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Amalgamation of Physics-Based Cutting Force Model and Machine Learning Approach for End Milling Operation

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Abstract

The application of data-driven or machine learning models is becoming imperative in recent times to analyze manufacturing process attributes. These models use input and output datasets to evolve the relationship similar to human perceptions. The development of a reliable data-driven model is challenging due to the necessity of conducting numerous experiments, the presence of outliers and noise in the datasets, process disturbances, etc. The data-driven models can be scaled easily by accommodating new variables and attributes to evolve progressively. Alternatively, physics-based models establish an explicit relationship between process variables and desirable attributes based on scientific knowledge and a set of assumptions, but its scalability is difficult. This paper presents the development of a hybrid cutting force model for end milling operation, combining both approaches to ensure that adequate process knowledge is captured. The outcomes of the proposed method are substantiated by performing a set of computational studies and end milling experiments.

Keywords: Machine Learning; Manufacturing; End Milling; Mechanistic force model; Cutting Constants;

1. Introduction

Cutting force is the primary source of multiple disturbances contributing to the deterioration of component accuracy significantly during metal removal operations. The prediction, monitoring, and control of cutting force are imperative to avoid or minimize faults such as tool breakage, tool wear, selection of cutting parameters, fixture errors, etc. The manufacturing industries are experiencing major transformations in recent times due to the evolution of Industry 4.0. The newer set of technological solutions necessitate real-time monitoring of manufacturing processes using sensors followed by data analytics to evaluate the status and adjustment of parameters. It will be necessary to have appropriate process knowledge embedded into the decision-making system for the adjustment of settings. As cutting force is linked with multiple process faults during metal removal operations, it is essential to have a reliable predictive model to assist in the decision making related to process faults. The present study attempts to develop a reliable process model for end milling operation which is commonly employed in most of the manufacturing industries to fabricate complex shapes in a variety of materials at higher accuracy and productivity.

The development of cutting force models for end milling is extensively studied and reported in the literature. The models can be categorized broadly in three groups; Mechanics-based analytical models, Artificial Intelligence (AI) based data-driven models, and Mechanistic models. The mechanics-based analytical models aim to correlate chip area and cutting force components through parameters such as shear angle, mean friction angle, chip flow angle, material properties, etc. [1, 2] whose realistic estimation is quite challenging. The data-driven models use machine learning techniques such as fuzzy logic[3] or Artificial Neural Networks[4, 5], to learn the relationship between process parameters and cutting forces. The implementation of data-driven models is restricted due to the requirement of a large number of datasets during the development stage. The Mechanistic model associates cutting force components with the uncut chip area using empirical constants. A set of experiments is conducted to establish an analytical relationship that assimilates the effect of tool and workpiece material properties, cutting geometry, etc. using non-linear curve fitting. The prediction accuracy of the Mechanistic model largely depends on the goodness of the relationship.

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The Mechanistic model was first introduced by correlating cutting forces with average chip thickness empirically [6]. The model was subsequently improved by Kline et al. [7] to estimate the variation of cutting forces with cutter rotation. The study used mechanistic constants as a function of average chip thickness, which lowered the prediction accuracy of the model at peak and valley positions [8]. The subsequent studies proposed the concept of instantaneous chip thickness and developed new relationship for the better prediction accuracy [9]. The significance of size effect was also highlighted on mechanistic constant at cutting condition with lower axial depth of cut, and the same was incorporated in the model with appropriate modifications [10]. The prediction accuracy of the model was improved further by the pre-processing of raw experimental data before the derivation of the relationship [11, 12]. Dang et al. [13] introduced the rubbing effect of the bottom cutting edge in the computational model using separate cutting constants [14]. The bottom edge cutting constants were extended further to estimate cutting forces during 5-axis milling [15] and micro-milling [16]. The application of a genetic algorithm is also explored while determining cutting constant relationship for end milling operation [17].

The determination of constant relationships during the development of the Mechanistic force model is quite complicated as it is entirely dependent on experimental force data, which is prone to uncertainties. The experimental data contains significant noise and outliers due to the process dynamics and characteristics of measuring instruments. The presence of such elements yield poorly fitted constant relationship and lower prediction accuracy of the model. The data-driven approaches can handle such uncertainty effectively while learning the relationship between input-output parameters similar to human perceptions. The present study aims to develop a hybrid cutting force model that can effectively deal with uncertainties involved in the determination of constant relationships by employing a machine learning-based approach. The study uses the conventional Mechanistic force model to predict deterministic parameters such as instantaneous cutting constants and cut geometry. The outcomes of the proposed model are substantiated further by conducting end milling experiments over a wide range of cutting conditions and its comparison with models existing in the literature.

2. Mechanistic Force Model

The Mechanistic force model divides end mill along the axial direction into number of disk elements (n) having equal thickness (dz). The engagement state of individual cutting disk (j) for each cutting flute (k) is evaluated at a given cutter rotation angle (ϕ_i) to estimate cutting forces. The tangential ($F_T(i, j, k)$), radial ($F_R(i, j, k)$) and axial ($F_A(i, j, k)$) cutting force components for each disk element are correlated with the uncut chip thickness $t_c(i, j, k)$ using cutting constant relationship expressed as Eq. 1.

In Eq. 1, $t_c(i, j, k)$ and $\beta(i, j, k)$ represent instantaneous uncut chip thickness and angular position of j^{th} disk element and k^{th} flute at a cutter rotation angle ϕ_i. The instantaneous uncut chip thickness $t_c(i, j, k)$ is defined as the shortest distance between two consecutive tooth passes at $\beta(i, j, k)$ which can be expressed geometrically using Eq. 2 as a function of feed per tooth (f_{pt}). The angular position $\beta(i, j, k)$ can be determined using Eq. 3, where ϕ_p, θ_h, R_c represents pitch angle, helix angle and radius of the cutter respectively. Fig. 1 shows the schematic diagram of flat end milling operation and depicts various parameters used during modeling of cutting forces.

$$\begin{bmatrix} F_T(i,j,k) \\ F_R(i,j,k) \\ F_A(i,j,k) \end{bmatrix} = dz\ t_c(i,j,k) \begin{bmatrix} K_T(i,j,k) \\ K_R(i,j,k) \\ K_A(i,j,k) \end{bmatrix} \tag{1}$$

$$t_c(i,j,k) = f_{pt}\ sin\ \beta(i,j,k) \tag{2}$$

$$\beta(i,j,k) = \phi_i + (k-1)\ \phi_p + \left((j-1)\ dz + \frac{dz}{2}\right) \frac{tan\ (\theta_h)}{R_c} \tag{3}$$

The elemental Feed $F_F(i, j, k)$, Normal $F_N(i, j, k)$ and Axial $F_A(i, j, k)$ forces for each engaged disk element (j) and cutting flute (k) at cutter rotation angle (ϕ_i) can be obtained by resolving elemental components using 3-D transformations as Eq. 4. The total cutting force at a given cutter rotation (ϕ_i) can be determined by integrating forces acting on each engaged disk element and cutting flute as Eq. 5.

$$\begin{bmatrix} F_F(i,j,k) \\ F_N(i,j,k) \\ F_A(i,j,k) \end{bmatrix} = dz\ t_c(i,j,k) \begin{bmatrix} cos\ \beta(i,j,k) & -sin\ \beta(i,j,k) & 0 \\ sin\ \beta(i,j,k) & cos\ \beta(i,j,k) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} F_T(i,j,k) \\ F_R(i,j,k) \\ F_A(i,j,k) \end{bmatrix} \tag{4}$$

$$\begin{gathered} \begin{bmatrix} F_F(\phi_i) \\ F_N(\phi_i) \\ F_A(\phi_i) \end{bmatrix} = \sum_{j,k} dz\ T^1_{i,j,k} \begin{bmatrix} K_T(i,j,k) \\ K_R(i,j,k) \\ K_A(i,j,k) \end{bmatrix} \\ T^1_{i,j,k} = \begin{bmatrix} cos\ \beta(i,j,k)\ t_c(i,j,k) & -sin\ \beta(i,j,k)\ t_c(i,j,k) & 0 \\ sin\ \beta(i,j,k)\ t_c(i,j,k) & cos\ \beta(i,j,k)\ t_c(i,j,k) & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{gathered} \tag{5}$$

The magnitude of axial force component (F_A) is negligible during flat end milling in comparison to Feed (F_F) and Normal (F_N) components and it is not considered subsequently in the study. Eq. 6 represents a system with two force components relevant to flat end milling.

$$\begin{gathered} \begin{bmatrix} F_F(\phi_i) \\ F_N(\phi_i) \end{bmatrix} = \sum_{j,k} dz\ T^2_{i,j,k} \begin{bmatrix} K_T(i,j,k) \\ K_R(i,j,k) \end{bmatrix} \\ T^2_{i,j,k} = \begin{bmatrix} cos\ \beta(i,j,k)\ t_c(i,j,k) & -sin\ \beta(i,j,k)\ t_c(i,j,k) \\ sin\ \beta(i,j,k)\ t_c(i,j,k) & cos\ \beta(i,j,k)\ t_c(i,j,k) \end{bmatrix} \end{gathered} \tag{6}$$

The terms $K_q(i, j, k)$ ($q = T, R$), in Eq. 1 & 6 are termed as Mechanistic constants which correlates instantaneous uncut chip thickness with force components. The constant relationship is determined by performing end milling experiments under the specific conditions for a given combination of tool and workpiece material. The process of determining the relationship between cutting constants and instantaneous uncut chip thickness is summarized in the subsequent subsection.

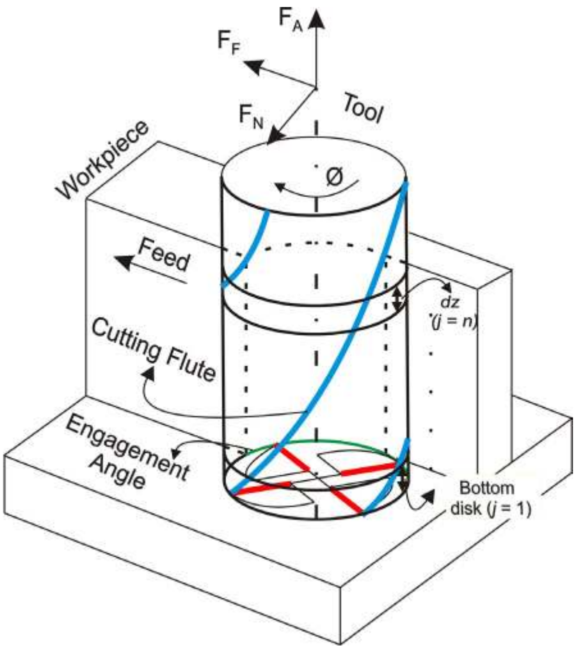

Fig. 1. Schematic of End Milling Process

3. Calibration of Cutting Constant

It is reported in the literature that the prediction accuracy of the Mechanistic force model is greatly dependent on the constant relationship. The relationship captures the various process attributes such as shearing and ploughing phenomenon, tool-workpiece material properties, cut geometry parameters (radial and axial immersions), etc. Therefore, the determination of constant relationships is considered a critical step in the cutting force model development. This section presents the machine learning-based approach viz. Artificial Neural Network (ANN) to establish the relationship between instantaneous uncut chip thickness and constants. A summary of an existing analytical approach adopted from the literature is also presented for continuity and comparative assessment. The fundamental difference among the approaches is the process of establishing the relationship between the cutting constant and chip thickness.

3.1. Analytical Approach

Wan et al. [11] proposed an analytical approach to predict cutting constants by correlating it with instantaneous uncut chip thickness. The approach determines non-linear relationships between instantaneous cutting constants $K_q(i, j, k)$ $(q = T, R)$ and uncut chip thickness $t_c(i, j, k)$ using curve fitting technique. The systematic procedure to determine cutting constant relationship is summarized in Fig. 2 and explained below:

1. The cutting force components are recorded as a function of cutter rotation angle $F_s^m(\phi_i)$ $(s = F, N)$ by performing end milling experiments. The cutting force components are substituted in Eq. 7 to determine constant values $K_q(\phi_i)$ $(q = T, R)$ as a function of uncut chip thickness for one revolution of the cutter.

$$\begin{bmatrix} F_F^m(\phi_i) \\ F_N^m(\phi_i) \end{bmatrix} = dz\ T_i^3 \begin{bmatrix} K_T(\phi_i) \\ K_R(\phi_i) \end{bmatrix} \tag{7}$$

$$T_i^3 = \begin{bmatrix} \sum_{j,k} cos\beta(i, j, k)\ t_c(i, j, k) & -\sum_{j,k} sin\beta(i, j, k)\ t_c(i, j, k) \\ \sum_{j,k} sin\beta(i, j, k)\ t_c(i, j, k) & \sum_{j,k} cos\beta(i, j, k)\ t_c(i, j, k) \end{bmatrix}$$

2. As elemental cutting force components $F_s^m(i, j, k)$ $(s = F, N)$ cannot be measured, the constants $K_q(\phi_i)$ $(q = T, R)$ obtained as a function of cutter rotation angle (ϕ_i). It necessitates simplification of instantaneous uncut chip thickness $t_c(i, j, k)$ to the average chip thickness $t_{avg}(\phi_i)$ at corresponding cutter rotation angle (ϕ_i) using Eq. 8-9.

$$t_{avg}(\phi_i) = \frac{\sum_{j,k} t_c(i, j, k)\ \ w(i, j, k)}{\sum_{j,k}\ w(i, j, k)} \tag{8}$$

$$w(i, j, k) = \frac{j\ dz\ tan\ (\theta_h)}{R_c} \tag{9}$$

3. The non-linear relationship between cutting constants $K_q(\phi_i)$ $(q = T, R)$ and average chip thickness $t_{avg}(\phi_i)$ is derived subsequently using curve fitting technique (Eq. 10).

$$K_q(\phi_i) = a_q\ e^{-b_q\ t_{avg}\phi_i} + c_q \qquad (q = T, R) \tag{10}$$

4. The terms $K_q(\phi_i)$ $(q = T, R)$ and $t_{avg}(\phi_i)$ are replaced with $K_q(i, j, k)$ $(q = T, R)$ and $t_c(i, j, k)$ respectively in Eq. 10 to obtain the necessary relationship (Eq. 11) which is used subsequently to predict cutting force $F_s^m(\phi_i)$ $(s = F, N)$ using Eq. 6.

$$K_q(i, j, k) = a_q\ e^{-b_q\ t_c(i,j,k)} + c_q \qquad (q = T, R) \tag{11}$$

The reliability of the relationship obtained using the approach, as mentioned above, is completely dependant on the data points used and fitness of the curve. The data points are prone to have many uncertainties and noise as these are extracted from machining experiments. These limitations result in improperly fitted relationships and reduced prediction accuracy of the Mechanistic force model.

3.2. Machine Learning Approach

This section presents a data-driven approach employing ANNs in establishing the non-linear relationship between cutting constants and instantaneous uncut chip thickness. The approach to evaluate cutting constants $K_q(\phi_i)$ $(q = T, R)$ and average chip thickness $t_{avg}(\phi_i)$ values at each cutter rotation angle (ϕ_i) is identical to the previous approach discussed in Section 3.1. The determination of a non-linear relationship using curve fitting is replaced with the supervised ANN to learn the

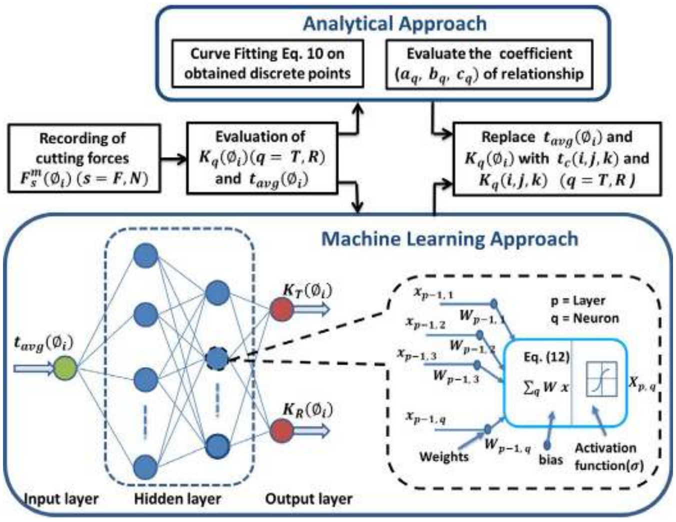

Fig. 2. Calibration of Cutting Constant

relationship similar to the human brain. The supervised ANN model uses known combinations of $t_{avg}(\phi_i)$ (as an input) and $K_q(\phi_i)$ ($q = T, R$) (as outputs) to learn the relationship using an architecture depicted in Fig 2. The ANN is a computational model of a human brain that acquires knowledge of performing a certain task by learning through examples instead of being programmed. The ANN consists of processing constituents termed as neurons, which develops a regulated network by identifying casual relationships among input and output. The neurons are organized in well-structured layers such as an input layer, one or a few hidden layers and an output layer. The present work necessitates an input layer consisting of a single neuron representing $t_{avg}(\phi_i)$ and the output layer comprising of two neurons representing $K_q(\phi_i)$ ($q = T, R$).

This study uses a multi-layer feed-forward ANN, which transfers the information through a network of interconnected neurons from the input layer to the output layer via hidden layers. The output value of a neuron ($x_{p,q}$) for layer (p) is determined by weighted sum of neurons corresponding to the previous layer ($p-1$) as Eq. 12. The term σ represents the activation function, which transforms linear input to the non-linear output value. The hyperbolic tangent (*tanh*) function is employed in the present study to normalize output value between $[-1, 1]$. The hyperbolic tangent activation function is advantageous as it provides the convenience of mapping model inputs to strongly negative and positive values. The term bias is added to improve the flexibility of ANN by varying the intercept of the regression line. The number of hidden layers and neurons in each hidden layer is determined iteratively based on the performance of the ANN. The satisfactory performance of the network was observed with a network having two hidden layers having 20 and 10 neurons, respectively.

$$x_{p,q} = \sigma \sum_q W_{p-1,q}\, x_{p-1,q} + bias \tag{12}$$

The training of ANN is accomplished using the Levenberg-Backpropagation algorithm in combination with Bayesian regularization [18]. This algorithm is ideal for regression problems as in the present study owing to its efficiency and ability to optimize weight distribution for avoiding overfitting of the network [19]. The training was initiated using random weights ($W_{p,q}$) associated with each neuron. The input data is fed to the network to predict output data (y) and compared subsequently with the actual value of target output (t). The square of the difference between predicted (y) and target output (t) value termed as an error (E) is backpropagated through the network to alter the weights of the neurons using Eq. 13-14. Here, α is the learning rate that regulates the step size of the gradient for the subsequent iteration. The backpropagation process is reiterated until the maximum number of iterations (n) was reached.

$$E = \sum_{i=1}^{k} (t_i - y_i)^2 \qquad k = Number\ of\ datasets \tag{13}$$

$$W_{p,q}^{n+1} = W_{p,q}^{n} + \alpha \frac{\partial E}{\partial W_{p,q}} \tag{14}$$

The ANN model is validated using testing datasets after completing the training without providing the output vector. If the estimation with output dataset is satisfactory, the developed ANN model can be applied to prediction of instantaneous cutting constants $K_q(i, j, k)$ ($q = T, R$) corresponding to input values of instantaneous uncut chip thickness $t_c(i, j, k)$. The values of $t_c(i, j, k)$ computed from analytical model can be substituted in ANN now to predict cutting forces $F_s^m(\phi_i)$ ($s = F, N$). Fig. 2 summarizes the overall procedure of estimating constants and cutting forces using both approaches.

4. Computational and Experimental Results

The Mechanistic model outlined in Section 2 is implemented in the form of a computational program using MATLAB® [20] to predict cutting forces during the end milling operation. The cutting constants relationship is determined using both approaches outlined in Section 3. A set of machining experiments is conducted at different cutting conditions summarized in Table 1 for establishing constant relationships and examining the effectiveness of the proposed approach. Test 1 is used to establish cutting constant relationships while other tests are used to examine the efficacy of the proposed approach in predicting cutting forces. A 3-axis CNC vertical milling machine and piezoelectric table dynamometer (Kistler 9257B) are used for conducting machining experiments and recording of cutting forces, respectively. The experiments are conducted using Aluminium 6061-T6 workpiece material, whereas a solid carbide end mill with short overhang is used to minimize the effect of tool deflections.

4.1. Determination of Cutting Constants

The analytical approach summarized in Section 3.1 uses the curve fitting technique to determine the non-linear relation-

Table 1. Machining Conditions

Test No.	RDOC (mm)	ADOC (mm)	Feed (mm/min)
1	6	0.8	400
2	2	2	300
3	4	6	300
4	6	10	300
5	4	2	400

Workpiece	:	Aluminium 6061-T6
Tool	:	Solid Carbide (Kennametal - 4CH1600DK022A)
Spindle Speed	:	2000 RPM
Cutter Diameter	:	16 mm
No. of Flutes	:	4
Helix Angle	:	30°

ship between cutting constant and instantaneous chip thickness expressed using Eq. 11. The measured cutting force data for one revolution of the cutter is recorded as a function of cutter rotation angle (ϕ_i) using cutting conditions corresponding to test 1 (Table 1). Subsequently, $K_q(\phi_i)$ $(q = T, R)$ and $t_{avg}(\phi_i)$ are evaluated using Eq.7 and 8 at each ϕ_i and mathematical expression stated in Eq. 10 is derived to extract coefficients (a_q, b_q, c_q) $(q = T, R)$. Figure 3 depicts the fitted curve along with the values of coefficients.

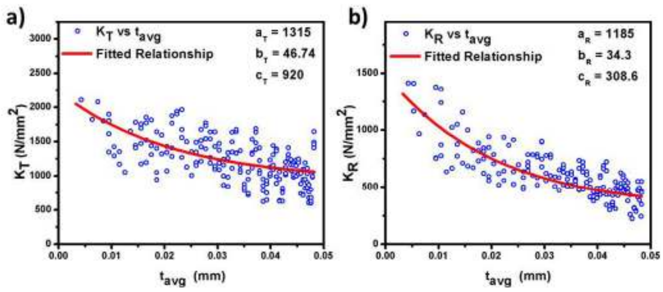

Fig. 3. Cutting Constant (Analytical Approach)

The machine learning toolbox of MATLAB® [20] has been used to develop the ANN model outlined in Section 3.2 for determining cutting constant relationships. The ANN requires a large number of datasets for effective extracting of the relationship between input and output. The cutting forces were recorded at a higher frequency of 3600 readings per revolution for cutting conditions corresponding to Test 1. The forces associated with one flute of the cutter (900 readings) are used to determine $K_q(\phi_i)$ $(q = T, R)$ and $t_{avg}(\phi_i)$ using Eq. 7 and 8 respectively. The flute is partially engaged in the cut during test 1 which yielded about 786 discrete combinations of $K_q(\phi_i)$ $(q = T, R)$ and $t_{avg}(\phi_i)$ for the training. The dataset obtained was normalized between [0, 1] using the Max-Min method and rearranged randomly before dividing into training (70%) and testing (30%) datasets. The datasets were presented to the ANN model using topology summarized in Section 3.2. Figure 4 shows the performance and regression plots obtained for the ANN model developed in the present study.

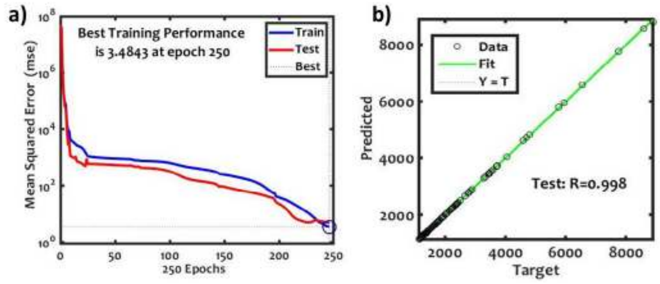

Fig. 4. ANN Model: (a) Performance Plot; (b) Regression Plot

4.2. Experimental Verification

The effectiveness of the proposed machine learning-based approach in establishing the relationship of cutting constants with instantaneous uncut chip thickness is examined by conducting end milling experiments over a wide range of cutting conditions (Radial Depth of Cut (*RDOC*), Axial Depth of Cut (*ADOC*), Feed rate) summarized in Table 1 (test 2 to 5). The cutting forces estimated using constant relationships estimated using both approaches outlined in Section 3 are compared subsequently with experimentally measured values obtained using a dynamometer (Kistler 9257B).

Figure 5 shows the comparative assessment of cutting forces predicted using both approaches with experimentally measured signals corresponding to cutting conditions presented in tests 2-4 (table 1). These tests aim to assess the prediction accuracy of both approaches with the variation of cutting widths (*RDOC* and *ADOC*) while maintaining feed rate constant. The subsequent experiment corresponding to test 5 (Table 1) aims to investigate the effect of feed rate variation on the prediction accuracy of the model. Figure 6 depicts the comparison of predicted and measured cutting forces at a higher value of the feed rate in comparison to other cases. It can be seen that the ANN approach predicts the profile and magnitude of cutting forces accurately in comparison to the analytical approach for all cases. The lower prediction accuracy of the analytical approach can be attributed to the poor approximation of relationship by curve fitting technique owing to the presence of outliers and noise in the experimental data. Based on the outcomes, it can be concluded that the machine learning-based model realizes the relationship between uncut chip thickness and cutting constant better in comparison to the analytical approach, thereby enhancing the prediction accuracy of the Mechanistic force model. However, it is observed that the normal component (F_N) of the cutting force is predicted consistently higher which needs further investigation and analysis.

5. Conclusions

This paper presented a hybrid model that aims to combine the merits of physics-based Mechanistic models and machine learning-based data-driven models in estimating cutting forces during the end milling operation. The proposed models are implemented in the form of computational programs and series

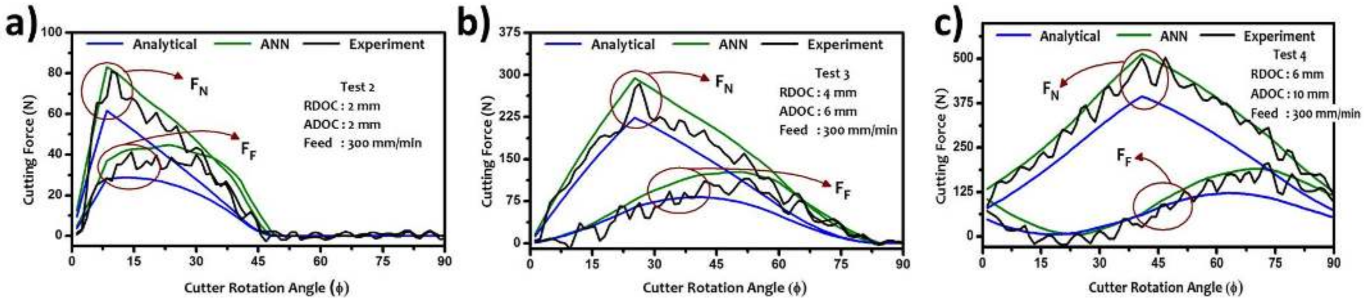

Fig. 5. Comparison of Measured and Predicted Forces: (a) Test No. 2; (b) Test No. 3; (c) Test No. 4

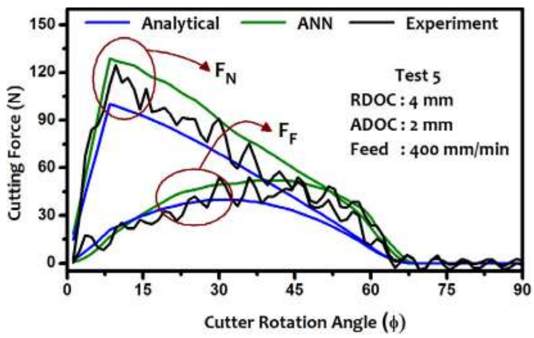

Fig. 6. Comparison of Measured and Predicted Forces (Test No.5)

of end milling experiments are performed over a wide range of cutting conditions. Based on the outcomes of the present study, it has been realized that the hybrid model presented in this study can predict the instantaneous cutting forces variation accurately. The machine learning-based model predicts the consistently higher value of cutting force in normal direction, which necessitates further investigations for improvement in the model. The model presented in this paper can be improved further by replacing the learning approach or varying ANN parameters. The present work uses shallow networks and the application of modern networks such as Recurrent Neural Networks (RNN) or reinforcement learning can be applied for better realization of the relationship.

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