



Background/Research Introduction

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上海交通大学
SHANGHAI JIAO TONG UNIVERSITY



I. Basic Introduction



Zhengrui Tao

Education Background

✓ Sept. 2017 - March 2020

M.Sc. in Mechanical Engineering, Shanghai Jiao Tong University

Major GPA: 3.61/4.00, Overall GPA: 3.75/4.00

✓ Sept. 2013 - June 2017

B.Eng. in Mechanical Design, Manufacturing and Automation,
Harbin Institute of Technology, WEIHAI

Major GPA: 92.30/100, Overall GPA: 91.80/100;



Honors & Awards

- **Shanghai Outstanding Graduates (Top 1%)** 2019
- **National Graduate Scholarship (Top 1%)** 2019
- **Sandvik Coromant Scholarship (Top 3%)** 2018
- **Shandong Province Outstanding Graduates (Top 2%)** 2017
- **National Undergraduate Scholarship (Top 1%)** 2016





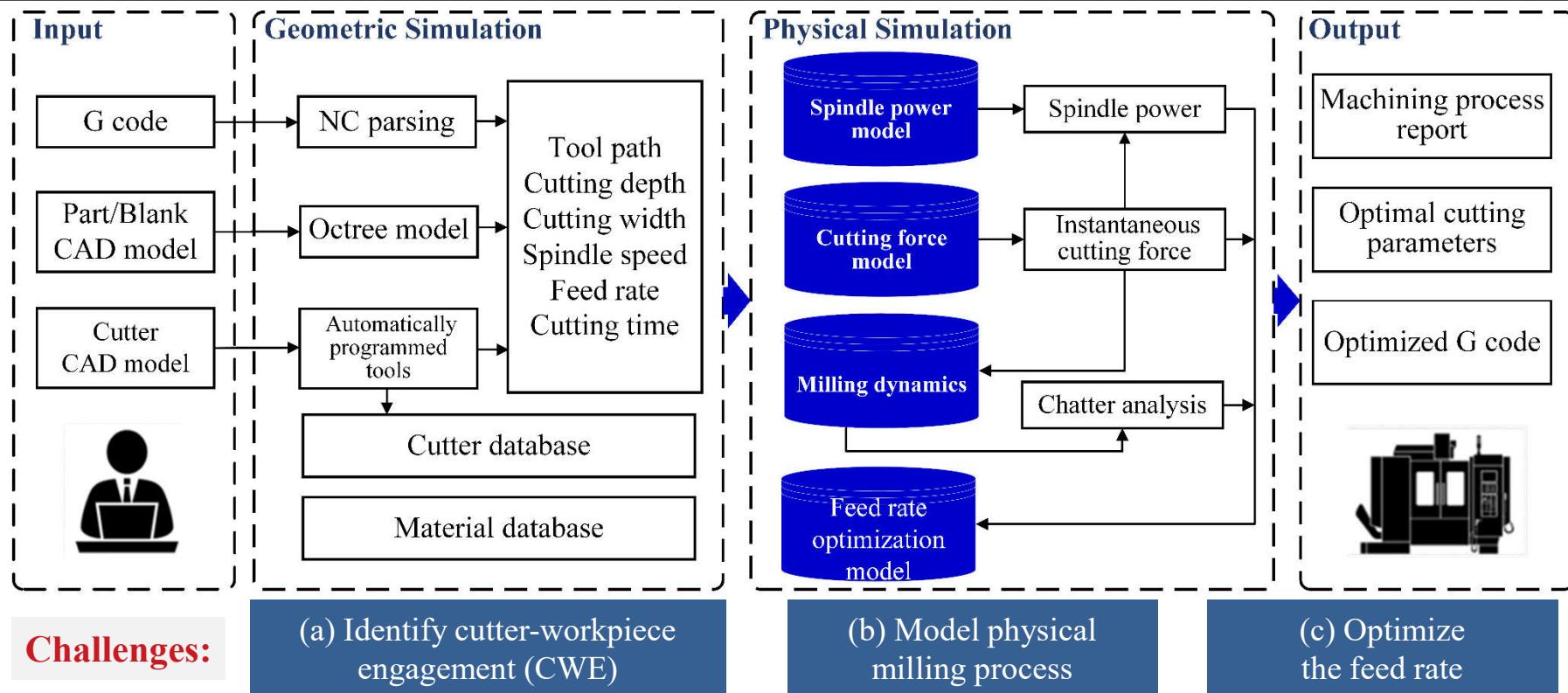
II. Research



Virtual Machining System: Chatter Stability Analysis & Feed Rate Optimization

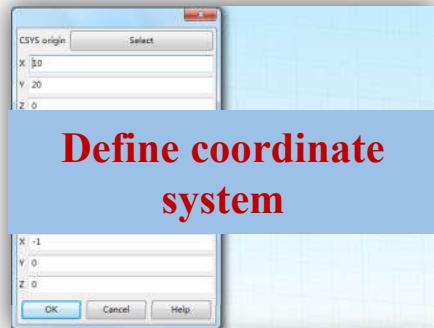
Background: In order to optimize milling process, computer-aided design (CAD) and computer-aided manufacturing (CAM) are integrated based on material removal rate and chatter stability analysis.

Key words: Geometric simulation; Chatter stability analysis; Cutting parameters optimization

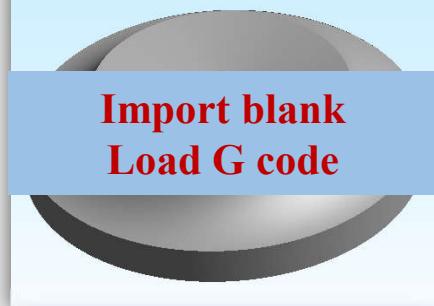




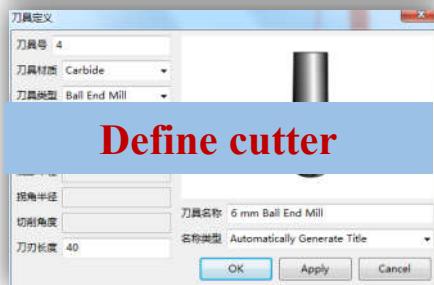
Virtual Machining System



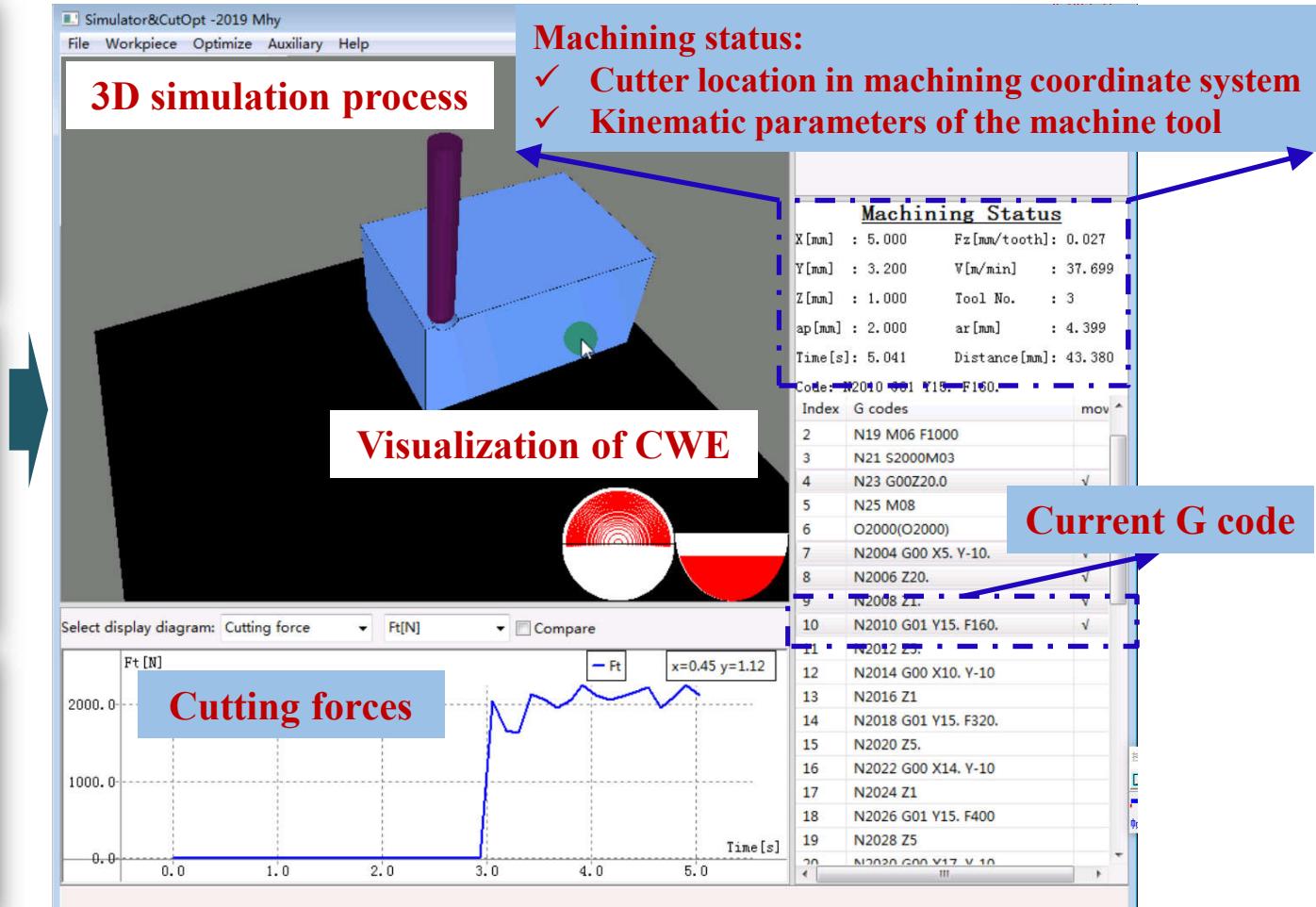
Define coordinate system



Import blank
Load G code

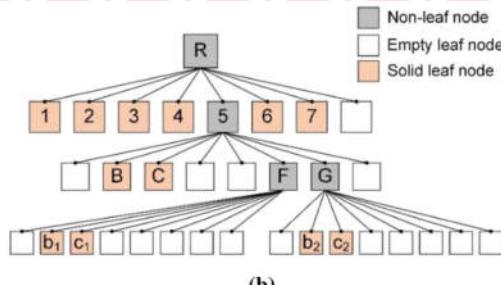
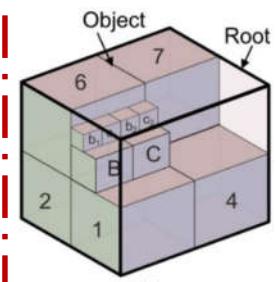


Define cutter





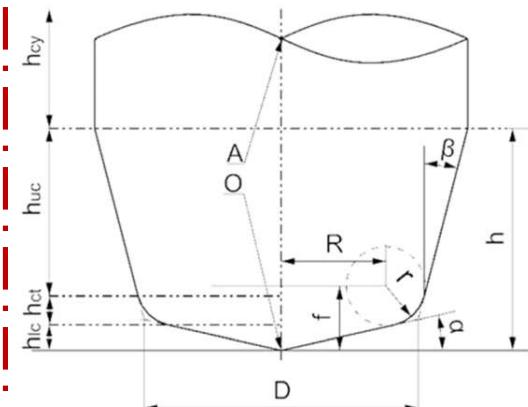
Geometric Simulation



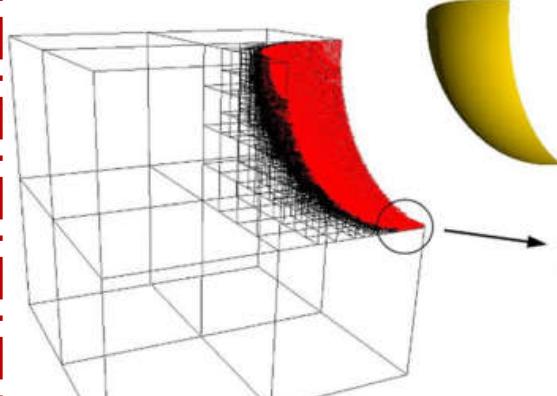
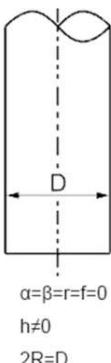
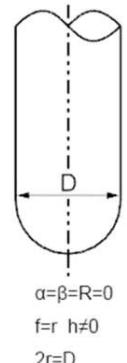
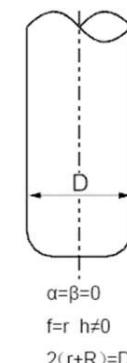
(a) Octree model

	child pointer	solid mask	leaf mask
32	8	8	8
5			
F	01100000 01100000	01100000 01100000	
G	01100000 01100000	01100000 01100000	

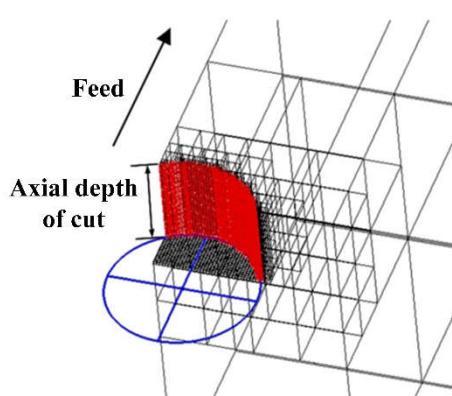
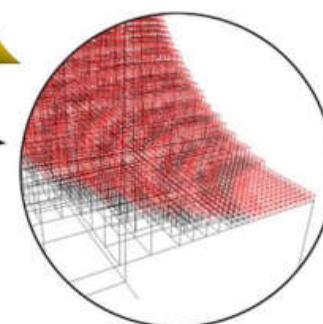
(a) Octree model



(b) Automatically programmed tools



(c) Boolean operation

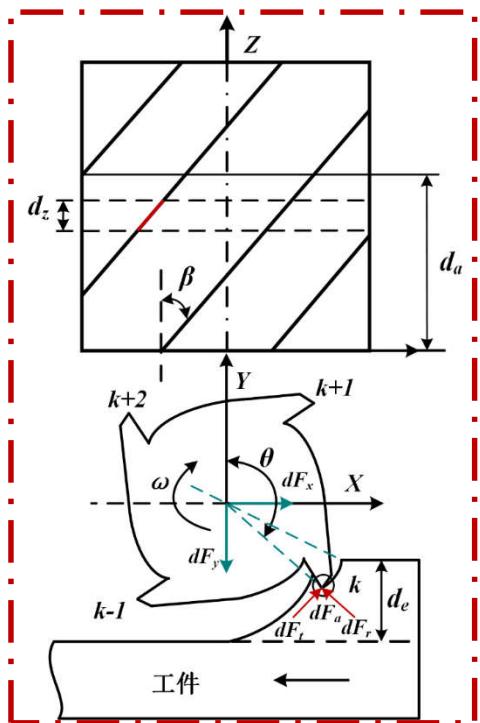


(d) geometrical parameters extraction



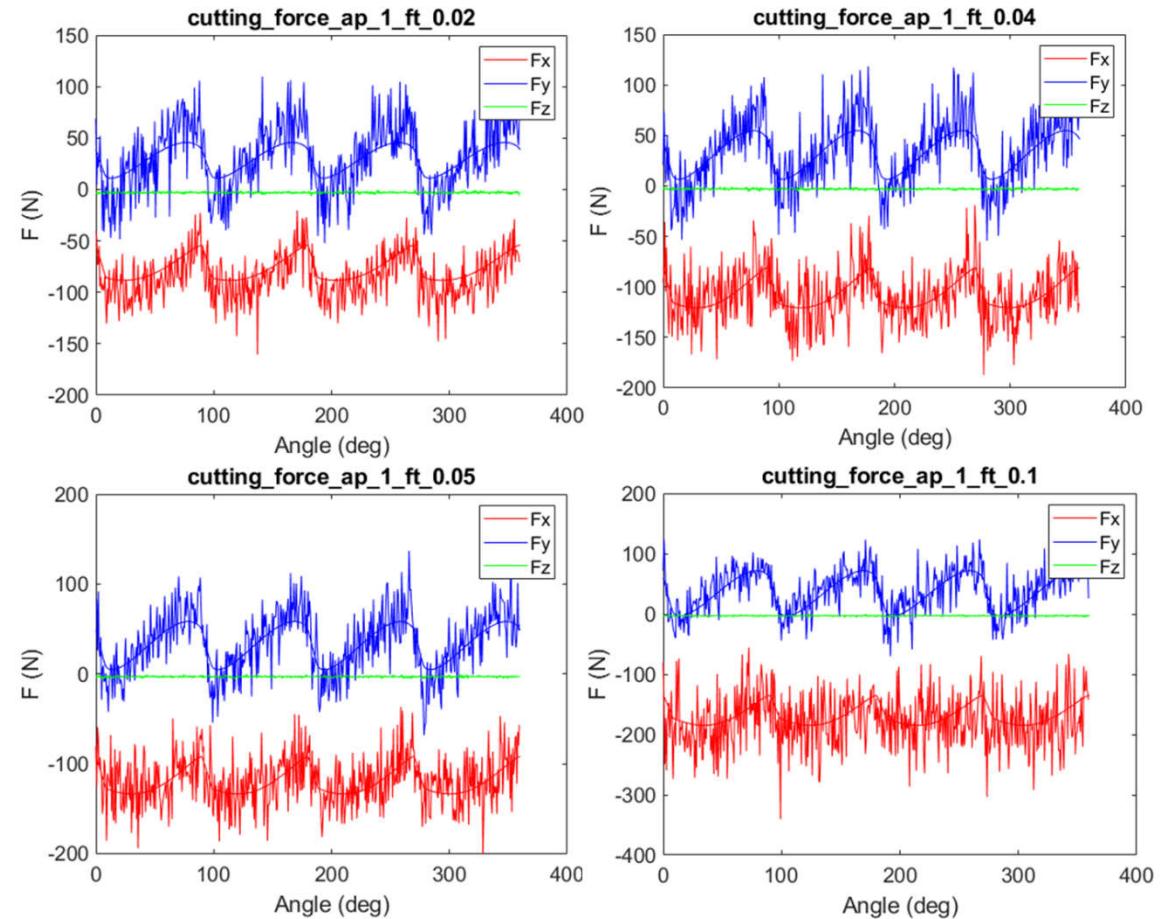
Physical Simulation: Cutting force model

(a) Cutting force model



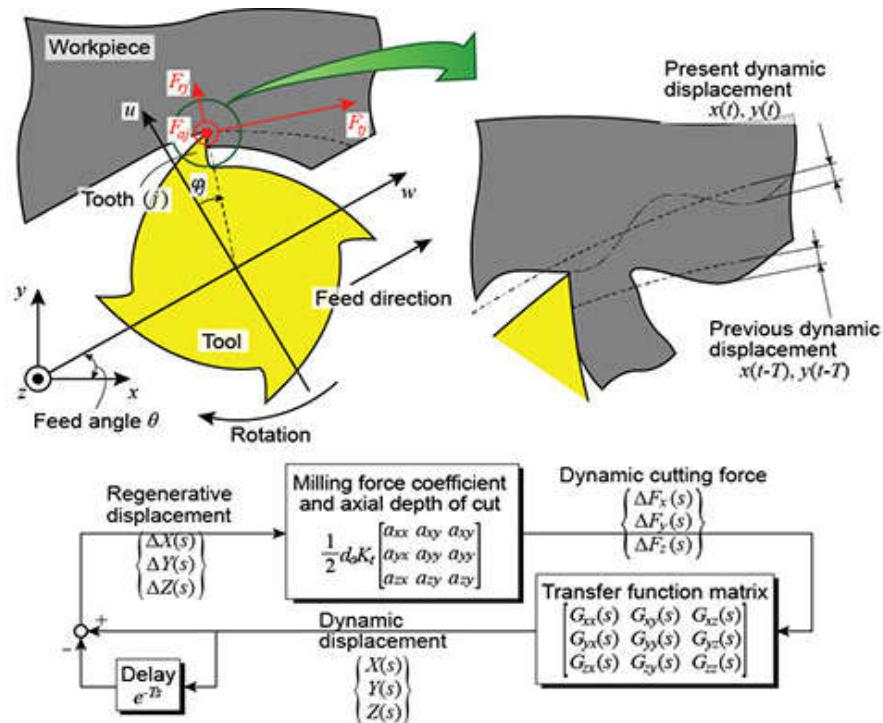
$$\begin{cases} dF_{t,j}(\phi, z) = (K_{tc} h_j(\phi, z) + K_{te}) ds \\ dF_{r,j}(\phi, z) = (K_{rc} h_j(\phi, z) + K_{re}) ds \\ dF_{a,j}(\phi, z) = (K_{ac} h_j(\phi, z) + K_{ae}) ds \end{cases}$$

(b) Comparison of cutting force

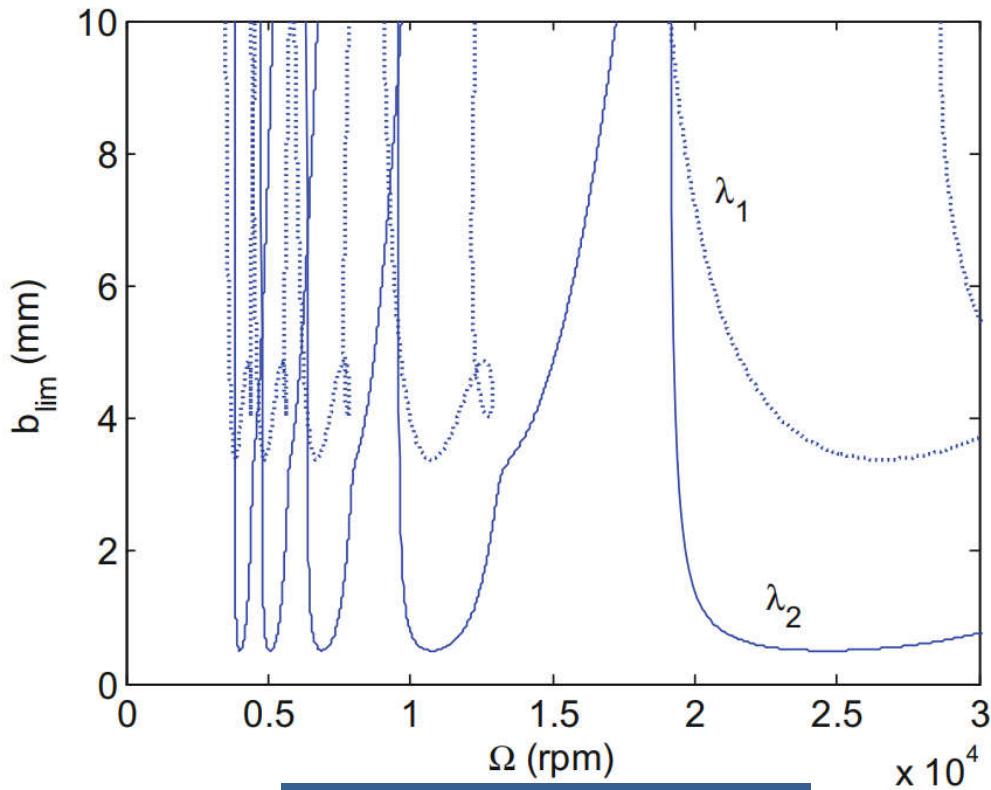




Physical Simulation: Chatter stability analysis



(a) Milling dynamics



(b) Stability Lobe Diagram

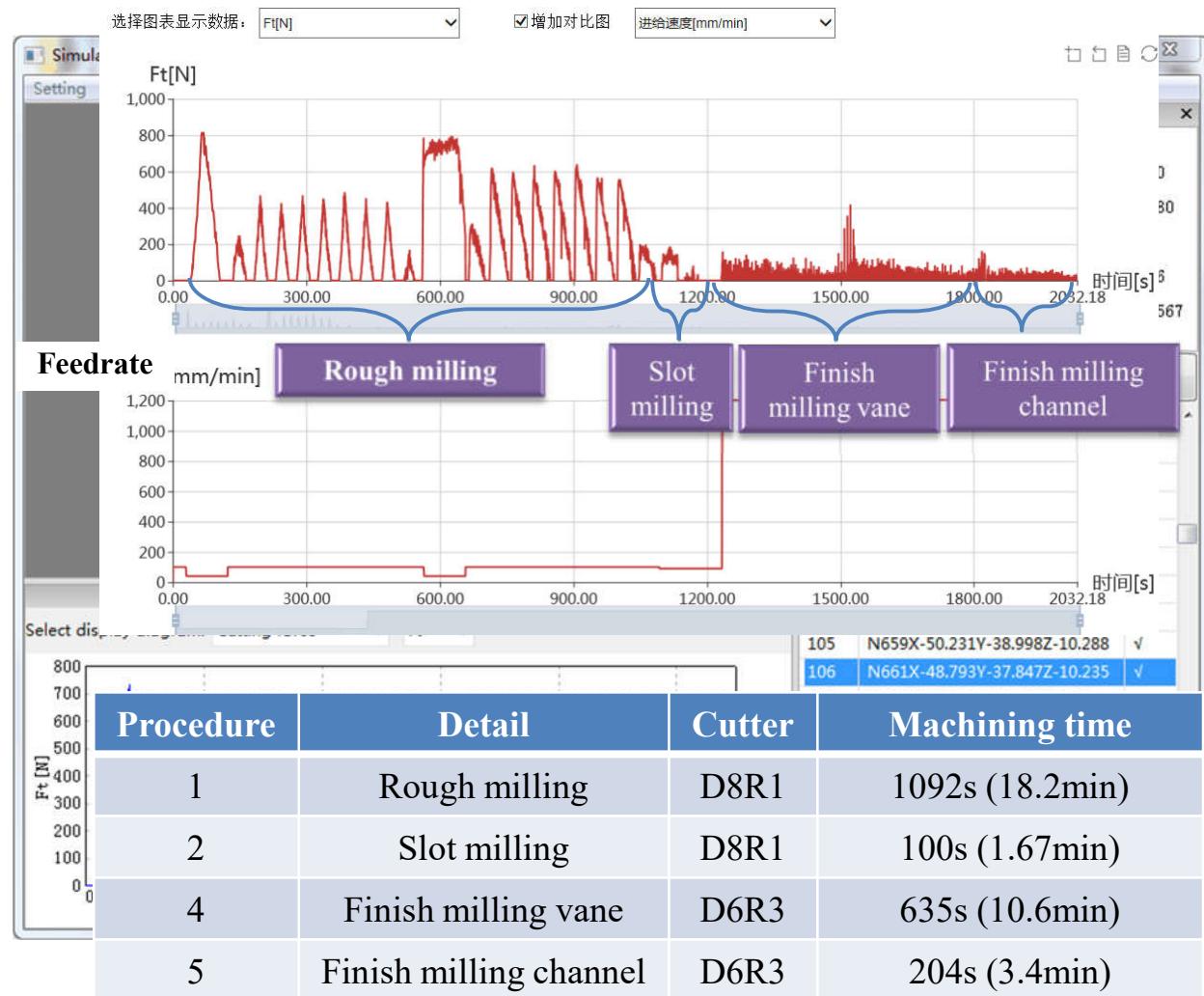


Case study: machining process optimization of a turbine composed of 10 vane channels

(a) Workpiece blank



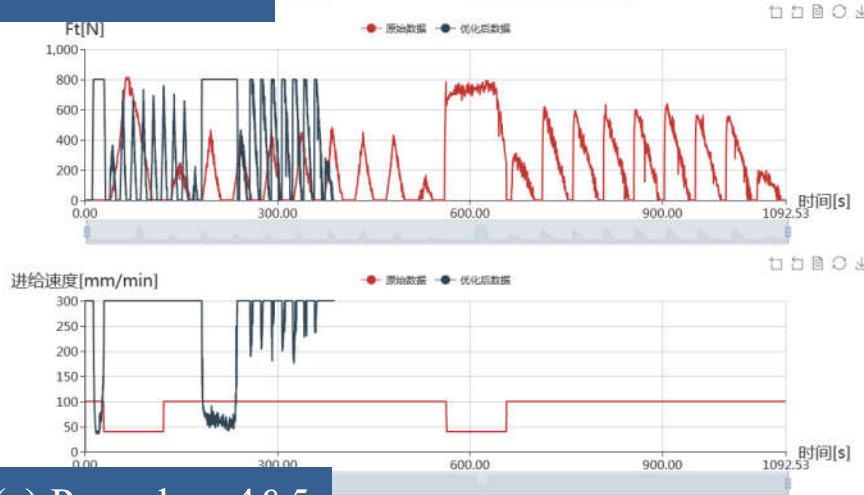
(b) Turbine



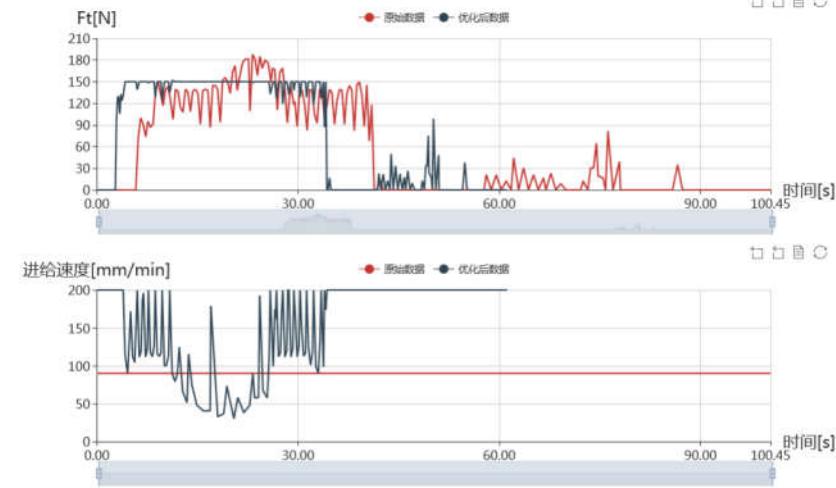


Case study: machining process optimization of an turbine composed of 10 vane channels

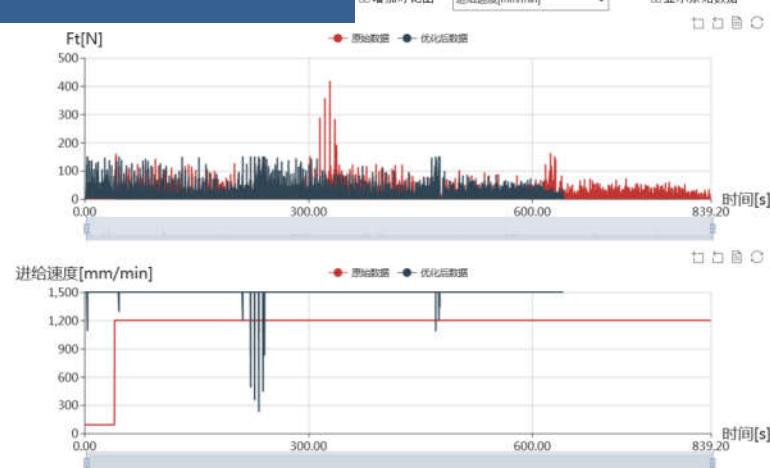
(a) Procedure 1



(b) Procedure 2



(c) Procedure 4&5

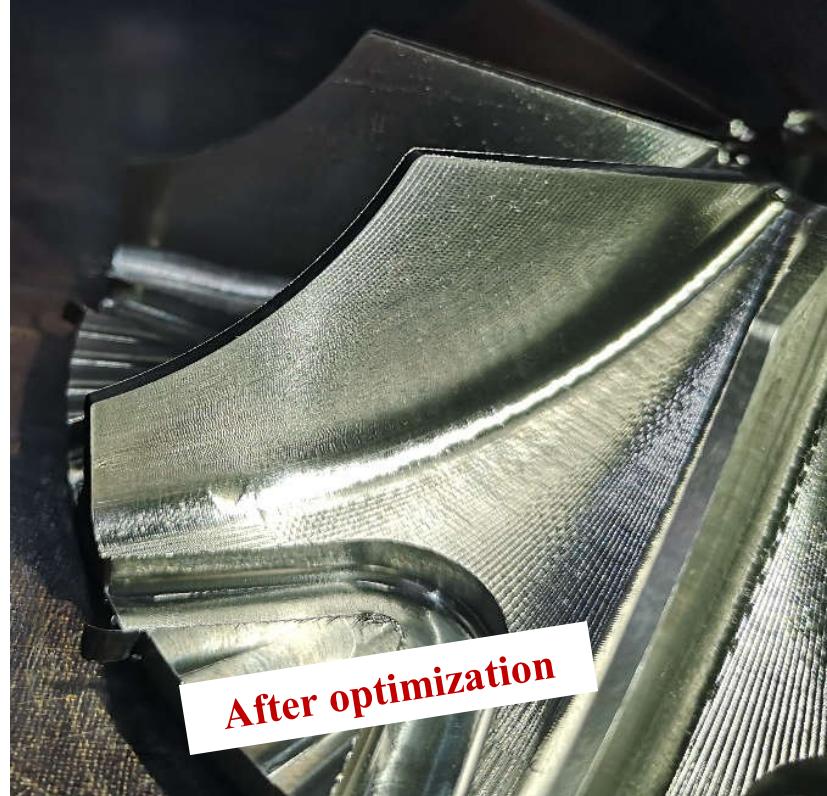


Procedure	Machining time	Optimized machining time	Efficiency Improvement
1	1092s (18.2min)	390s (6.5min)	64%
2	100s (1.67min)	62s (1.03min)	61%
4	635s (10.6min)	641s (10.7min)	24%
5	204s (3.4min)		

Average cycle time reduced by 43%



Case study: machining process optimization of an turbine composed of 10 vane channels



Surface finish improved 7.4-fold

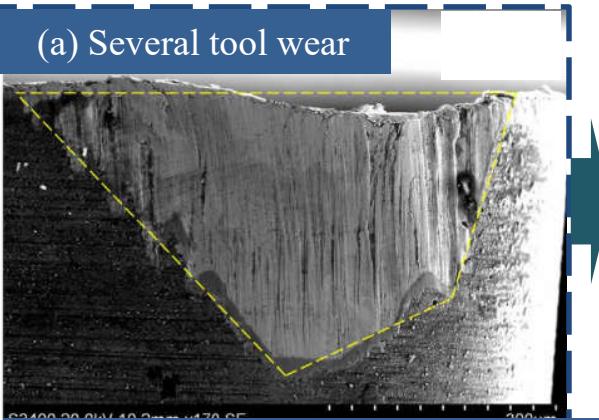


Tool Condition Monitoring: Diagnostics, Prognostics, and Remaining Useful Life Prediction

Background: In high performance NC machining, tool condition monitoring and fault diagnosis are widely needed. Accurate tracking of tool state and timely tool change are the key factors to ensure machining quality and improve production efficiency.

Key words: Diagnostics; Prognostics; Remaining Useful Life Prediction

(a) Several tool wear



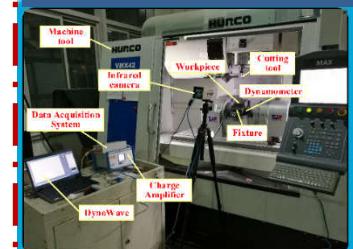
Traditional Solution

- Based on cumulative cutting length, time, chip color and cutting noise
- Machine downtime and directly check the cutting edge state

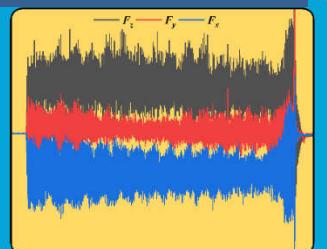
Existing Problems

- Tool replacement is conducted too early and waste tool life
- Unnecessary downtime and affect work schedule

(b) Structure of data-driven TCM systems



Machining process monitoring



Data Acquisition

Maximum/RMS/Variance/
Kurtosis/Skewness/Peak-to-
peak/Crest factor

Amplitude and dominant frequency/
signal power in specific frequency ranges/
statistic features of band power spectrum

Wavelet Energy

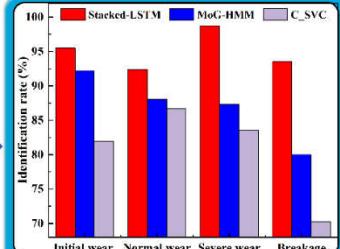
Feature Engineering

Support Vector Machine

Deep learning methods

Random Forest

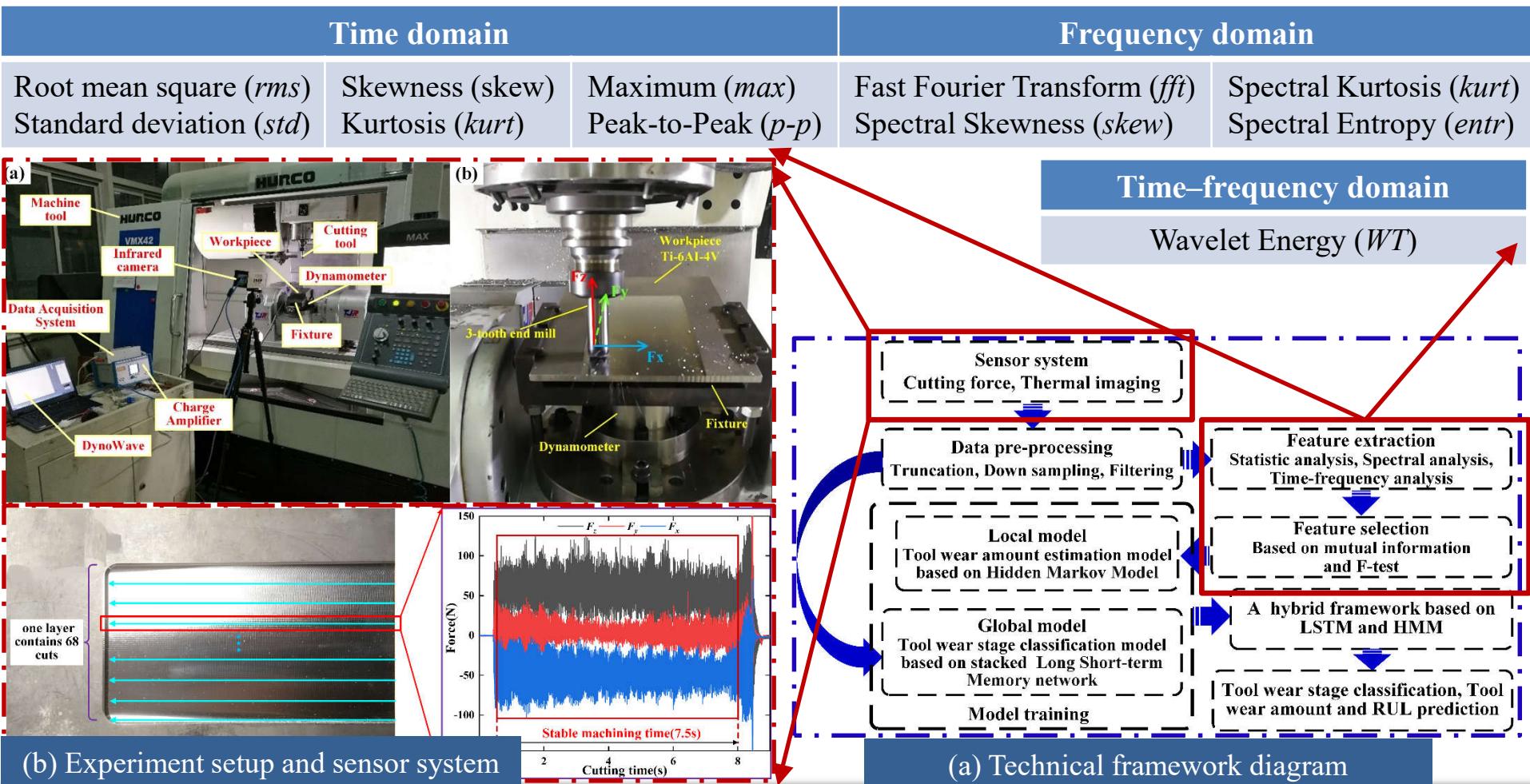
Model Training



Model Testing

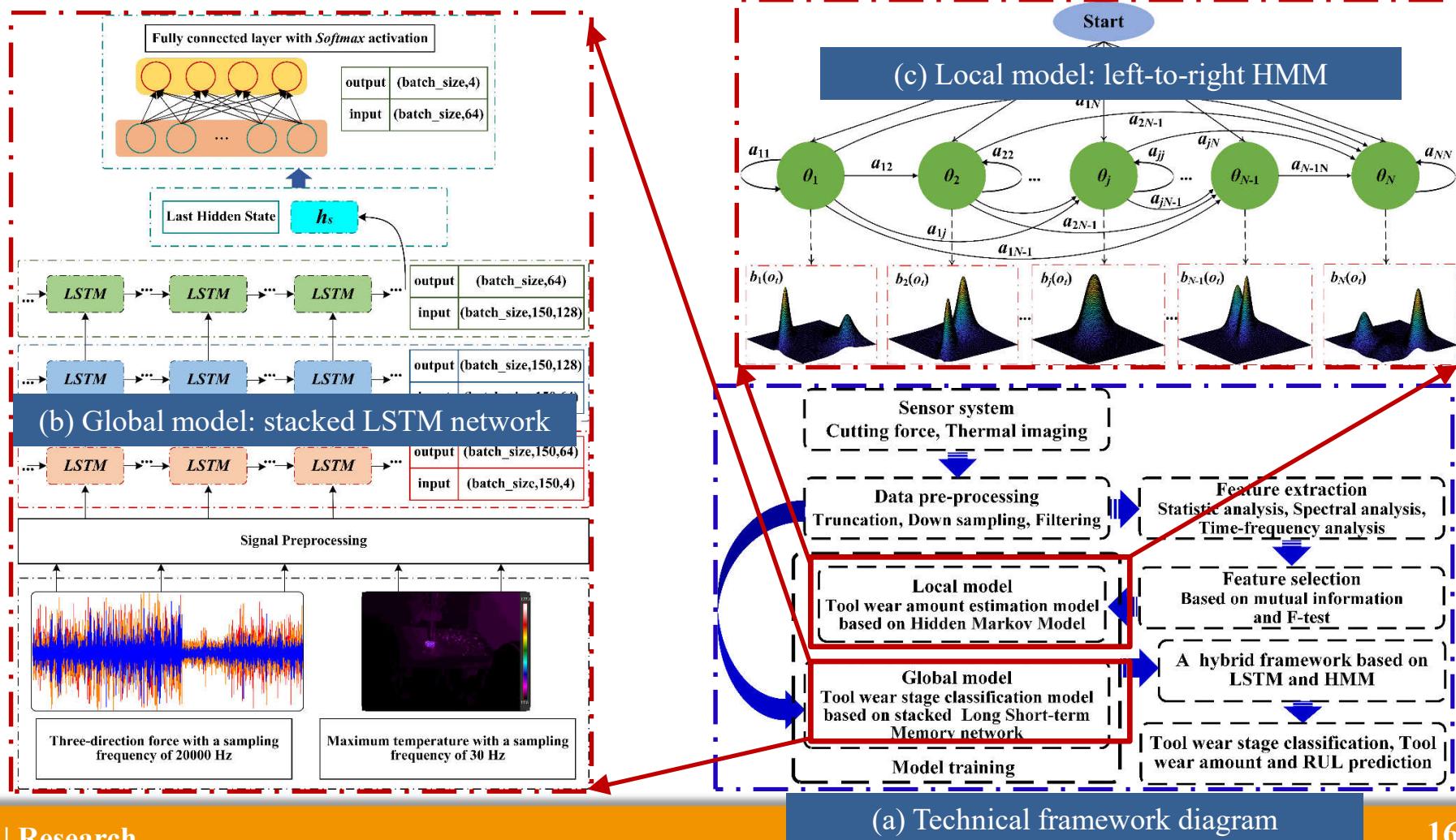


Tool condition monitoring based on long short-term memory and hidden Markov model hybrid framework





Tool condition monitoring based on long short-term memory and hidden Markov model hybrid framework





Tool condition monitoring based on long short-term memory and hidden Markov model hybrid framework

(a) Tool wear stage classification accuracy

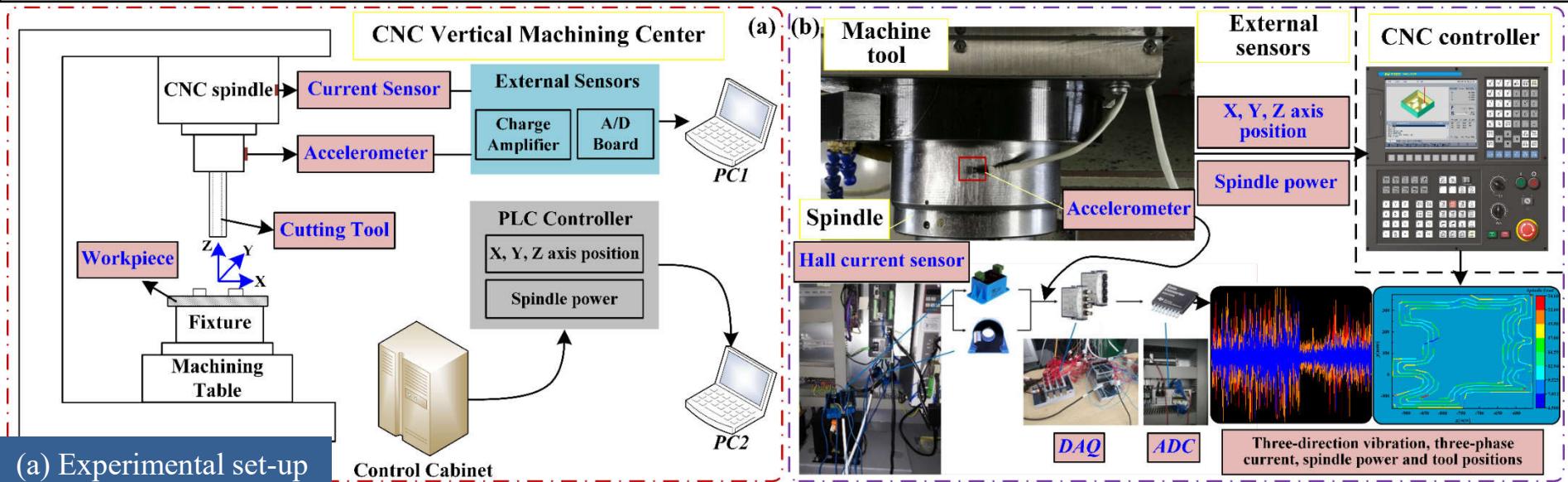
Testing dataset	Wear stage	Methods			
		sLSTM network	3-layers vanilla RNN	Feedforward NN	SVC
C1	Initial	0.9549	0.9123	0.8039	0.8188
	Normal	0.9238	0.8712	0.8427	0.8878
	Severe	0.9875	0.863	0.7921	0.8455
	Breakage	0.9351	0.7903	0.7	0.7128
	Average	0.9503	0.8592	0.7847	0.8162
C2	Initial	0.9687	0.8944	0.8125	0.8153
	Normal	0.9528	0.922	0.8452	0.8864
	Severe	0.9612	0.8635	0.8012	0.8323
	Breakage	0.9345	0.9324	0.8542	0.8645
	Average	0.9543	0.9031	0.8283	0.8496
C3	Initial	0.942	0.892	0.8459	0.8945
	Normal	0.9512	0.798	0.7625	0.7928
	Severe	0.9189	0.7355	0.6985	0.7315
	Breakage	1	0.7563	0.7632	0.8345
	Average	0.953	0.7955	0.7675	0.8133
Overall average		0.9525	0.8526	0.7935	0.8264

(b) Wear amount and RUL Prediction performance

$MSE = \frac{1}{T_c} \sum_{c=1}^{T_c} [Wear_{real}(c) - \widehat{Wr}_m(c)]^2$	MSE
LSTM-HMM	6.4197
CNN	190.613
C1	10.6058
C2	13.5193
C3	10.1816
average	166.568
$Er_c = RUL_{Real}(c) - RUL_{Prediction}(c)$	$S_c = \begin{cases} exp^{-\ln(0.5) \cdot (Er_c/30)}, & \text{if } Er_c \leq 0 \\ exp^{+\ln(0.5) \cdot (Er_c/50)}, & \text{else} \end{cases}$
$Accuracy = \frac{1}{T_c} \sum_{c=1}^{T_c} e^{- Er_c / RUL_{real}(c)}$	$Score = \frac{1}{T_c} \sum_{c=1}^{T_c} (100 \times S_c)$
LSTM-HMM	93.12
CNN	84.68
C1	88.87
C2	89.81
C3	90.6
average	84.39
$Score$	$Accuracy$
LSTM-HMM	0.9706
CNN	0.8625
C1	0.9399
C2	0.9475
C3	0.9527
average	0.873
$Methods$	$C1$
LSTM-HMM	0.9706
CNN	0.8625
$Methods$	$C2$
LSTM-HMM	0.9399
CNN	0.9297
$Methods$	$C3$
LSTM-HMM	0.9475
CNN	0.8269
$Methods$	average
LSTM-HMM	0.9527
CNN	0.873



Remaining useful life prediction based on convolutional and stacked LSTM network



Machining smartphone backplate under dry milling operation

(b) Cutting parameters

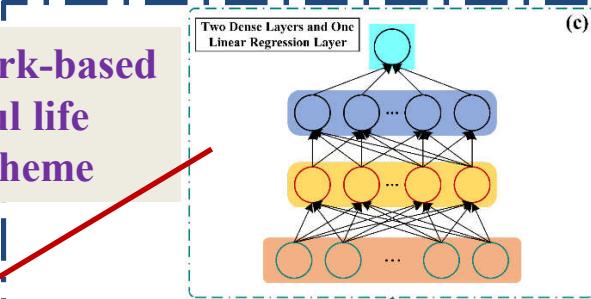
No.	Cutting speed (m/min)	Feed (mm/z)	Cutting depth (mm)	Cutting width (mm)
1	75	0.03	1.2	2
2	75	0.04	1.2	2
3	50	0.03	1.2	2



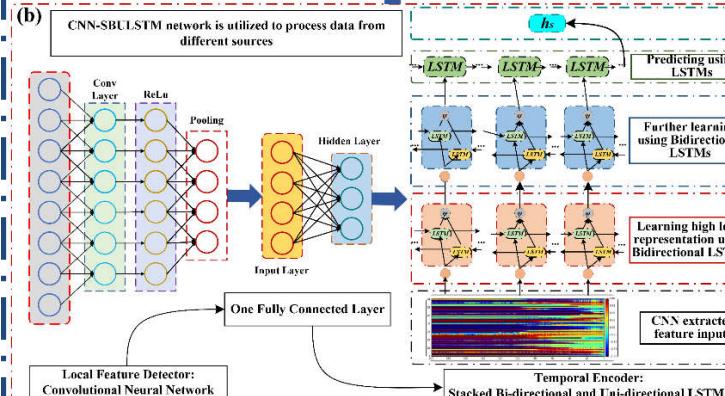
Tool remaining useful life prediction based on convolutional and stacked LSTM network

CNN-SBULSTM network-based tool remaining useful life prediction system scheme

(c) Regression



(c)



(b) Feature extraction and pattern recognition

Three-layers CNN is firstly utilized for local feature extraction

Stacked model of two-layers BLSTM network and one-layer ULSTM network is designed to denoise and encode the temporal information

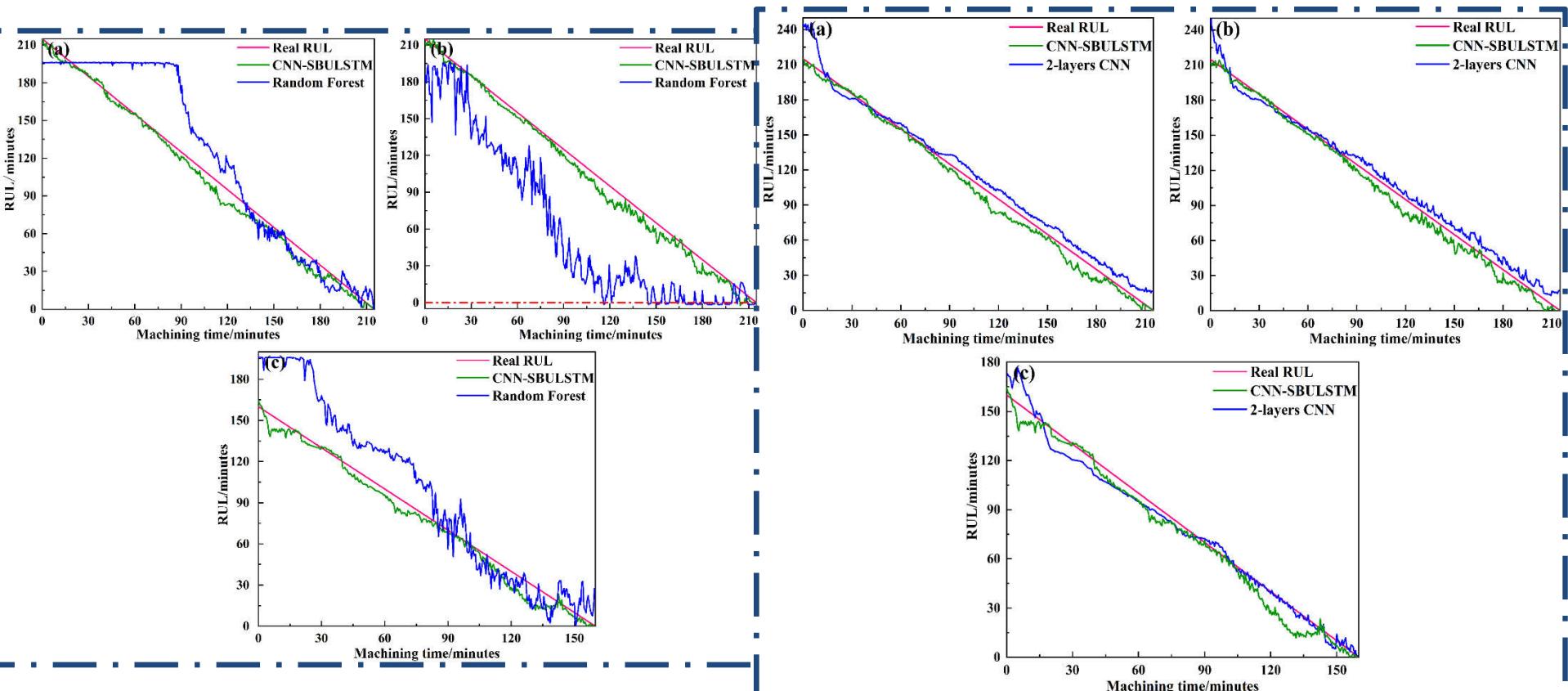
(a) Data pre-processing

Three-direction vibration and Three-phase current with a sampling frequency of 25600 Hz

Spindle power and tool position with a sampling frequency of 33 Hz



Tool remaining useful life prediction based on convolutional and stacked LSTM network



RUL prediction results:
CNN-SBULSTM network vs Random Forest

RUL prediction results:
CNN-SBULSTM network vs 2-layer CNN



Tool remaining useful life prediction based on convolutional and stacked LSTM network

(a) Performance comparison

Classical machine learning models

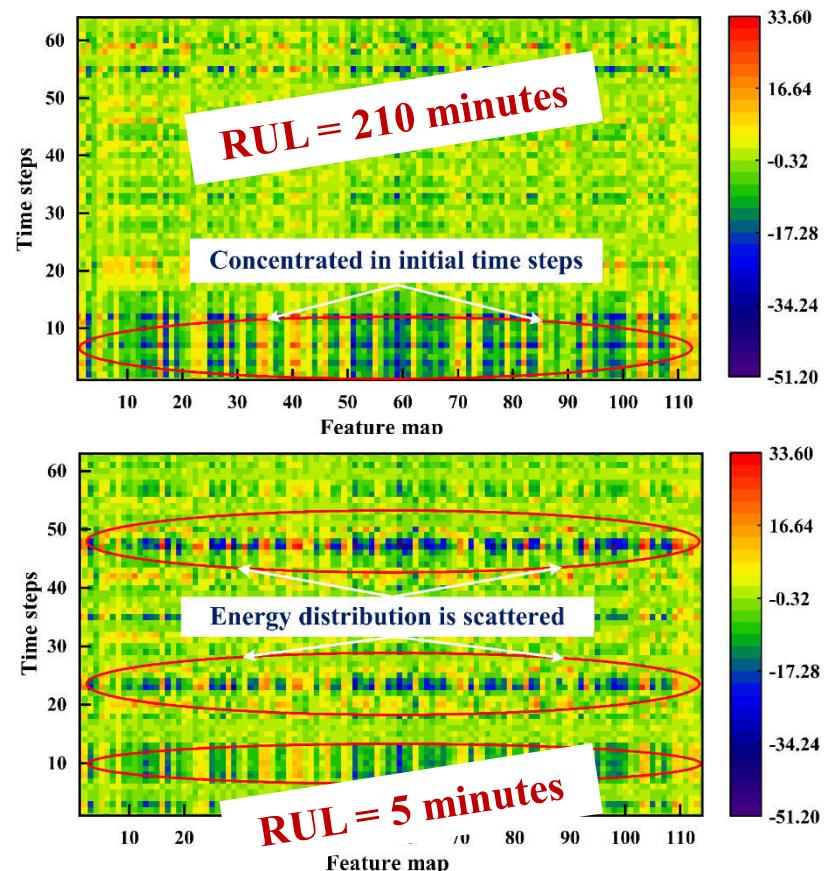
Models	Score	RMSE	Accuracy
SVR	57.5	35.2	0.7
RF	64.03	33.81	0.71
Feed-forward NN	56.5	38.35	0.67
22-layers BLSTM network	87.85	12.26	0.85
6-layers ULSTM network	77.04	23.47	0.75
2-layers CNN	88.42	8.07	0.86
CNN-SBULSTM	88.66	7.81	0.89

Deep learning models

Reasons for performance improvement

- ✓ CNN
- ✓ Dropout operation
- ✓ BLSTM layer

(b) CNN extracted features visualization

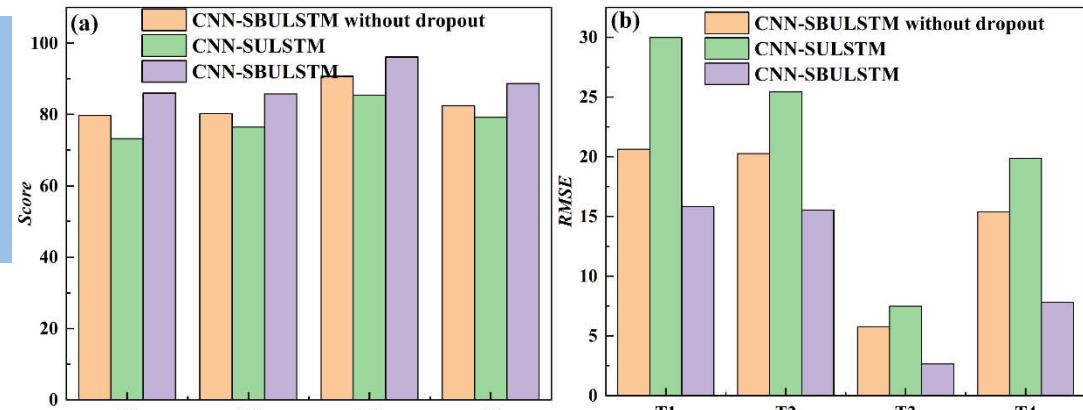




Tool remaining useful life prediction based on convolutional and stacked LSTM network

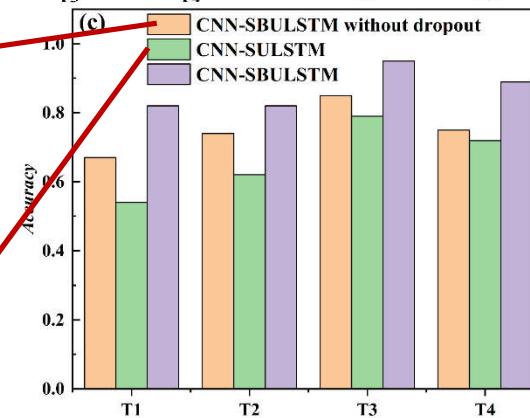
Reasons for performance improvement

- ✓ CNN
- ✓ Dropout operation
- ✓ BLSTM layer



Dropout layer: The applied dropout layers can relieve possible overfitting

BLSTM layer: BLSTM layer enable the SBULSTM network to consider the full context of each time step

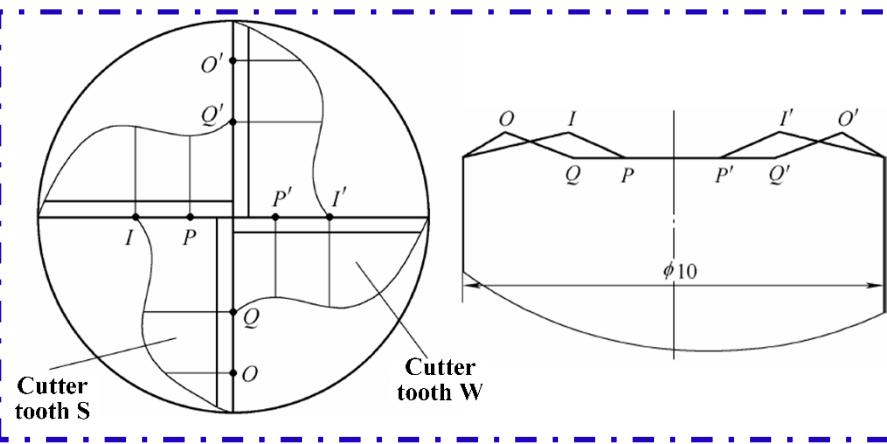




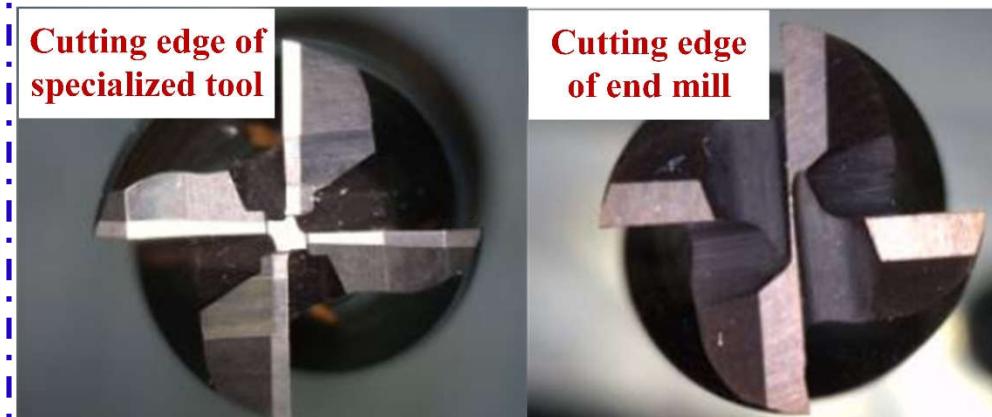
Research on Helical Milling Specialized Tool for CFRP/Titanium alloy

Background: To machine titanium holes without burr and CFRP holes without delimitation under dry cut condition during aircraft assembly site, a Helical Milling Specialized Tool with distributed multi-lattice end cutting edges is designed based on the chip-splitting principle and the movement characteristics of helical milling.

Key words: Chip-splitting; Helical milling; Multi-point front cutting edge



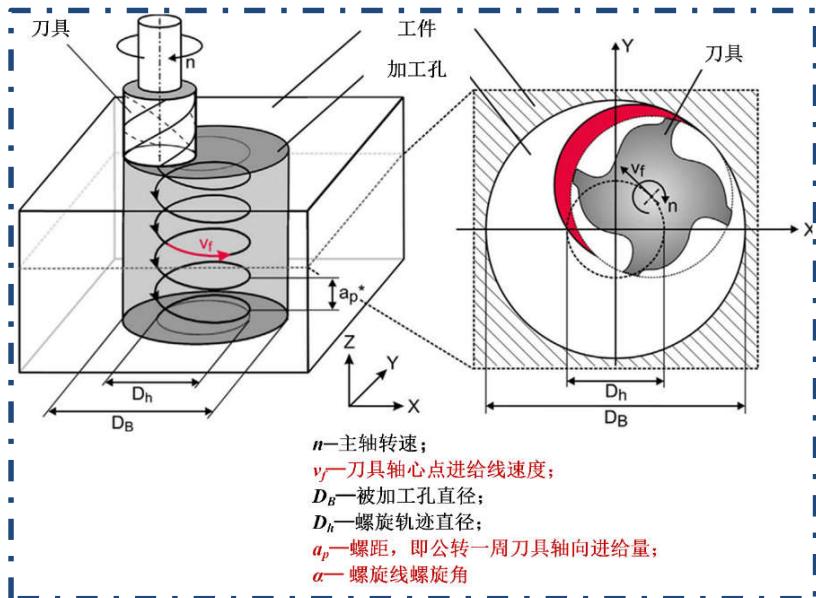
(a) Multi-point front cutting edge



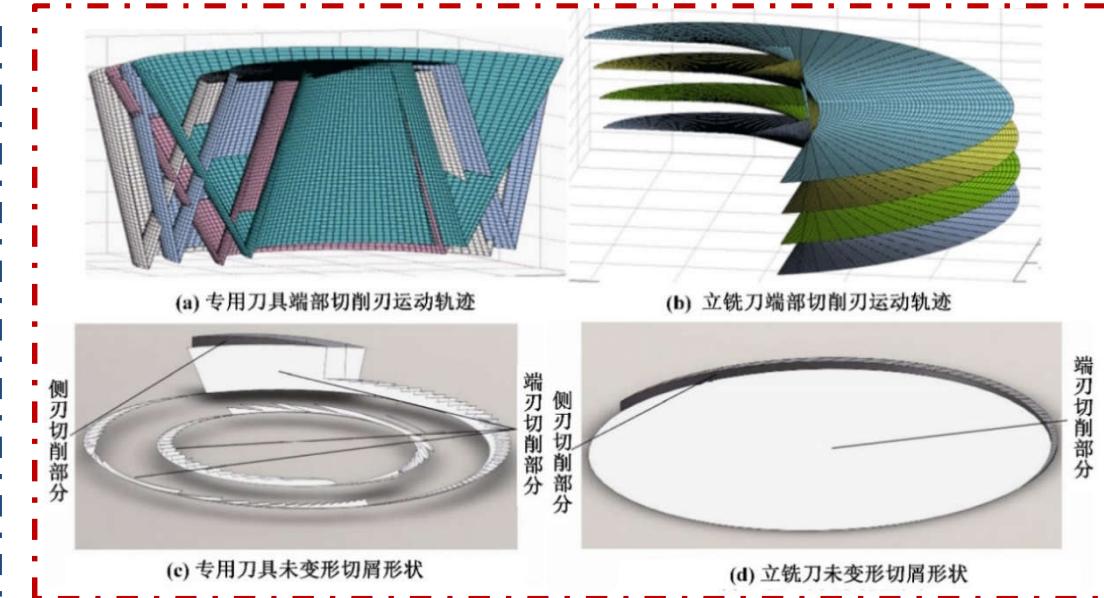
(b) Cutting tool



Chip separation simulation



(a) Kinematics analysis



(b) Motion trajectory and undeformed chip simulation

- ✓ The superposition of specialized tool end-edge motion path to achieve chip separation
- ✓ The undeformed chip obtained by the end edge of the specialized tool is two rings, and the joint is weak, easy to be separated, and the chip separation effect is good



Cutting Performance for CFRP/Titanium Alloy

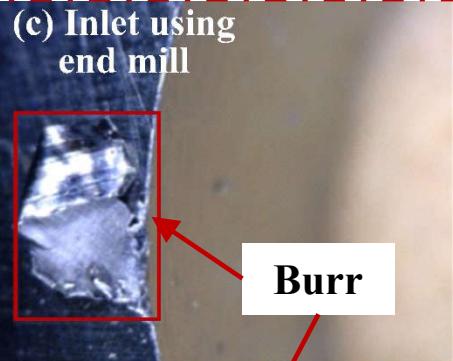
(a) Inlet using specialized tool



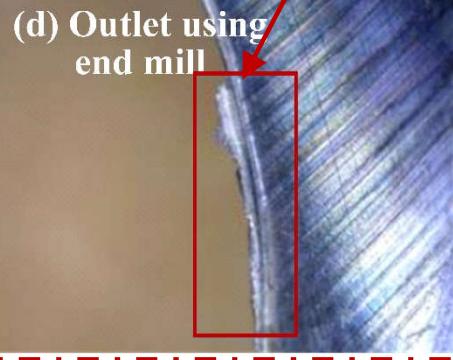
(b) Outlet using specializing tool



(c) Inlet using end mill



(d) Outlet using end mill



Chip generated by specialized tool



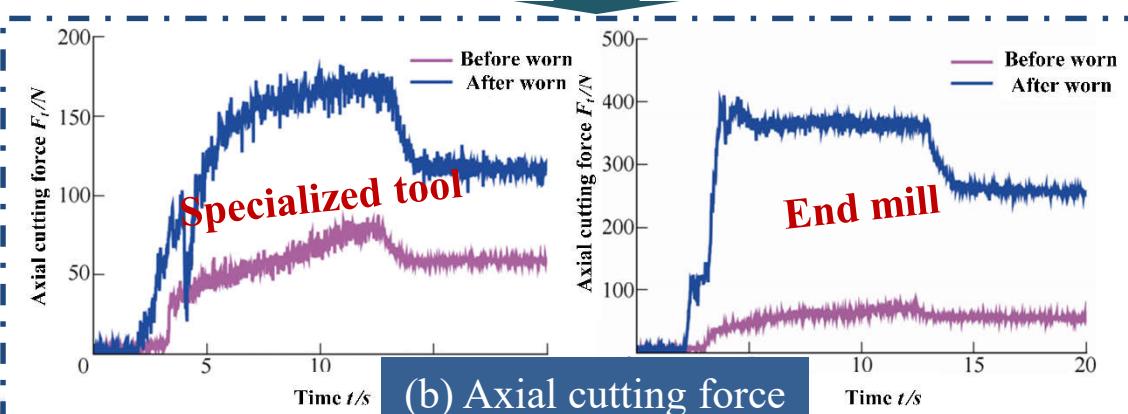
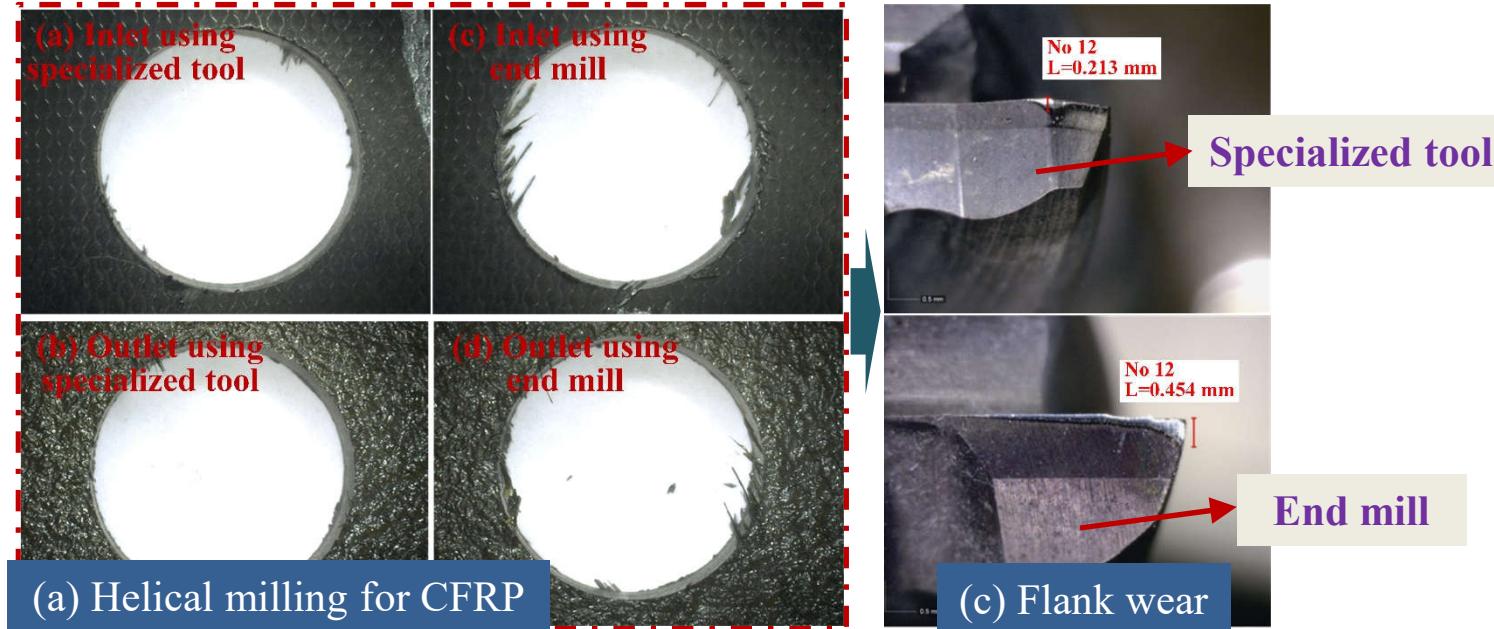
(b) Chip morphology

(a) Helical milling for Titanium Alloy

The hole quality is better than that of the end mill and
chips are mostly C-type chips and short band chips



Cutting Performance for CFRP/Titanium Alloy



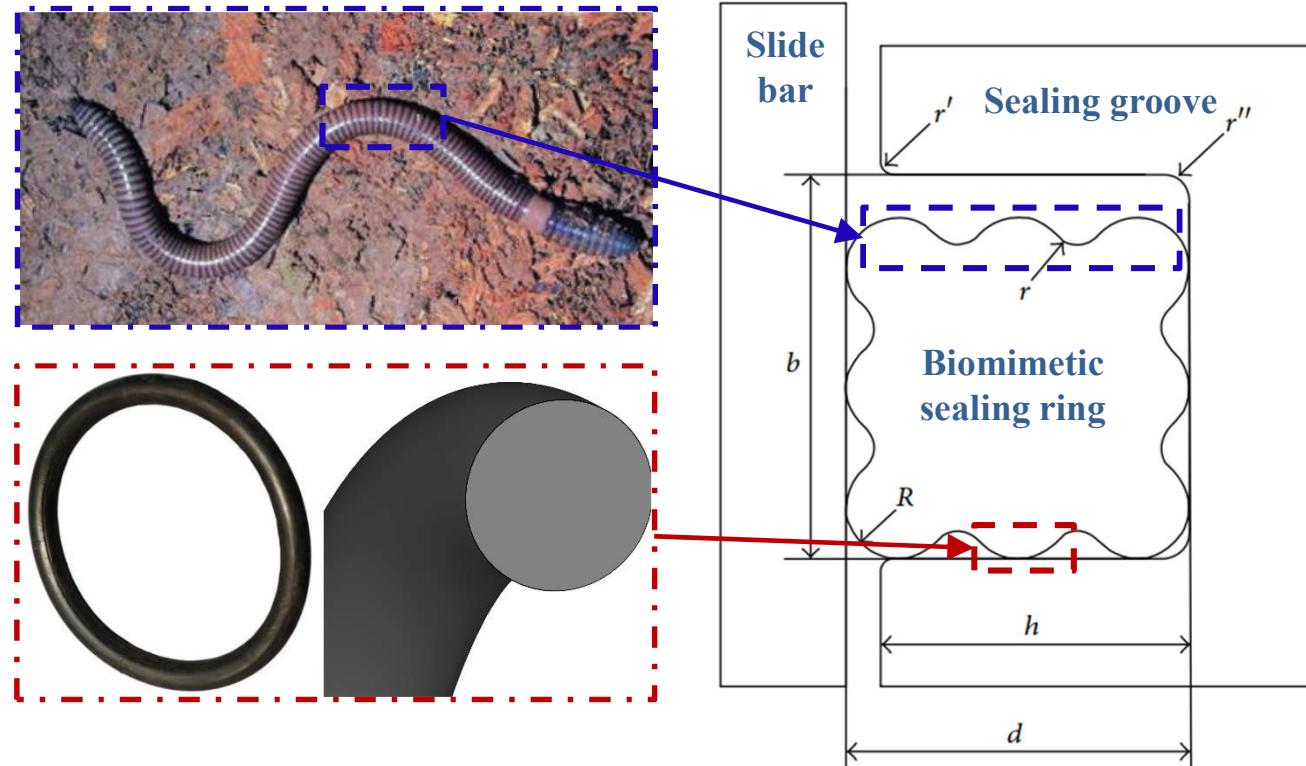
After making 12 holes, axial cutting force and flank wear is less than these of end mill, which means much longer service life



Structural Design and Sealing Performance Analysis of Biomimetic Flexible Sealing Ring

Background: In order to reduce the failure probability of rubber sealing rings in reciprocating dynamic seal, a new structure of sealing ring based on bionics was designed.

Key words: Bioinspired structure design; Rubber seal; Finite element method



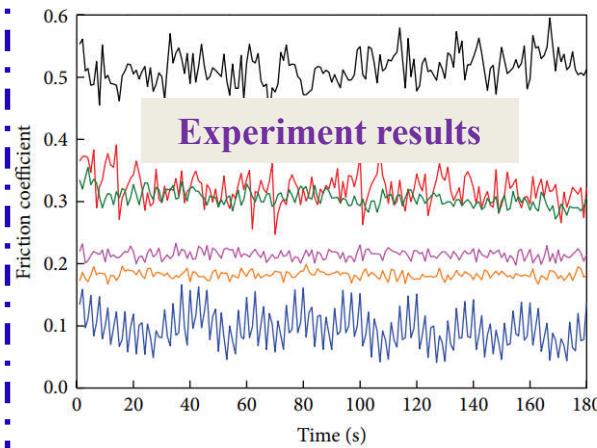


Finite Element Model

(a) Material Constitutive of Rubber:
Mooney-Rivlin model

$$W = C_1(I_1 - 3) + C_2(I_2 - 3)$$
$$\sigma = \frac{\partial W}{\partial \epsilon}$$

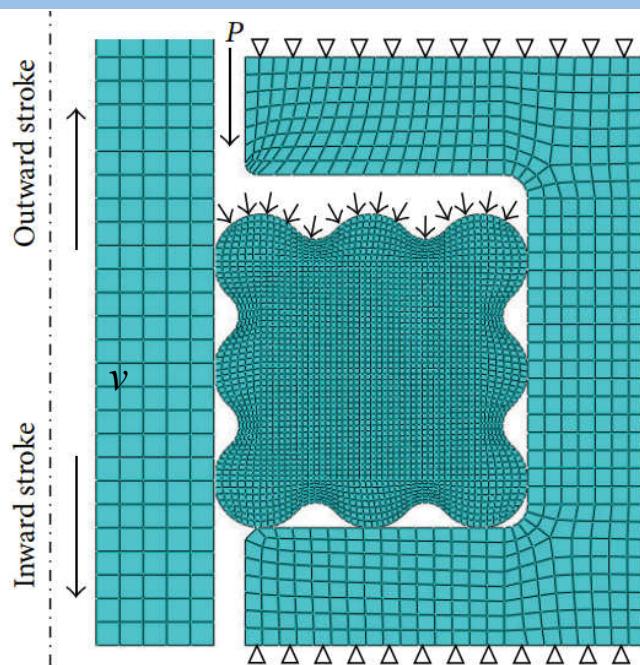
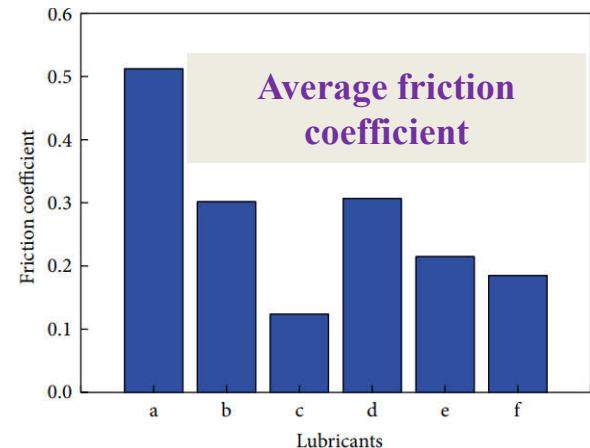
(b) Friction Coefficients



(c) Loading and Boundary Conditions

- ✓ Step 1: precompression (0.3 mm) to simulate the installation
- ✓ Step 2: medium pressure ($P = 3$ Mpa) was loaded on the working surface
- ✓ Step 3: apply the axial velocity ($v = 0.2$ m/s) at slide bar

(a) No lubricant (d) Water-base mud
(b) Water lubrication (e) Oil-base mud
(c) Oil lubrication (f) Oil-base lubricant

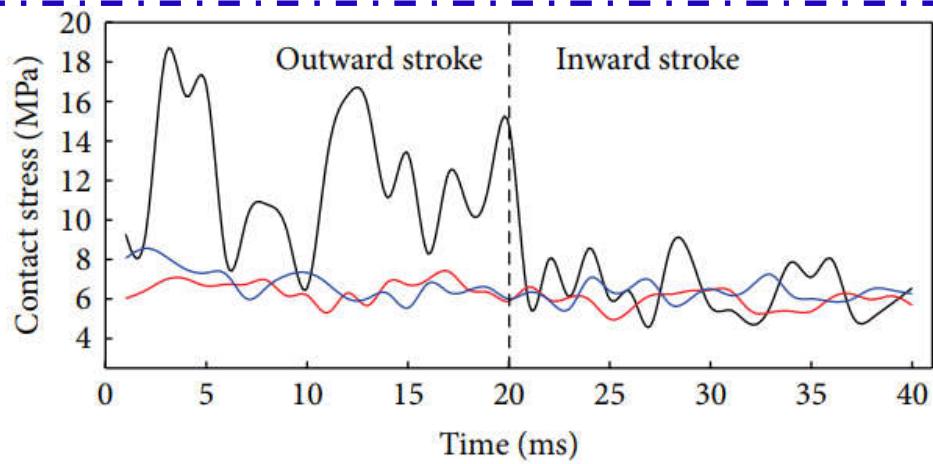
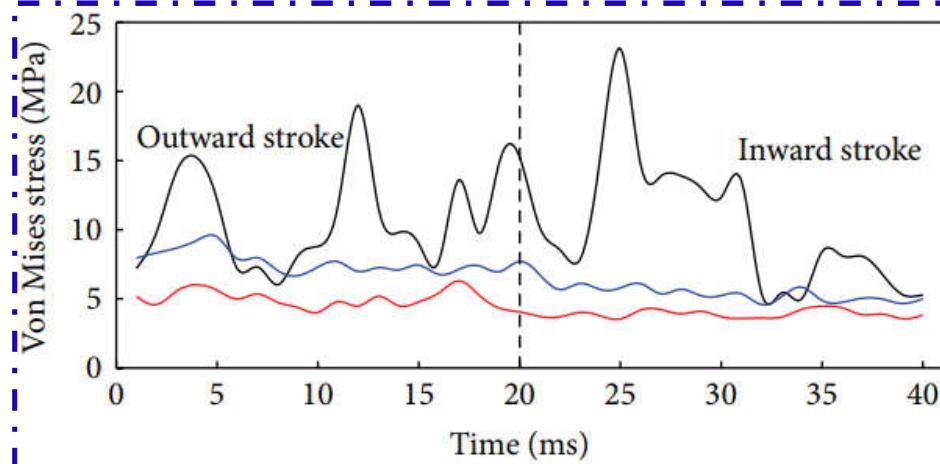




Reciprocating Dynamic Sealing Performances

(a) Comparison with Other Sealing Rings

— Rectangular ring
— O-ring
— Biomimetic ring



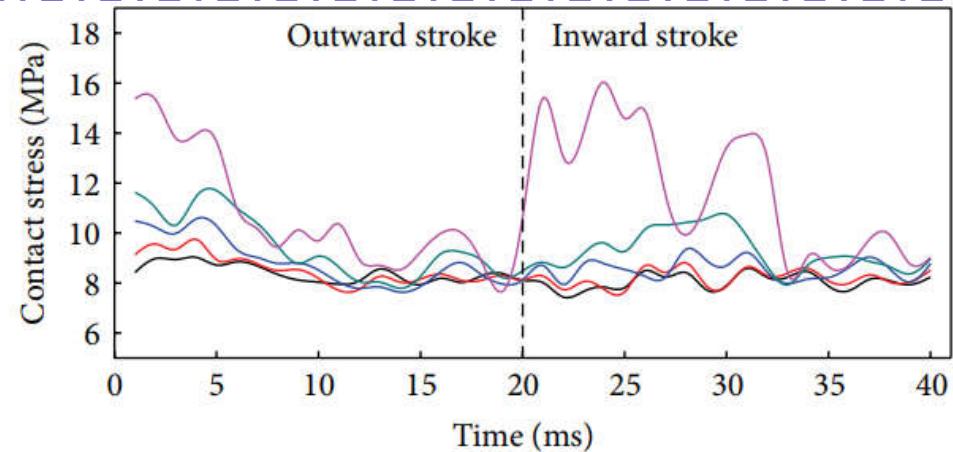
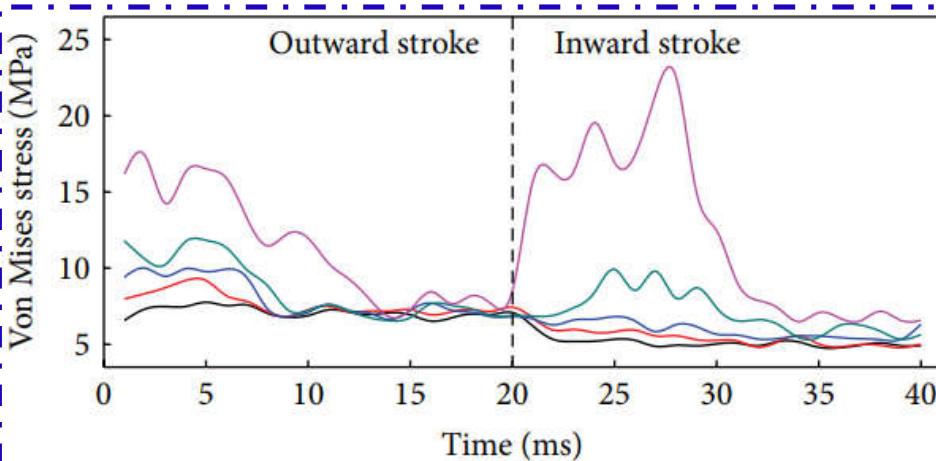
- ✓ Von Mises stress distributions of O-ring and biomimetic ring are more even
- ✓ Contact stress fluctuation of rectangular ring is more violent in outward stroke; serious creeping phenomenon appears
- ✓ Therefore, rectangular ring is prone to be torn or result in fatigue failure. While biomimetic ring has the same sealing performance as O-ring, but biomimetic ring can avoid rolling and distortion in reciprocating dynamic seal, which means much longer working life



Reciprocating Dynamic Sealing Performances

(b) Friction Coefficient Effect

— 0.15 — 0.20
— 0.25 — 0.30
— 0.35



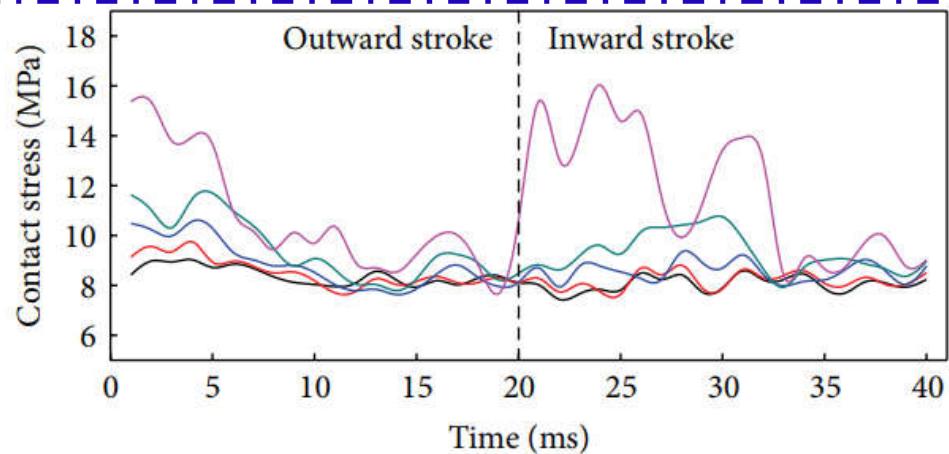
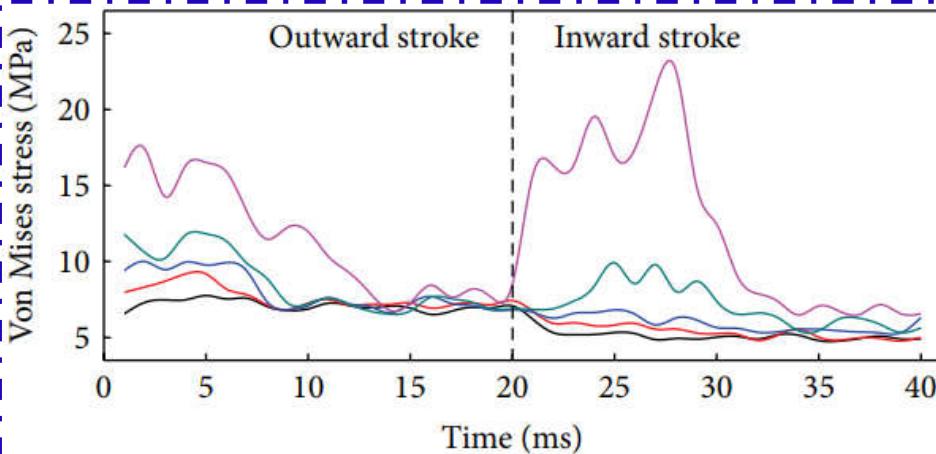
- ✓ At the beginning of the reciprocating motion, the von Mises stress and contact stress are higher than those in the later reciprocating motion
- ✓ Von Mises stress and contact stress increase with the increasing of friction coefficient
- ✓ When friction coefficient is larger than 0.3, creeping phenomenon appears



Reciprocating Dynamic Sealing Performances

(b) Medium Pressure Effect

— 0.15 — 0.20
— 0.25 — 0.30
— 0.35



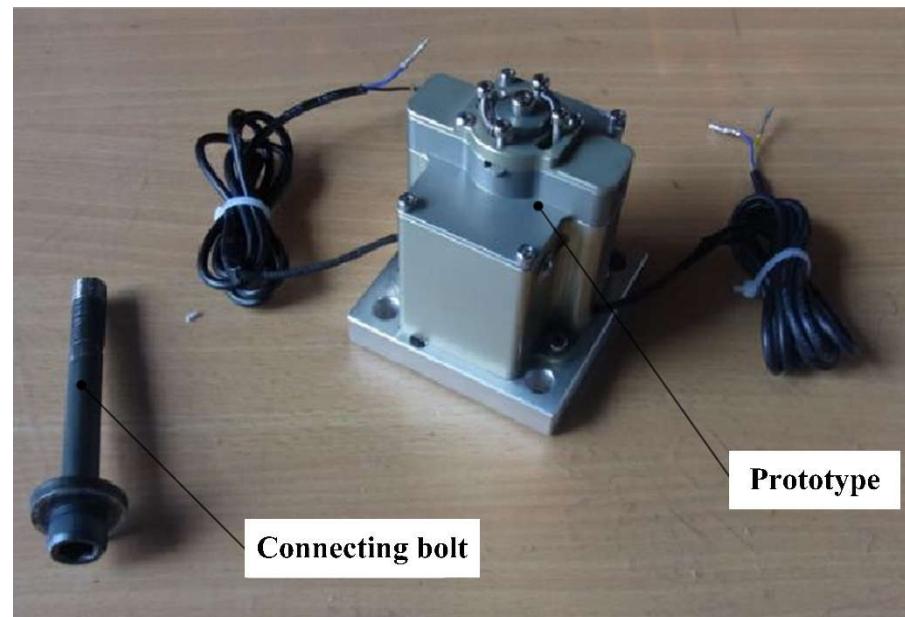
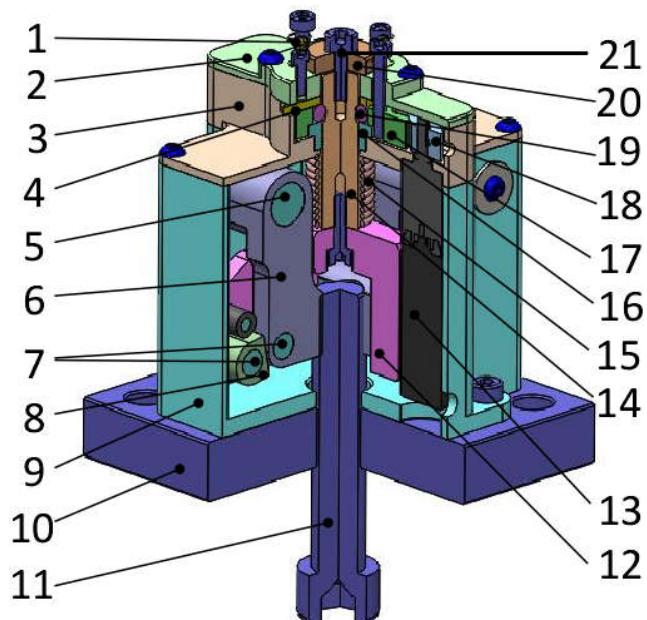
- ✓ At the beginning of the reciprocating motion, the von Mises stress and contact stress are higher than those in the later reciprocating motion
- ✓ Von Mises stress and contact stress increase with the increasing of friction coefficient
- ✓ When friction coefficient is larger than 0.3, creeping phenomenon appears



Research and Development of Low-Shock Non-Explosive Separation Device

Background: develop a low-shock non-explosive separation device that would connect the launch vehicle and small satellite reliably, and release the locking constraint when receiving separation signal

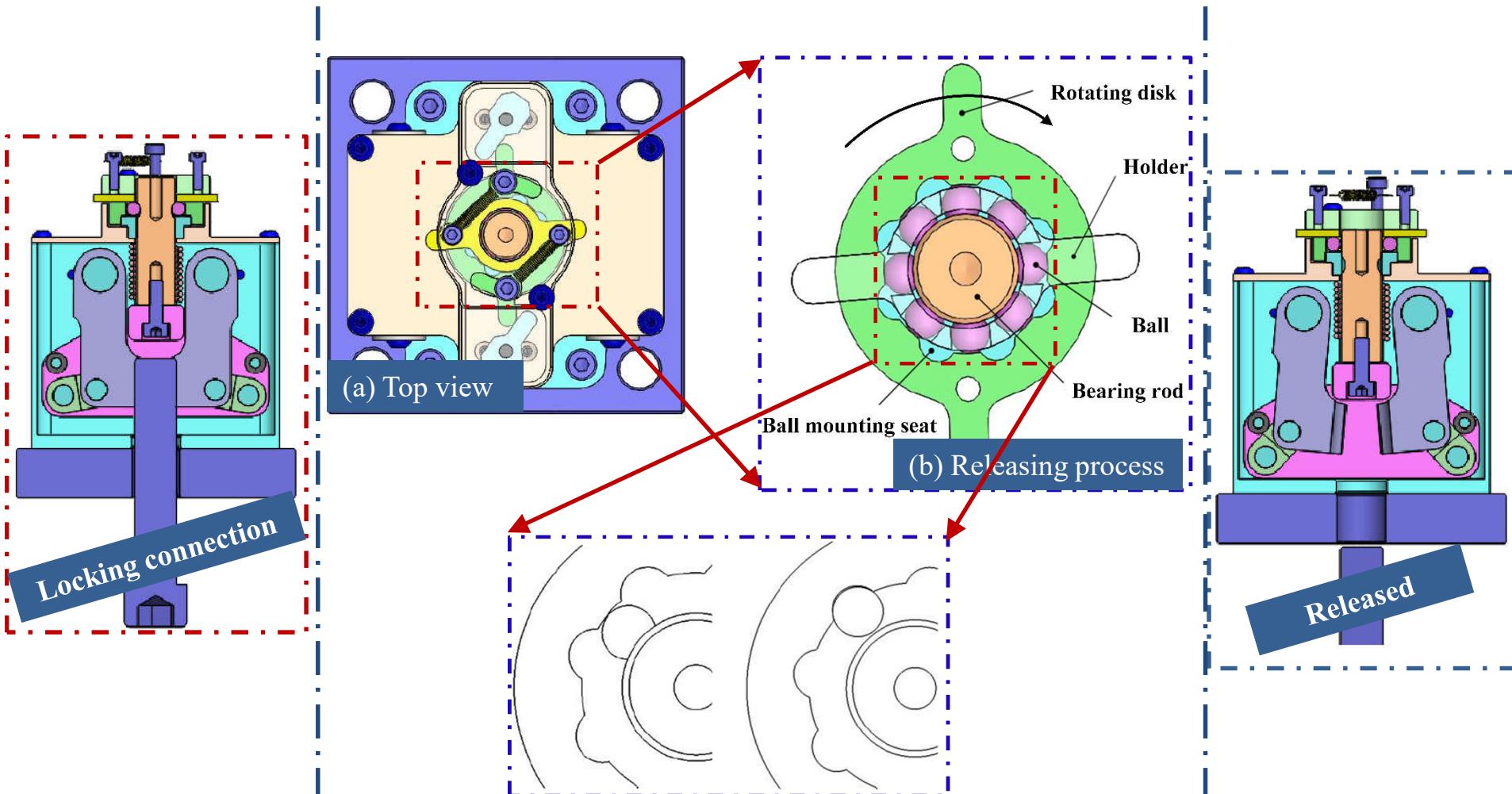
Key words: Separation device; Low shock; Segmented nut



1. Reset spring; 4. Holder; 6. Release clamp; 10. Base; 11. Connecting Bolt; 13. DC motor; 14. Bearing rod
15. Release spring; 19. Ball; 21. Reset Bolt



Working Mechanism





III. Publications & Presentations



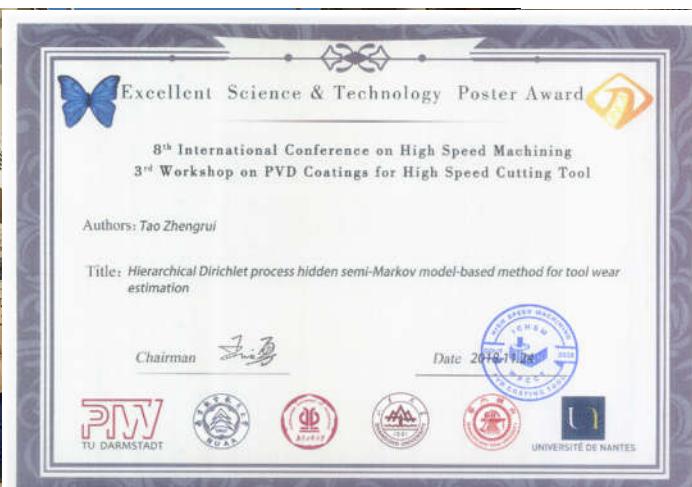
6 SCI-indexed papers and 2 EI-indexed papers in the field of condition monitoring, mechanical manufacturing, and precision measurement

1. Z. Tao, Q. An, G. Liu, M. Chen. A Novel Method for Tool Condition Monitoring Based on Long Short-Term Memory and Hidden Markov Model Hybrid Framework in High-Speed Milling Ti-6Al-4V. *International Journal of Advanced Manufacturing Technology*, 105 (2019) 3165-3182. (*Published, IF=2.496*)
2. Z. Tao, J. Dang, J. Xu, Q. An, M. Chen, L. Wang, F. Ren. Eddy Current Distance Measurement Calibration Method for Curved Surface Parts Based on Support Vector Machine Regression. *Journal of Shanghai Jiaotong University* in Chinese with English abstract, 2019. (*Accepted, IF=0.955*)
3. Z. Tao, J. Dang, J. Xu, Q. An, F. Ren, L. Wang. High-precision calibration method and application for coating thickness measurement of curved surface based on eddy current displacement sensor. *Journal of Zhejiang University (Engineering Science)* in Chinese with English abstract, 2019. (*Accepted, IF=1.018*)
4. Q. An, J. Chen, Z. Tao. Experimental investigation on tool wear characteristics of PVD and CVD coatings during face milling of Ti-6242S and Ti-555 titanium alloys. *International Journal of Refractory Metals and Hard Materials*, 86 (2020) 105091. (*Published, IF=2.794*)
5. Q. An&, Z. Tao&, X. Xu, M. El Mansori (&co-first authors). "A Data-driven Model for Milling Tool Remaining Useful Life Prediction with Convolutional and Stacked LSTM Network." *Measurement*, 2019. (*Accepted, IF=2.791*)
6. J. Li, Z. Tao, X. Cai. Experimental and Finite Element Analysis of the Formation Mechanism of Serrated Chips of Nickel-based Superalloy Inconel 718. *International Journal of Advanced Manufacturing Technology*, 2019 (*Under Review*)
7. X. Xu, Z. Tao, Q. An, M. Chen. "A Multimodal Based on Deep Learning and Multi-sensor Information Fusion for Monitoring and Diagnostics." *Measurement*, 2019. (*Under Review*)
8. C. Cai, X. Liang, Q. An, Z. Tao. "Experimental Study on the Cooling/Lubrication Performance of Dry and Supercritical CO₂-based Minimum Quantity Lubrication in Peripheral Milling Ti-6Al-4V." *International Journal of Precision Engineering and Manufacturing-Green Technology*, 2019. (*Under Review*)



2 conference papers and a China patent

1. Z. Tao, Q. An, M. Chen. Cutting Performance Evaluation of Helical Milling Specialized Tool for CFRP/Titanium Alloy. *14th China-Japan International Conference on Ultra-Precision Machining Process*, Harbin, Sept 13-15, 2018 (**Best Paper**).
2. Z. Tao, G. Liu, Q. An, M. Chen. Hierarchical Dirichlet Process Hidden Semi-Markov Model-based Method for Tool Wear Estimation in High-Speed Milling Ti-6Al-4V. *8th International Conference on High Speed Machining*, Guangzhou, Nov 22-24, 2018 (**Excellent Poster**)
3. M. Chen, F. Ren, Z. Tao. "Non-contact Type Measuring Method and Device for Metal Surface Coating Thickness." China Patent, CN109141325A (*In Public*);

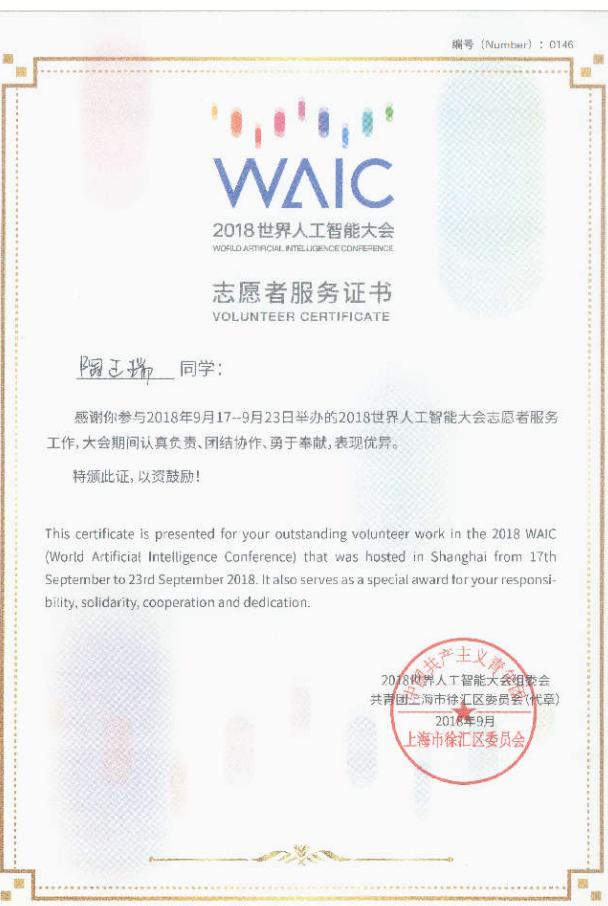




IV. Other Activities



Volunteer: The First International Import Expo; 2018 Shanghai International Marathon; 2018 WAIC (World Artificial Intelligence Conference)





Internship – Data analyst at the Engine Systems Dept. of FCA company; Software developer at the Clobotics





Teaching Assistant - Course: *Introduction to Engineering*





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Thank you!

