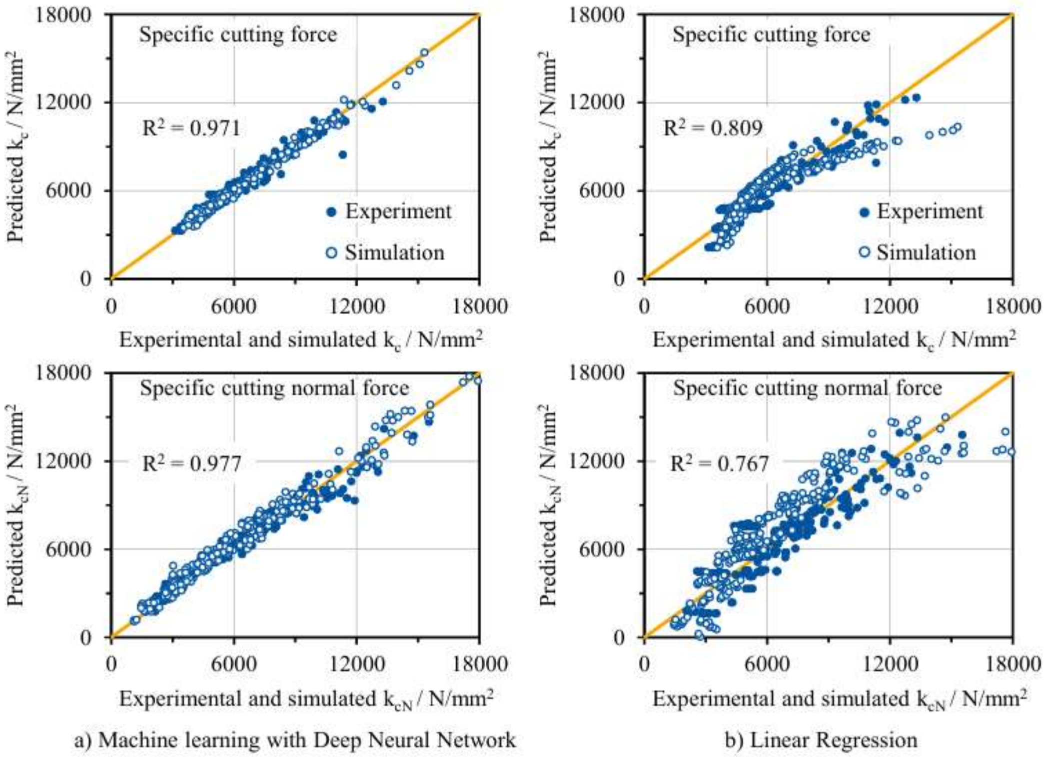

Fig. 7 Observed v/s predicted values

Figure 6 shows a comparison of predicted values from a traditional linear regression model with those from a DNN trained on hybrid data (540 data sets). Compared to the linear regression model, the DNN model has a far higher coefficient of determination (R^2) of 0.971 / 0.977, which means it is much more accurate in predicting particular cutting forces (R^2 = 0.809 / 0.767). When mechanical stresses were raised due to greater flank wear (VB), the ML model's prediction inaccuracy was shown to rise as well. At high wear levels, the tool's topography becomes unstable owing to chipping, and this impacts the simulation results. Learning rates and activation functions aren't the only hyperparameters that matter for prediction accuracy; other important ones include layer count, neurone count, weight initialization, scaling methods, mini-batch sizes, momentum, and training iterations. In what follows, we apply a sensitivity analysis to a subset of these hyperparameters in terms of RMSE.

4.2. Analysis for sensitivity of model

Using the Taguchi approach, we developed and evaluated the training program. Due to the random selection of the evaluation set, the ML model underwent three rounds of training. As a measure, we looked at the mean RMSE of the rescaled data. The ML model's convergence curve with regard to the RMSE of the scaled data is shown in Fig. 7.

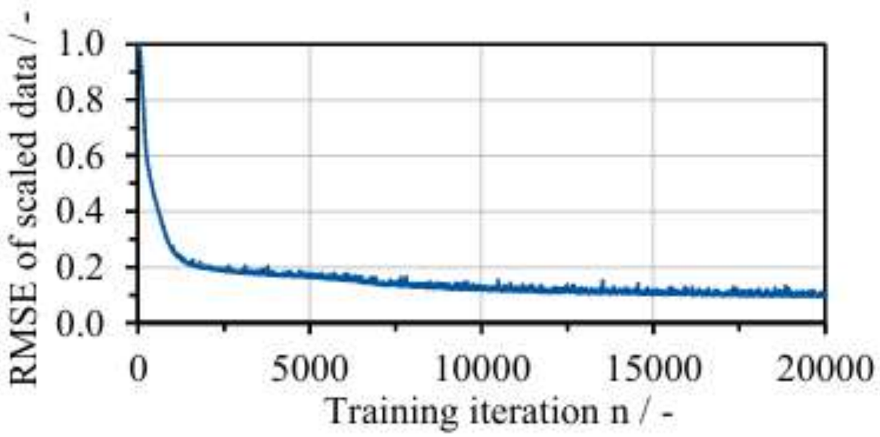

Fig. 8 Convergence of training data

The root-mean-squared error (RMSE) changed little between the 15,000 training cycles and the convergence. In addition, the ML model is being trained continually by executing additional FEM simulations.

5. Conclusion

The authors of this work provide a mixed method for predicting cutting forces in CNC milling tool that makes use of a supervised machine learning (ML) model. A deep neural network (DNN) was used in a batch system to allow for continuous training with fresh data sets. An amalgamation of orthogonal cutting trials and 2D FEM chip formation models resulted in hybrid data sources. This work provided important scientific contributions in the following areas:

- By a wide margin, the ML model outperformed the more conventional linear regression model in predicting individual cutting forces.

- A lot goes into the results produced by machine learning and DNN models; these are not just "black boxes"; the hyperparameters and model architecture that are chosen are critical.
- There was a lot of promise in the ML model for cutting process prediction. In addition to forecasting cutting forces in particular, the model may be used in the future to forecast mechanical load-based tool wear in machining operations.

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