A Random Forest Regression Model for Predicting Residual Stresses and Cutting Forces Introduced by Turning IN718 Alloy

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Abstract

Random Forest algorithm has been utilized in this paper for creating a regression model to predict residual stresses and cutting forces introduced by turning IN718 alloy. Residual stresses and cutting forces are crucial to deformations of thin-walled parts. Meanwhile, it is difficult to determine a specific regression equation expression between the dependent variables (surface residual stresses, max compressive residual stresses, cutting forces) and independent variables (depth of cut, feed rate, cutting speed). Random forest algorithm has the superiority as it can build regression relation between variables using many regression trees rather than a specific equation. Multiple sets of simulations were finished by the finite element method to obtain the regression training data. A series of turning and residual stresses measurement experiments with different turning parameters were conducted to ensure the accuracy of the regression training data. From the research, predicted residual stresses and cutting forces were consistent with simulation results, and the prediction errors were controlled within the acceptable range. The research could contribute the further investigation of thin-walled part deformation control.

Keywords: Random Forest regression, Residual stresses, Cutting forces, Finite element method

Introduction

The nickel-based superalloy IN718 has good mechanical properties and corrosion resistance even in high temperature [1], resulting in that it has a full application in some aero-engine parts, especially thin-walled parts. Residual stresses and cutting forces introduced by machining are crucial to the deformation of these thin-walled parts. Thus, it is of great importance to predict residual stresses and cutting forces for the further investigation of thin-walled part deformation control.

Residual stresses could be compressive or tensile stresses. Tensile residual stresses could be harmful for fatigue life, corrosion and wear resistance, and compressive residual stresses have positive influence on these aspects [2]. The Surface residual stress introduced by turning IN718 alloy might be tensile or compressive, while the residual stress in the subsurface is usually compressive. Residual stress prediction has been much investigated. Yuan Ma [3] developed a model to predict surface residual stresses after end milling by cutting forces and temperature, and a prediction equation was proposed. One research [4] utilized finite element simulations to predict the residual stress introduced by machining titanium and nickel alloys, pointing out that the tool geometry influences the residual stress. The surface residual stress became more compressive if edge radius increased. The surface residual stress became more tensile if the tool had been coated. These researches could contribute to decrease residual stresses for minimizing machining parts deformation and to control overlarge tensile residual stresses for better performance of machining parts.

Cutting forces would be generated during machining. Cutting forces influence the tool-workpiece system, having possibilities to lead unexpected dynamic displacement response between the systems [5]. Cutting forces also influence the generation of residual stresses. Therefore, many methods were proposed to predict cutting forces. Nik Masmiati [6] suggested one mathematical model for predicting cutting forces based on response surface methodology. The mathematical model was a second-order polynomial equation. Predictions of cutting forces could help improve the surface quality and select cutting parameters.

Random Forest algorithm was proposed by Breiman [7], and it can improve the prediction accuracy of the model by summarizing a large number of regression trees. Random Forest algorithm facilitates the calculation of the nonlinear effects of variables and can reflect the interaction between variables. Therefore, it can express nonlinear relations of dependent and independent variables.

This paper's aim is researching a new method to predict surface residual stresses (SRS), max compressive residual stresses (MCRS) and cutting forces introduced by turning IN718 alloy. Different from many previous investigations that developed prediction model through specific equations, Random Forest was utilized for expressing nonlinear relations of dependent variables (SRS, MCRS, cutting forces) and independent variables (feed rate, cutting speed, depth of cut). This algorithm has a superiority with which it can build regression relations without specific equations.

Prediction Procedures

A series of finite element simulations were carried out to get the residual stress and cutting force data. Turning experiments under different sets of cutting parameters and measurements of residual stresses were carried out for validating FEA results. Eventually, Random Forest was applied for constructing the statistical predictions of residual stresses and cutting forces.

A. Random Forest regression

Turning parameters can influence residual stresses and cutting forces much, and thus can be used as independent variables to predict residual stresses and cutting forces. Typically, a specific regression equation, such as polynomial

ISBN: 978-1-7281-5112-2

equation [8] or Logistic equation [9], is needed in a regression model, but it is challenging to find an accurate and concise equation to describe relations in turning parameters, residual stresses and cutting forces. Random Forest algorithm [10] can solve the problem because it uses regression trees rather than an equation to finish the regression process. Random Forest regression consists of multiple regression trees, and the generating process of regression trees is shown below. Data sets (1) (2) (3) show the training data of one regression tree.

$$S = \{(p_1, s_1), (p_2, s_2), \cdots (p_i, s_i), \cdots, (p_n, s_n)\} \quad (1)$$

$$C = \{(p_1, c_1), (p_2, c_2), \cdots (p_i, c_i), \cdots, (p_n, c_n)\} \quad (2)$$

$$F = \{(p_1, f_1), (p_2, f_2), \cdots (p_i, f_i), \cdots, (p_n, f_n)\} \quad (3)$$

where S represents surface residual stress data set. C represents max compressive residual stress data set. F represents cutting force data set. p_i is a three-dimensional vector including depth of cut, feed rate, cutting speed. s_i represents surface residual stresses. c_i represents max compressive residual stress. f_i represents cutting force.

For the turning IN718 alloy, surface residual stresses are stresses on the machining surface. Max compressive residual stresses occur approximately 100 microns below the surface. The regression model aims to fit elements in S, C, and F separately. Take data S for example, if one regression tree has M leaves, it means that the regression tree divides p into M units which are $R_1, R_2, \cdots, R_M$ and has M different prediction value of surface residual stresses which are $t_1, t_2, \cdots, t_M$. The purpose is to generate regression tree which has the minimum value of formula (4).

$$MSE = \frac{1}{n}\sum_{m=1}^{M}(t_m - s_i)^2 \quad (4)$$

Where prediction value t_m can be expressed as equation (5)

$$t_m = ave(s_i | p_i \in R_m) \quad (5)$$

The regression tree generation process for surface residual stress is to decide every splitting variable j, which can be depth of cut, cutting speed or feed rate in this paper, and decide every splitting point s which is the splitting value of one turning parameter. Formula (6) can be used to get j and s.

$$min_{j,s}[min_{c_1}\sum_{p_i \in R_1(j,s)}(t_1 - s_i)^2 + min_{c_2}\sum_{p_i \in R_2(j,s)}(t_2 - s_i)^2] \quad (6)$$

Where $R_1(j,s) = \{p | p^j \leq s\}$ and $R_2(j,s) = \{p | p^j > s\}$ are two parts after being split.

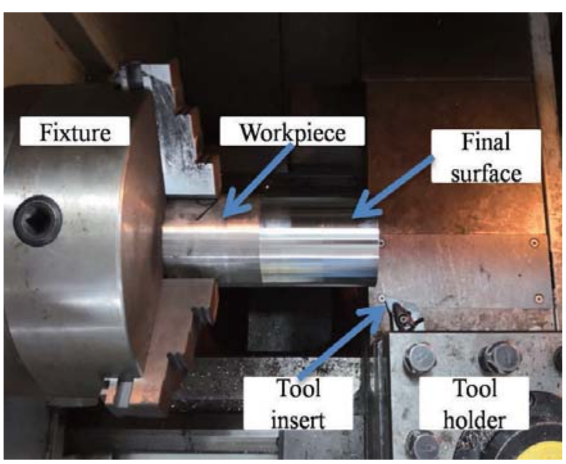

Fig. 1 Turning appearance at experiment lathe [11]

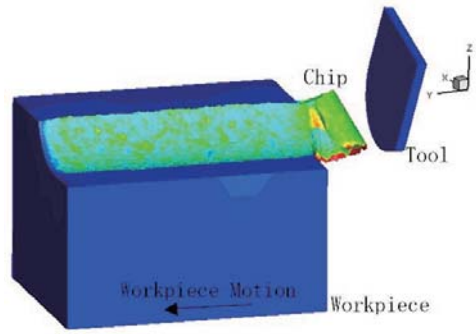

Fig. 2 Finite element turning model

As described above, a series of regression trees are built, and each regression tree has different training data selected from known data randomly, therefore having different prediction values. The mean value of all predictions is what the Random Forest algorithm intends to get.

B. Experiments and simulations

Fig. 1 shows the tool holder and tool insert were from Sandvik Corp. The tool holder's type is DDHNR2525M1504, while the tool insert's type is DNMG150412-SMR1105. The workpiece's material is IN718 alloy. Workpieces are tube shaped, and their outside and inside diameters are 76 mm and 58 mm, respectively. Table I shows the experimental turning parameters. After the turning process, the X-ray measurement method and electrolytic corrosion were utilized to get SRS and MCRS beneath the surface.

TABLE I Experiment machining sets

No.	Feed rate f (mm/r)	Depth of cut a_p (mm)	Cutting speed v (m/min)
1	0.4	0.8	30
2	0.1	0.4	60
3	0.4	0.2	120

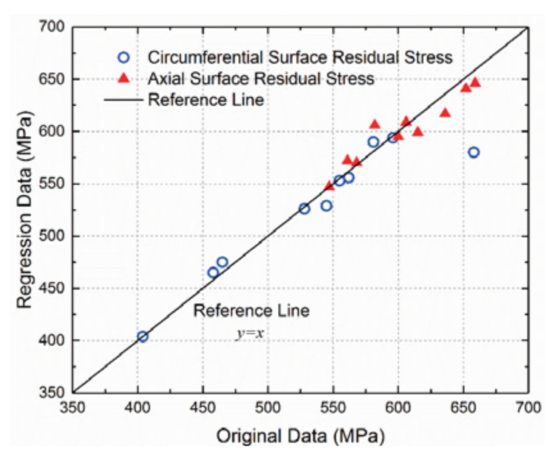

Fig. 3 Original versus regression data of surface residual stress

ISBN: 978-1-7281-3112-2

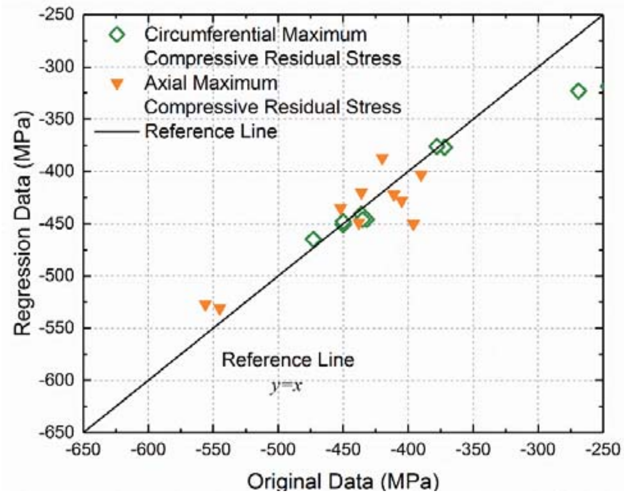

Fig.4 Original versus regression data of max compressive residual stress

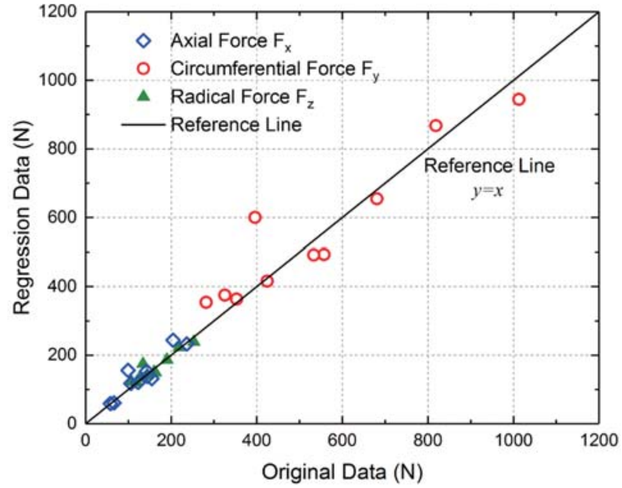

Fig. 6 Original versus regression data of cutting forces

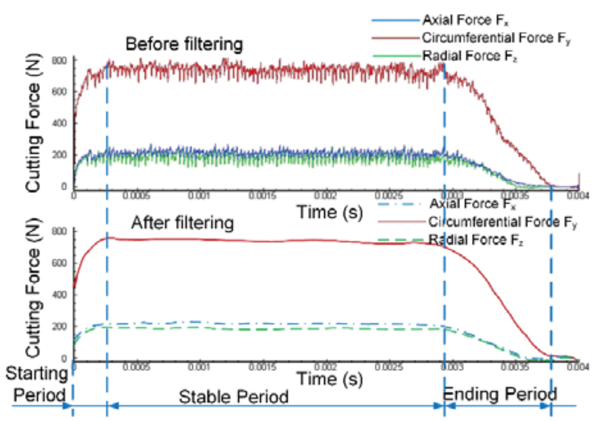

Fig. 5 Cutting forces before and after filtering

Fig. 2 shows the simulation model, which is simplified from the real experimental condition. The shown model is the state after cutting. Axis y represents circumferential direction, while axis x represents the axial direction. Axis z represents the radical direction. The simulation model was adjusted and refined considering the residual stress data acquired from experiments, and therefore, more training data obtained from the model was convincing.

Results and Discussions

As shown in Fig. 3 and Fig. 4, original data obtained from simulations and regression data obtained from Random Forest regression are compared. The closer the data point is to the reference line, the higher the regression accuracy is. However, the R^2 value is controlled around 0.85 to prevent overfitting. Circumferential and axial directions of SRS and MCRS data are regressed. The data points are close to the reference line, meaning that the Random Forest algorithm has a good regression effect.

Fig. 5 shows cutting forces acquired from one simulation. Simulated cutting forces have noisy data, while the noisy data can be removed after filtering. The cutting forces variation can be divided into three periods, which are starting period, stable period, and ending period. During the starting period, the

TABLE II Predicted values versus original values

Sets	Variables	Original values	Predicted values	Errors
	Axial SRS (MPa)	600.5	621.5	21.0
	Axial MCRS (MPa)	-327.0	-420.1	93.1
v=50 m/min	Circumferential SRS (MPa)	532.4	567.4	35.0
a_p=0.3 mm	Circumferential MCRS (MPa)	-298.0	-377.8	79.8
f=0.6 mm/r	Axial force F_x(N)	196.0	215.6	19.6
	Circumferential force F_y (N)	827.7	860.1	32.4
	Radical Force F_z (N)	216.5	219.7	3.2
	Axial SRS (MPa)	587.6	597.4	9.8
	Axial MCRS (MPa)	-524.9	-458.2	66.7
v=100 m/min	Circumferential SRS (MPa)	547.6	539.4	8.2
a_p=0.6 mm	Circumferential MCRS (MPa)	-492.7	-446.5	46.2
f=0.2 mm/r	Axial force F_x (N)	141.5	146.1	4.6
	Circumferential force F_y (N)	475.8	559.4	83.6
	Radical Force F_z (N)	149.2	171.1	21.9

ISBN: 978-1-7281-5112-2

cutting tool contacts the workpiece gradually, resulting in increased cutting forces. After the starting period, the tool contacts with the workpiece completely, making a stable period. The cutting forces decrease to zero in the ending period because the workpiece is 5 mm long while the cutting length is 6 mm. Therefore, when the cutting tool finishes workpiece cutting gradually, the cutting forces will fall to zero. Cutting forces during the stable period are approximately constants, and these constants are seen as the average values of cutting forces in the period. These constants, representing cutting forces, are regressed shown in Fig. 6, and the R^2 value is controlled around 0.85 to prevent overfitting. Most data points are close to the reference line.

Table II shows predicted results of different variables under two sets of cutting conditions. Original values were obtained from finite element simulations which are refined by experiments. Predicted values were acquired from Random Forest regression model. The max and min predicting error of residual stress were 93.1 MPa and 8.2 MPa. The predicting precision is acceptable because this material's stresses are always very high. As for cutting forces, the max error is 83.6 N, while the min error is 3.2 N, which is also acceptable because of the high hardness and high cutting forces.

Conclusion

Three sets of turning experiments and measurements of residual stresses have been carried out. One finite element simulation model was built and validated by experiment results. A series of simulations under different turning parameters were finished to obtain the training and testing data of Random Forest regression.

For the training data, the precision of Random Forest regression R^2 was controlled around 0.85 to prevent overfitting. All regressed data points of predicting variables (axial SRS, axial MCRS, Circumferential SRS, Circumferential MCRS, Axial force F_x, Circumferential force F_y and Radical force F_z) were close to the reference line.

For the testing data, two sets of turning simulations were selected. The max and min predicting error of residual stress were 93.1 MPa and 8.2 MPa. Cutting forces' max error was 83.6 N, while the min error was 3.2 N. Predicted residual stresses and cutting forces were consistent with simulation results, and the prediction errors were controlled within the acceptable range.

Acknowledgment: Thanks to AECC Shenyang Liming Aero-engine Co., Ltd for financial support and AdvantEdge tool help.

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ISBN: 978-1-7281-5112-2