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Material removal rate prediction with force signals and machine learning in magnetically driven internal finishing

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Abstract
Magnetically driven internal finishing (MDIF) is a novel internal polishing technique that employs an external magnet to drive a magnetic polishing tool to achieve material removal (MR) in internal surfaces. It has localised finishing and corrective polishing abilities. Modelling the material removal rate (MRR) can provide better control of the polishing process. However, the complex interaction between the polishing tool and the workpiece in MDIF results in oscillating polishing forces which are significantly different from conventional polishing processes. This makes the bottom-to-up physical modelling of MRR very challenging. Herein, we developed a novel broad echo state learning system (BESLS) to predict MRR in MDIF based on the polishing force under various polishing conditions. The MRR is represented by the removal depth of the polishing footprint. The results show that the BESLS model can achieve a predicting error as low as 7.5%. The proposed method will boost the in-process control to achieve uniform removal in MDIF and may also be further applied to other polishing processes.

Keywords: Material removal rate; magnetically driven internal finishing; data-driven modelling; polishing force

1. Introduction

Magnetically driven internal finishing (MDIF) is a novel internal polishing method that utilizes an external rotating magnet to drive a magnetic tool inside the workpiece to achieve material removal and surface finish improvement [1, 2]. Owing to its high flexibility and efficiency, MDIF may be applied for finishing various internal surfaces such as conformal cooling channels, bearing rings and sanitary pipes. Modelling of the material removal rate (MRR) in MDIF is important for process monitoring and control. Zhang et al. [3] proposed an analytical model of material removal rate considering the intermittent sliding wear mechanism. This physics-based model is validated to have a predicting error of 10% for MRR. However, this model is not suitable for online process monitoring.

Recently, data-driven modelling methods have been attracting enormous attention in manufacturing fields. However, the existing machine learning (ML) methods for MRR modelling usually need a large number of data sets and a long computation time. Besides, no literature is found to apply ML approaches in MRR modelling of MDIF.

Herein, we proposed a broad echo state learning system (BESLS) for predicting MRR in MDIF based on polishing forces. The methodology of the data-driven model will be introduced in Section 2 and the model will be validated by an MDIF experiment in Section 3. The results will be summarized in Section 4 followed by a concluding remark.

2. Methodology

To capture the dynamic characteristics of the complex MDIF process, a novel BESLS architecture is proposed. This BESLS is a flat network consisting of an input layer, a hidden layer and an output layer. The input layer is the process parameters and the statistical features of the polishing force signals. The hidden layer is divided into a feature layer and an enhancement layer. The enhancement layer is a typical broad learning system (BLS) while its nodes are replaced by reservoirs with echo state properties [4,5], as shown in Figure 1.

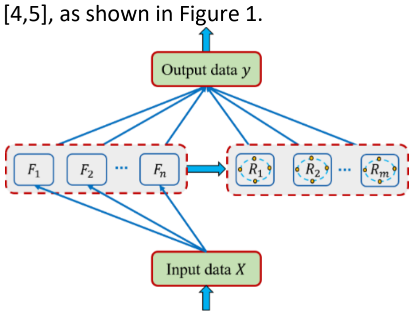

Figure 1. Schematic diagram of the proposed BESLS

Suppose that the training data set is $\{(X,Y)|X \in R^{N\times M}, Y \in R^{N\times 1}\}$, where N and M represent the number of samples and the dimension of features, respectively. X is the sample input matrix and Y is the corresponding label. We assume that there are n feature node groups in the feature layer, and each group contains p feature nodes. Firstly, the input matrix X is randomly mapped to n groups of features, and the i-th group of mapped features can be expressed as Eq. (1):

$$F_i = \varphi i\,(XW_{F_i} + \beta_{F_i}),\, i = 1,2,\dots,n \qquad (1)$$

where φi is a linear activation function, W_{F_i} and β_{F_i} denote randomly generated weight matrix and bias term, respectively.

To obtain a better feature representation of the input data X, W_{F_i} needs to be fine-tuned by a sparse auto-encoder. Then, all feature nodes in the feature layer are concatenated as Eq. (2):

$$F^n = [F_1, F_2, \dots, F_n] \qquad (2)$$

Subsequently, F^n is further transferred to the enhancement layer to strengthen the features. Assuming that the enhancement layer contains m reservoirs, and each reservoir contains q neuron nodes, where q is set to 100. Herein, the output F^n of the feature layer is transferred to each reservoir of the enhancement layer separately, while there is no state transfer among reservoirs. As such, the j-th group of enhancement nodes can be represented as Eq. (3):

$$R_j(n) = \psi_j\left(W_{in}^j F^n(n) + W_{res}^j R_j(n-1)\right), j = 1,2,\dots,m \quad (3)$$

where W_{in}^j and W_{res}^j are the input weight matrix and the j-th reservoir weight matrix, respectively.

All enhanced nodes are also cascaded into Eq.(4):

$$E^m = [R_1, R_2, \dots, R_m] \quad (4)$$

Finally, all the feature nodes of the feature layer and the enhancement layer are merged as the output of the hidden layer, as written in Eq. (5):

$$H = (F^n | E^m) \quad (5)$$

Therefore, the proposed BESLS can be expressed as Eq. (6):

$$\hat{Y} = (F^n | E^m)\left(\frac{W_F}{W_E}\right) \triangleq HW \quad (6)$$

where W is the weight matrix that connects the hidden layer nodes to the output layer and can be calculated by the ridge regression in Eq. (7):

$$W = (\lambda I + H^T H)^{-1} H^T Y \quad (7)$$

where Y is the actual label of the sample, λ and I denote a non-negative regularization constant and an identity matrix with proper dimensions, respectively.

3. Experiments

Figure 2 shows the schematic of MDIF. The polishing tool is a sphere magnet coated with silicon carbide (SiC) abrasives. It is placed inside the workpiece and driven by the external four-pole magnets. The dominant process parameters are gap distance, tool diameter, abrasive size and bonding strength between the abrasive and the sphere magnet. To acquire the process signals for MRR modelling, a Kistler 9256C1 dynamometer is utilized to measure the polishing force. The sampling rate is set as 50 kHz. The polishing force is an oscillation signal near zero point with multiple impact signals.

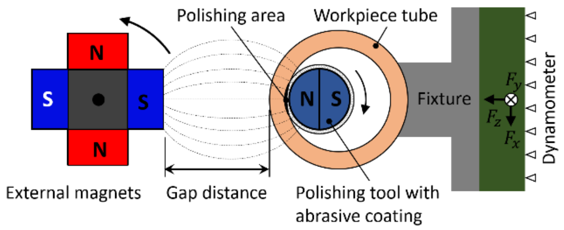

Figure 2. Schematic showing the working principle of MDIF

Single-point polishing experiments with various process parameters are conducted, as listed in Table 1. The total polishing time is 10 min. The polishing forces are recorded for only 20 s in each polishing experiment, which contains sufficient features for the data-driven model. After polishing, the depth of the polished profile is measured by a profilometer to represent the MRR.

Table 1 Polishing parameters in the MDIF experiments

Parameters	Value
Spindle speed	1,600 rpm
External magnets	NdB magnet 20 × 10 × 6 mm
Workpiece tube	OD: 19 mm, ID: 15 mm, L: 50 mm, 316L stainless steel
Gap distance	8, 10, 11, 12, 13 and 18 mm
Mass ratio of epoxy glue AB part (bonding strength)	3:7, 4:6, 5:5, 6:4 and 7:3
Abrasive size	3, 36.5 and 75 µm
Tool diameter	4.2, 6.3 and 8.3 mm

4. Results and discussion

The polishing force signals consist of three directions, i.e., X, Y, and Z, where Fz is the normal polishing force, Fx is the shear force and Fy is the lateral force. In each direction, 19 statistical features (e.g., maximum, minimum, average, frequency factor, frequency variance, frequency standard deviation, etc.) are extracted in the time domain and frequency domain, respectively, and a total of 19 × 3 signal features are extracted. A total of 56 sets of available sample data were collected, of which 40 sets of sample data were randomly selected for model training, and the remaining 16 sets were used for testing. The root-mean-square deviation (RMSE) is used to evaluate the prediction accuracy of the proposed model, as written in Eq. (8):

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[y(n) - \hat{y}(n)]^2} \quad (8)$$

where N is the number of the test samples, $y(n)$ and $\hat{y}(n)$ denote target value and predicted value of the n-th sample.

To verify the effectiveness of the proposed model, three-direction force signal features (Fxyz), the fusion of process parameters and three-direction force signal features (PFxyz), and the fusion of process parameters and Z-direction force signal features (PFz) are used to predict MRR respectively, and the prediction results are shown in Figure 3. Results show that the PFz features give the best prediction of MRR and its RMSE is only 7.2 µm, equivalent to a prediction error of 7.5%. And the total training and testing time is within 1 s, showing its high computational efficiency.

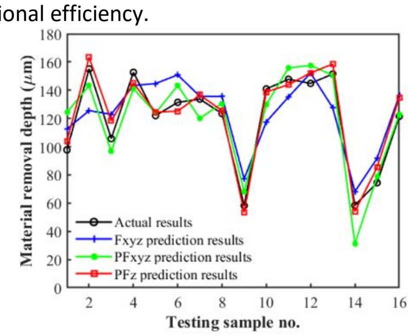

Figure 3. The prediction results of the proposed model

5. Conclusion

In this study, we proposed a novel broad echo state learning system (BESLS) model for material removal rate (MRR) prediction in magnetically driven internal finishing (MDIF) based on the polishing force data. This model shows a predicting error of 7.5% on MRR, which is better than the physics-based model. The proposed method provides a promising data-driven solution for monitoring complex abrasive finishing processes. Future studies will focus on the application of the proposed model in process control of MDIF and other abrasive finishing processes.

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